MSc Graduation thesis:

Youth care waiting list dynamics:
A discrete Event Simulation approach

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February 2011

Acknowledgments

This master thesis is the final project in the engineering curriculum of the TU Delft master program "Engineering and Policy Analysis". For the realization of this thesis I am indebted to many people.

First my gratitude goes out to INITI8, for providing this challenging research topic with a clear societal relevance and for making the currently used SD model and gathered historical sources available.

From TU Delft, I want to thank my thesis committee for their help and patience. Joseph Barjis for being the projects first supervisor, Mamadou Seck for sharing his knowledge in, data analysis and model validation, Alexander Verbraeck for being the chairman of the committee and for providing the guidance to overcome the data study barrier. In particular, my gratitude goes out to Els van Daalen for her input on SD modelling, for providing extensive punctual feedback and most of all for providing personal support and understanding.

Finally, I would like to thank my friends and family for their support and patience through this long journey. Hans en Klaartje for their endless reading. To my parents for their financial support through the study, my mother for being interested and asking countless questions, my father for not asking questions. My sister Leonie and brother from another mother Michiel for being the best friends I could ever wish. My girlfriend, Tessa, for her patience and believe in better times after the thesis.

Arjan van der Hout
Scheveningen, februari 2011

Abbreviations

AH	Ambulatory Care
BJZ	Bureau Jeugdzorg
DES	Discrete Event Simulation
DH	Day Care
FIFO	First in First out
PI	Performance indicators
PZ	Foster Care
RH	Residential Care
SD	System Dynamics
SIRO	Service in Random Order

Executive Summary

This thesis evaluates the insights a developed Discrete Event Simulation model provides, in addition to currently used System Dynamics model, in the youth care decision-making process.

The publicly funded Dutch youth care sector is an example of a complex heavily resource bounded health care system with a high intolerance to failure. The Youth Care Act defines the legal entitlement of youth care to children within an acceptable waiting time of maximum nine weeks. Last decades the youth care sector faced long waiting lists and over utilized resources. Additional government funding did not result in a structural solution.

Effective decision making in the youth care sector is complex and in-transparent due to horizontal and vertical aggregations layers (Leewen, Naborn et al. 2008). The national performance indicators measure the number of children on the waiting lists and the waiting time for each child. The care provision process of a care provider is subdivided in independent parallel sub-process aggregated to four care types, which require different resources. The distinct care types are; Ambulatory care, Day care, Residential care and Foster care. Effective youth care management requires creating insight into the interrelations between the anticipated child demands, possible capacity policies for the care types and the resulting waiting times for individual children. Due to this complexity and the high intolerance to failure for every child, youth care authorities and care providers require decision support models to oversee the consequence of their mutual capacity decisions.

Simulation modelling is one of the most commonly used Operational Research approach and many regard simulation as the technique of choice in the health care sector (Lowry 1992; Brailsford 2007). INITI8 is a consultancy company that supports the authorities and care providers in this complex and dynamic environments by providing simulation models. Two approaches to simulation modelling widely used in this demanding environment are System Dynamics (SD) and Discrete Event Simulation (DES). INITI8 currently uses simulation models based on the System Dynamics Paradigm. This research practically evaluates the additional insights a developed DES model provides, above currently used SD model, with historical data of a real world care provider over 2008 and 2009.

The delineated system in current research describes the logistic children flows through a care provider. Only actors, objects and documents that directly influence this logistic are considered in both currently used SD and in the developed DES model. Financial considerations serve as an important criterion for possible policy options. Taking into account to objective of current research, to compare two dynamics modelling approaches, the decision is made to focus on the dynamic children flows in the system, the financial functions are outside the scope of current research.

The essential difference between the SD and DES methodology is their difference in system aggregation. A SD model abstracts the system as a continuous quantity rather like a fluid no individual entities are distinct. A DES model disaggregates the system to individual entities, each of those entities can posses characteristics that determine their individual flow through the system. Literature argues that a DES model has benefits in comparison to a SD model for the modelling of real world systems that face heterogeneous entities, a large impact of individual variability and a high intolerance to failure for those entities, such as youth care. A precondition for those benefits in such a system is the availability or collectability of data to quantify the individual characteristics. Furthermore, the higher level of detail should be worth the required additional investments of time and costs.

Any Logic simulation software is used to build the DES model, because it enables an object oriented model structure and the mixing of processes oriented flowchart with individual state charts in one model. This is required to capture the complexity of the different layers, the independent process sub-models for the four care types and the complex coupling between children and trajectories

The transformation from a aggregated to a disaggregated model requires disaggregation of model inputs. In the SD model, perfect mixing of children is assumed, every child receives the same set of care services. A disaggregated DES model requires determining the individual path, of children and the care services they receive through, the care providers system. This involves determining the

conditionality relation between a child's possible parallel, overlapping and sequential care services. Unlike the SD model, the DES model distinguishes individual entities on the waiting list a queue mechanism needs to be defined to determine the ordering of those entities on the waiting list.

The complex process of deriving heterogeneity and conditionality relations between the care services is data dependent and time consuming. A large part of the data is required to create a system history, in order to distinguish the care services assigned to new children from additional care services assigned to previously registered children. The analysis shows that a large part of the demand variability observed at the independent care systems is created by the additional care services assigned to previously registered children. Furthermore, a large variability in individual treatment times and significant conditionality relations between a child's care services were found.

A general difficulty of simulation in the youth care sector with regard to the validation data is found. Due to the infinite nature of the youth care process, the treatment times of multiple months until multiple years, the large variability in those treatment times and the auto-correlation of monthly waiting list data, a large time span of validation data is required to determine accurate statistic estimators. The available data set of 29 months is too small for a quantitative validation of the models based on these statistics.

The SD model, configured with a stochastic children inflow function, is not ably to abstract the variability in monthly waiting list behaviour observed in the real world system. The DES model abstracts a comparable variability and stability in monthly trajectory waiting list behaviour as observed in the output of the real world system, which increases the credibility of the DES model. Furthermore, the observed real world trajectory waiting list outputs lie in the boundaries of the stationary DES model output space. This provides a proof that the observed waiting list dynamics in the real system can be produced by process variability in a stationary system. In comparison to the SD model, the DES model is more sensitive to changes in scenario's and capacity policies. Arguable, this conflicting insight is a result of the better abstraction of the process variability in the DES model. The large spread and variability in the DES waiting lists outputs provide insight in the complexity of decision-making in the youth care sector. It is difficult to distinct transient behaviour from stationary variability in the care provider system. A DES model can provide additional insight in the stationary system behaviour.

Further research into the applied queue mechanisms in the real world system is indispensable to provide accurate quantitative insight into the waiting lists and waiting time behaviour. From experimentation with the DES model, it is concluded that because of the interaction between the queue mechanisms and the withdrawal mechanism, not only the waiting time distribution but also the average waiting times are sensitive to the applied queue mechanisms. Furthermore, the sensitivity of the system to changing scenarios and policy options is dependent on the queue mechanism applied in the system. The DES model cannot provide accurate quantitative predications without a better insight into the real world queue mechanisms and priority. The DES model can be used to create qualitative insight into the system, controlled for the stability of the conclusions for different queue mechanisms.

A proof of concept of DES modelling in the youth care sector is provided, further research is necessary for a successful implementation.

Contents

Part 1: Problem signalisation and definition

Chapter 1
Introduction

In recent decades, health care demand and costs have dramatically increased, while health care organizations have been under severe pressure to provide improved health care for their patients. As a result, nowadays health care systems face unprecedented levels of challenge, scale and complexity. The increasing societal and political pressure on the heavily resource constrained health care systems is daunting. Due to this overwhelming complexity and the high intolerance to failure in these systems, the health care authorities and care providers require tools to foresee the consequence of their decisions (Kuljis, Paul et al. 2007)**.**

Simulation modelling is one way to explore the consequences of alternative decision scenarios. It is one of the most commonly used Operational Research approach and many regard simulation as the technique of choice in the health care sector (Lowry 1992; Brailsford 2007). It has advantages over other techniques in its flexibility, ability to deal with complexity, variability and uncertainty, and its use of graphical interfaces to facilitate communication with and comprehension by health care professionals (Brailsford and Hilton 2001).

Surprisingly, while the academic publications in health care simulation abound, the relatively small number of successful implementations would suggest that (outside academia) simulation modelling has been underused in the health sector compared with manufacturing and defence industry (Chanal and Eldabi 2010). Recent studies suggest that health care is either inexperienced in such methods or prone to failure. The amounts of unsuccessful experiences abound in health care literature. It might well be that the way in which modelling and simulation methods are often used in industry requires adaptation for health care (Carter and Blake 2005). Patients are not typical customers, mainly because they are more responsive and increasingly keen to exercise meaningful and informed choice. Furthermore, the health care sector is overly responsive and sensitive to political influence and control. Political intervention in health care is, usually closely linked to the so-called societal view. It is argued that the different health care stakeholders with their diverse interests and views impose a number of unique pressures that are not encountered in other industries. The systematic evaluation of complex health care policies often faces tough challenges which includes connecting different layers of influence (governmental, organizational, procedural) (Kuljis, Paul et al. 2007). Two approaches to simulation modelling widely used in this demanding environment are System Dynamics (SD) and Discrete Event Simulation (DES).

The Dutch youth care sector is an example of a complex heavily resource bounded health care system with a high intolerance to failure. The publicly funded youth care sector is sub divided in multiple autonomic regional systems, which either cover provinces or urbanized regions. The authorities of the provinces and urbanized regions are responsible for the management of their regional system. They face a multi-actor setting in which multiple public and private organizations cooperate. The complexity of operational and strategic management on regional level is steered by the distributed responsibilities (Leewen, Naborn et al. 2008). Last decades, the youth care sector has been suffering from long waiting lists, over-utilized resources and a growing budget demand.

INITI8 is a consultancy company that supports the authorities and care providers in this complex and dynamic environments by providing simulation models. INITI8 currently uses simulation models based on the System Dynamics Paradigm (SD). New request for detailed operational decision support arising from the youth care sector exceed the functionalities of currently used models. A disaggregated Discrete Event Simulation (DES) model is perceived a possible solution to close the current information gap in the youth care decision-making process. The intention of this thesis is to explore the insights that a Discrete Event Simulation (DES) model can provide in the complex youth care sector, in addition to the currently used System Dynamic model (SD).

1.1 Research background

This section introduces the background knowledge of the two main fields of the thesis; youth care and simulation. This knowledge forms a foundation for the research objectives provided in the following section.

1.1.1 Youth care

Youth care covers all forms of care available to parents and children to help with serious development and parenting problems. Youth care clients are young people up to the age of eighteen who are going through serious development and parenting problems and who do not receive sufficient support by the general systems that provide education, health care and social support. Care can be provided until the age of twenty-three if it is necessary to continue supporting a young person. Support is available not only to young people but also to the parents or guardians of youth who go through development and parenting problems.

The Dutch youth care system consists of 15 autonomic regional systems that cover the 12 provinces and the urbanized regions of Amsterdam, The Hague and Rotterdam. The organizational structure of the youth care sector, representing the annual financial flows in the system, is depicted in Figure 1-1. A series of relevant actors is recognized: the responsible Ministry, the provincial authorities, Bureau Jeugdzorg (BJZ) and the organizations that provide the actual care, the care providers. Figure 1-1 distinguished the 15 regional systems and the Ministry that controls the regional systems with their money flow.

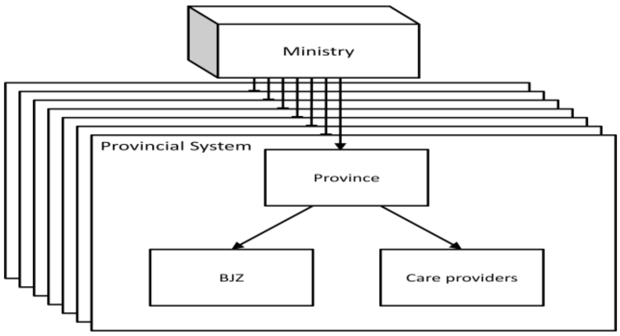


FIGURE 1-1 THE YOUTH CARE SYSTEM ORGANIZATIONAL AND FINANCIAL STRUCTURE

The youth care is funded by the provincial authorities in the context of the Youth Care Act (Commissie Financiering Jeugdzorg 2009). The Youth Care Act has two aims: to ensure that better care is made available to young people and their parents (the clients of the youth care process) and to strengthen their position in the process. The objective of the act is to give the client a central position in a more transparent youth care system. This principle is reflected by the following policy objectives (Ministry of Health Welfare and Sport 2005):

1. *The needs of the client come first*

In the past, youth care was organised around the availability of care capacities at the institutes and organizations. The youth care act takes the need of the client as its starting points instead of the available care capacity.

2. *Entitlement to youth care*

The youth care act has introduced an important new principle: a client is entitled to the care services indicated by the institutions of youth care. Furthermore, this care should satisfy certain conditions. An important condition, central to the current research, is a limited waiting time for the entitled care products. Performance agreements made between the actors in the youth care chain stated this condition at a maximum waiting time of nine weeks.

3. *A single access point to the youth care system*

Each province or regional system has an independent youth care agency [Bureau Jeugdzorg (BJZ)], which acts as the single access point in its area of for all youth care. The youth care agency has the sole responsibility to independently asses the needs of youth who present themselves with problems.

To avoid capacity driven care need assessments and to create transparency to parents and children in need of support.

1.1.2 Simulation

Computer simulation is used not only in engineering applications, but also in economics, business, management science, public administration, social science and health care. It is a relatively cheap and convenient investigative tool for imitating the real world. The expanding use of simulation in such diverse fields marks it out as an important tool for research and decision-making. Robinson (2003) defines simulation as:

"Experimentation with a simplified imitation (on a computer) of a real world system as it progresses through time, for the purpose of better understanding and/or improving that system"

Simon (1998) proposes that simulation is not only an aid for studying poorly understood systems but can itself be a source of new knowledge. This is because, in practice, knowledge is constructed from the roof down, not from the foundation up, and that makes it possible to discover incrementally finer details at lower and more fundamental levels.

Two simulation methodologies frequently used in health care are System Dynamics (SD) and Discrete Event Simulation (DES). While each approach represents certain facets of the world, both approaches also simplify specific facets of the real world (Meadows 1980; Pidd 2004). Both methodologies are build upon fundamental assumptions, which are rarely questioned within a respective modelling community (Lorenz and Andreas 2006; Morecroft and Robinson 2006; Chanal and Eldabi 2008). When applying a methodology without being aware of these assumptions there is a risk of accepting a wrong conclusion (the abduction risk). Interpreting the important facets of the real world is dependent on the specific problems at hand.

The fundamental difference between the SD and DES methodology lie in the different assumptions regarding the roots of complex behaviour (Brailsford and Hilton 2001; Lorenz and Andreas 2006). Behaviour in the SD methodology is assumed to arise from endogenous, deterministic and structural properties of the system. Behaviour in the DES methodology is assumed to arise from the interaction of stochastic processes. Both deterministic and stochastic models have important roles to play in the analysis of a particular system to ensure we do not become trapped in either deterministic fantasy or unnecessary mathematical detail (Morecroft and Robinson 2006). Where the facets of the real world and their implications are not clearly understood (which is likely to be the motivation for modelling) both type of models can provide important and possibly differing insight.

1.2 Research framework

The research framework makes the research setting, problem and objectives transparent. After which the research objective is broken down in practical research questions to provide a direction to the research.

1.2.1 Problem owner and research setting

The consultancy company INITI8 is considered the problem owner of the current research. It is a progressive, innovative company focused on solving inter-organizational bottlenecks in logistical processes and networks. The company supports organizations in the youth care system to keep their processes manageable by providing insight in their planning and control cycle. Two main products are distinguished: business intelligence to evaluate implemented policies and simulation modelling to evaluate possible policy options. Their currently used simulation models are based on the SD methodology.

A system diagram can be used as a starting point for a discussion of the youth care system. Such a diagram provides an overview of the problem owner, other actors and stakeholders, the system to be analyzed, policy measures, external influences and outcomes at a quick glance. A system diagram helps to structure the problem and to define the system. Bots (2002) provides an extensive discussion of system diagrams. Figure 1-2 presents a highly aggregated system diagram of the research setting.

Noticeably, the problem owner does not directly influence the system. The problem owner can provide knowledge and advice solutions to the actors that can influence the system. Furthermore, the provincial or regional youth care system is visualized as part of a bigger system, the national youth care chain.

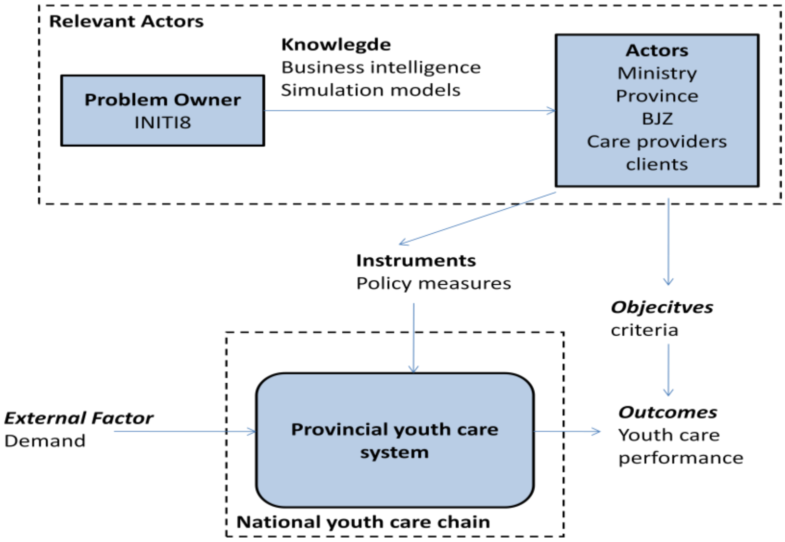


FIGURE 1-2 YOUTH CARE SYSTEM DIAGRAM ADAPTED FROM BOTS(2002)

1.2.2 Problem formulation

R.L Ackoff indicates the importance of a clear problem formulation in societal problem solving:

"Successful problem solving requires finding the right solution to the right problem. We fail more often because we solve the wrong problem than because we get the wrong solution to the right problem." (Ackoff 1974)

The simulation analyst must take extreme care to ensure that the problem owners agree and understand the problem formulation. Therefore, the statements in the problem formulation have to be precise and easy to understand. The problem owner as introduced in previous sections is a consultancy company of which the consultants are educated, skilled and experienced in the field of simulation and statistical analysis.

As introduced in previous section, children in the Netherlands are legally entitled to youth care within an appropriate delivery time. Performance agreements between the actors in the youth care sector determined a delivery time for each child of *nine weeks*. Furthermore, the needs of the client comes first, care assessments are made independently from capacity availability. This organizational context creates a necessity in the youth care sector to align the resource capacity with the anticipated future demand. The twelve provinces and three regional systems have the formal responsibility for aligning the capacity of the autonomic care providers in their region with the anticipated demand to assure fulfilment of the performance agreement. INITI8 supports the care providers and province by providing decision support models. The objective of these models is to provide understanding of the child waiting list behaviour and to evaluate the impact of various capacity strategies, a care provider can implemented, on this behaviour. The models serve as negotiation tools in the process of aligning the anticipated demand, the capacity strategy and the anticipated care provider performance.

The definition of a problem is the difference between what is considered desirable and the present reality, in other words the gap between the facts and the norms (Hoogenwerf 1987). The problem gap can best by described by the experienced limitations of currently used SD care provider model:

The currently used SD model provides insight in the expected aggregated system performance and the impact of various scenarios and strategies on the average system performance. The aggregated model cannot provide insight into the observed behavioural patterns of the system and the spread of *individual child performance measures created by the system variance and uncertainty. The youth care sector, in which every child counts, faces a high intolerance to failure for every child. Insight into the robustness of performance indicators in the current situation, for possible strategies of operation and for anticipated future scenario's is required.*

1.2.3 Research Objectives

The starting point of this thesis is the previously introduced problem regarding the availability of decision support information to evaluate care provider capacity strategies. More specific, the problem owner has the perception that a stochastic DES simulation model provides additional functionalities over the currently used SD model, which bridges the previously described problem gap. This section defines the research objectives subdivided for the youth care sector and the problem owner.

1. *Youth care sector perspective*

The research should contribute to operational and policy decision processes in the youth sector by helping to bridge the perceived information gap concerning current waiting list dynamics.

2. *Problem owner perspective*

The research should form contribution to the available knowledge within INITI8 by providing a proof of concept of additional insight of DES modelling in the youth care sector for current and potential partners of INITI8[1].

The synthesis of these objectives determines the main goal of the research:

The main objective of this research is to evaluate the additional insights a DES model can provide, in addition to the currently used SD model, in the youth care decision making process.

1.2.4 Research questions

This section frames the main research objective as a question that defines the issue under consideration. A question provides more direction to the research as it requires an answer. The efforts of this research are made in order to answer the following main question:

"What additional insights can a DES decision support model provide, in addition to currently used SD model, in the youth care capacity decision making process?"

This main question cannot be answered with a single statement and has many aspects to it. The main research question is tackled by answering several chronological sub-questions. The synthesis of these sub-questions answers the main research questions.

1. What are the model objectives for a decision support model in the youth care sector?
2. What are the expected benefits of a DES model in addition to currently used SD model?
3. What are the differences between the abstraction of the care provider system in an aggregated SD and disaggregated DES model?
4. What are the important heterogeneity and conditionality relations in the care provider system?
5. Can we abstract and quantify the care provider system in a DES simulation model?
6. Do the DES and SD model represent and correctly reproduce the behaviour of the real world system?

1 **Proof of concept** is a short and/or incomplete realization of a certain method or idea(s) to demonstrate its feasibility, or a demonstration in principle, whose purpose is to verify that some concept or theory is probably capable of exploitation in a useful manner.

1.3 Research Strategy

This section presents the techniques, methods and strategies used in order to answer the research questions and satisfy the research objectives.

1.3.1 Methodology

First, the main research strategy, which structures the sequencing activities through the research is first explained, followed by a description of the research methodologies used in the different phases of this research.

Research strategy

The main research focus lies on the design of a DES decision support tool to provide insight in the observed youth care dynamics, a design-oriented research approach is followed. It has been argued that designing involves more "perspiration than inspiration", the utility and satisfaction of future users stakeholders is critical in the design process (Verschuren and Hartog 2005). Therefore, empirical and evaluation research have a central role in the design process.

To be more specificthe steps of the Regulative Design Cycle (Strien 1986) serve as a guideline for this research.

1. **Signalize**. The problem is signalized and defined.
2. **Analysis.** The problem is analyzed the problem causes are identified and diagnosed.
3. **Design**. A plan is designed.
4. Try out. An intervention based on the plan is made.
5. **Evaluation**. The intervention is evaluated.

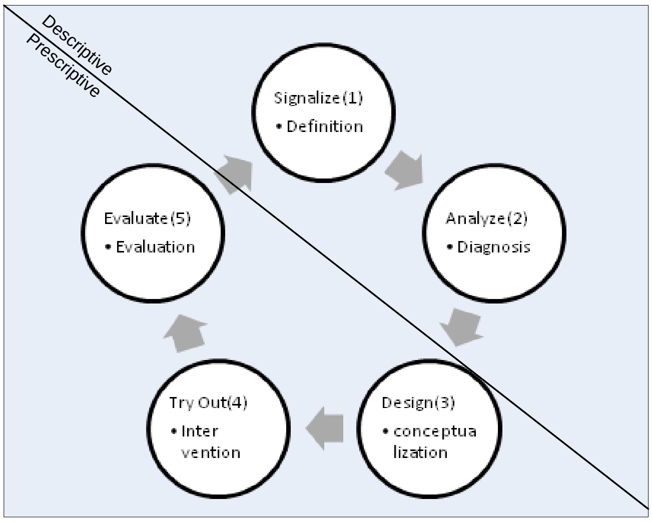


FIGURE 1-3 THE REGULATIVE DESIGN CYCLE (STRIEN 1986)

The research can be subdivided according to the nature of explanation, the first and second step are considered descriptive, the further steps prescriptive. In order to answer the different research questions a variety of research methods are used. The main research method in the descriptive part is desk research. In the prescriptive part of this thesis two main methods are used; a case study and a simulation.

Desk Research

Desk research is also known as secondary research because of the exclusive use of secondary data. This is data gathered from literature, databases, the internet etc. This research will use the gathered data and reflect on the data to arrive to conclusions (Verschuren and Doorewaard 1999). The diagnosis and analysis part of this research are done by desk research.

Simulation

Simulation is the process of designing a model of a real system and conducting experiments with this model for the purpose of either understanding the behaviour of the system or evaluating various strategies for the operation of the system (Shannon 1975). In addition to the case study, simulation allows to control the experimental setting and the variation of system variables. The following activities are part of a simulation project:

- *Model conceptualisation.* The abstraction of a real system by a conceptual model (Banks 1998). Conceptual models are a clear and unambiguous representation of the objects and relations under investigation.
- *Model specification.* The collection of empirical data and the specification of attribute values of the objects specified in the conceptual model in computer-recognizable simulation model (Banks 1998). The creation of an experimental design forms part of this activity.
- *Verification:* the process of determining that a model implementation accurately represents the developers conceptual description of the model and the solution to the model (Roache 1998). The initialization conditions, the run control conditions and the number of replications of the different treatments are determined in this activity.
- *Validation:* The process of determining the degree to which a model is an accurate representation of the real system from the perspective of the intended use of the model (Roache 1998). *Structural validation* is the checking of hypotheses on the behaviour of the simulation model. *Replicative validation* is the comparison of endogenous attributes values with the ones found in the real system. *Predictive validation* or *expert validation* whenever the plausibility of simulation model is tested by experts (Sol 1982).

These research methods use the following supporting research methods:

1. *Literature research.* Literature research will be used to create a theoretical background in the youth care field and the methodological simulation literature. Another important literature source are the interviews performed by Giesen (2008) and previous INITI8 projects.
2. *Data analysis.* Quantitative research is researching for knowledge that measures, describes and explains phenomena, or searches for knowledge to investigate, interpret, and understand phenomena. A dataset of the chosen case study of children flows through the care provider system over the year 2008 and 2009 is analyzed.
3. *Expert validation.* INITI8 experts will validate the used methods and made assumptions in this research.

1.3.2 Thesis structure

This section provides insight into the system structure, by making the link between the five steps of the regulative design cycle (Strien 1986), the thesis chapters and the research questions transparent. This first introductory serves as the first step of the regulative design cycle, the research problem is signalized and defined.

Part 2: Problem analysis and delineation
The second part of the thesis analyses the signalized problem. Chapter 2 introduces the multi actor setting of the youth care sector and formulates the model requirements in order to answer the first research question. Chapter 3 presents a literature study in the field of modelling and simulation serves as the input to a theoretical framework, of the strengths and weakness of the SD and DES simulation methodologies, in the youth care sector. Chapter 4 evaluates the currently used system dynamics model, the value of this chapter is two folded, it provides a practical evaluation of the found strengths and weaknesses of the SD methodology in the third chapter and it introduces a first conceptual overview of the processes in the delineated care provider system. The insight of Chapter 3 and 4 together answer the second research questions. Furthermore, Chapter 4 forms a practical foundation for the Design part of the research and it forms the comparison framework to answer the fourth research question.

Part 3: Design discrete simulation model
Following the regulative design cycle, the third part presents the design of a possible solution. The DES model serves as the to be designed solution in the scope of current research. Chapter 5 presents a conceptual model of the process, entities and relations in a care provider system. The presented conceptual model forms the foundation for the data study in Chapter 6 and the DES model specification presented in Chapter 7. The third research question is answered by a synthesis of Chapter 4, 5, 6 and 7. Chapter 6 answers the fourth research question by making the to be abstracted heterogeneity and conditionality relations transparent.

Part 4: Model try out
The fourth part of this thesis evaluates the outputs of the designed DES model. Chapter 8 validates the model and model assumptions. Chapter 9 cross-validates the sensitivity of the DES and SD model to changing scenarios and experiments. Chapter 8, 9 together provide the answer for the sixth research questions.

Part 5: Model evaluation this part presents a structured overview of the found answers to the research questions, a general remark towards the experiences of modelling and simulation in health and youth care, a set of recommendations for the problem owner and a reflection on the research process.

Part 2: Problem exploration, delineation and Analysis

Chapter 2
Problem Exploration and Delineation

The previous chapter signalized and defined the perceived problem in the decision making process of the youth care sector. This chapter first explores the process, care services, actors and coordination in the youth care sector, after which the relevant part of the system and the simulation requirements with regard to the defined problem are delineated.

2.1 Problem context youth care sector

2.1.1 Youth care process

The youth care system can be broadly described by a description of the flow of children through the system and the successive processes these children go through. A high-level overview of the procedures and children flows is depicted in
Figure 2-1. The Dutch youth care sector aims to provide care to children on demand. Children enter the system at the youth care agency (BJZ) at their own initiative. The BJZ entitles the child an indication for professional help if necessary. Such a formal indication includes a diagnosis and entitles the child to receive care at a care provider of its own preferences in the provincial or regional system. If the child does not receive an indication, the child flows back to the youth population. The child is treated at the care provider until the treatment objectives are reached or until the child decides to withdraw from the care services.

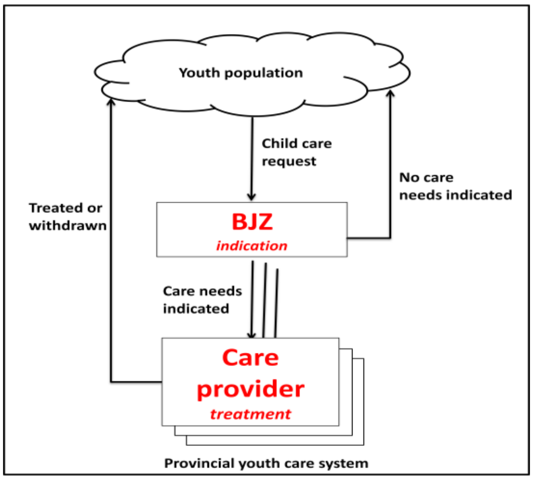


FIGURE 2-1 FLOWS AND PROCEDURES IN THE YOUTH CARE SYSTEM

2.1.2 Care services

Care provided in the context of the Youth Care Act is always voluntary care. As introduced in the previous section, the care needs of the clients come first. Every child's situation is unique. Therefore also the care services provided to these children should be flexible enough to adapt to these different situations. To achieve this flexibility in care services different care types can be combined and the composition of care services can be different for every child.

A first high level decomposition of the youth care services divides the youth care services according to the nature of their service. Two categories are distinguished:

1. *Youth assistance*. Supervision, guidance and pedagogic support delivered by therapists and social workers at either the home situation or at a residential youth care facility.
2. *Residential services.* The residential services include the whole of services which create a substitute for a structured and stable family situation. The child's family situation can for various reasons not be able to provide a stable development basis for the child. In this situation residential services provide the necessary extra structure and support to the child.

These two care categories can be further subdivided into four care types. These care types separate the provided care services according to their resource usage and is used by the care providers in the youth care sector in their capacity forecast (Giesen 2008; Westerflier 2008). The following four care types are distinguished (Entrea 2010; Stichting Jeugd formaat 2010):

1. *Youth assistance*

The subset of youth assistance services demarcates one care type: ambulatory care.

Ambulatory care (AH)
Care provided in the family situation is called ambulatory care. The care is provided in the client's home situation to provide raising and development assistance. The assistance is both provided to the child and to its parents. Ambulatory care provides solutions for problems related to the family's mutual communication, child development and parental raising skills, for example in case of light depression, behavioural problems or non functioning family circumstances. The care is focused on education of parents and child.

2. Accommodation services

Residential services demarcate three different care types: day care, residential care and foster care.

Day care (DH)
Day care is for children and youth with normal abilities in the age from two till eighteen with serious behavioural or developmental problems. The care is provided during day time and usually involves children to have school at the centre where the care is provided. The treatment takes place in groups of eight to nine children of approximately the same age and with similar problems. Combinations with ambulatory care in the family situation are possible.

Foster care (PZ)
In some situations it is better for children to (temporally) leave their family situation. A child can then reside in a foster family. A foster family provides shelter and supervision in their own family situation. Foster care can be combined with ambulatory care to support the child, the foster family and the child's parents.

Residential care (RH)
In some cases it is not possible to stay in a foster family, because intensive care to treat severe behavioural disorders is necessary. In such cases, children have more possibilities to charter additional aid and guidance in a residential care facility than in a foster family. Residential care is regularly combined with ambulatory care to coordinate the process between the child, the accommodation and the child's parents.

The difference between day care and residential care lies in the intensity of care services. Day care is a substitute of a family situation during day time, residential care is a twenty four hour substitute of the family situation. The difference between these care types and foster care lies in the location of care delivery.

The four introduced care types can be further subdivided into 8 claim types used in the indication documents of the BJZ which provide the entitlement for care. These claim types can be further subdivided into twenty care products which can be seen as the smallest micro stones of youth care services. The complex taxonomy of youth care services is presented in appendix A. The taxonomy uses Dutch names to avoid inconsistency in naming. . The upper half of the taxonomy presents the residential services, the lower half youth assistance. The four different care types are separated by coloured blocks. The pink block visualizes the subset of AH services, the blue block RH, the yellow block DH and the green block PZ. The eight distinguished claim types are presented by the left vertical block with blue lines. The twenty different care products are presented by the right box with blue lines.

2.1.3 Actors and responsibilities

The primary goal of this sub-section is to provide insights in the system and its behaviour by mapping the actor's functions and influences in the youth care process.

The national government

The national government (in the form of the Ministry of Volksgezondheid, Welzijn&Sport[2]) is ultimately responsible for the youth care system in the context of the youth care act. The government passes laws and regulations, defines the basic policy principles and makes funds available. The state also controls the performance of the different provinces.

Provinces and urban regions

The twelve provinces and three major urban regions (Amsterdam, Rotterdam and The Hague) are responsible for the youth care agencies and for ensuring the availability of care that people are entitled to under the Youth Care Act. To enable them to perform this role, the national government provides them funds in the form of two special purpose grants: one for the provision of care and one for the maintenance of the youth care agency.

The youth care agency (BJZ)

The Youth Care Act provides a legal status to the youth care agencies. Each of the Netherlands provinces and three major urban regions have a youth care agency. Young people and their parents can approach the youth care agency of their province or regions if the general organizations, such as schools and social support, are not able to help them sufficiently with their problem. The BJZ decides whether assistance is indicated. The most important function of the youth care agencies is assessing these requests for care and deciding what kind of care or support (if any) is required. The client's needs are considered in their own right, rather than in the context of available capacity. In other words, the agency makes an independent decision about what is needed. If the BJZ concludes that the client is in need of care, an indication document is created. This is a formal statement which contains the particular care types required on a care claim level. The youth care agency has the power to decide which various forms of care are indicated.

The care providers

The indication decision made by the BJZ expresses the care needs in terms of care claims. In order to ensure that the care type provided by the care providers are consistent with these care claims, care providers presently have to define their care provision on a similar basis. The provided care products subdivided the care claims in a set of provided care services. This approach offers flexibility to the care provider to select the most suitable care products and it offers a basis to a demand-led care attuned to the client's needs. Furthermore, the product types create a possibility to compare care providers and form the basis of a transition to output financing of the care provider services.

2.1.4 Coordination in the youth care chain

One of the main aims of the youth care act is to ensure coordination between the above introduced actors in the care chain. The provincial and regional[3] authorities are responsible for coordination. As such, every four years they are required to produce a provincial or regional policy framework; of course in close consultation with the other actors in the chain, using the national policy framework as a starting point. The provincial policy framework has to be approved by the central government before the provincial authorities can adopt it.

The provincial policy framework outlines the indication policy of the province's BJZ and it describes in broad lines the anticipated pattern of demand. The document is compiled on the basis of data from the BJZ and the care providers in the province. In addition, the province has to produce an annual operational implementation programme, which aligns the BJZ processes and the available care capacity at the care provider with the provincial policy framework and with the performance criteria

[2] Currently Ministriy of Volksgezondheid en Sport, former Ministry of Jeugd en Familie
[3] When referred to the provincial authorities in the following sections the same accounts for the authorities of the three regional systems

determined at national level. The implementation programme is drawn up in close cooperation with the BJZ and care providers in the province.
The BJZ and care providers have the responsibility to provide every quarter the information to the province necessary to evaluate the effectiveness of the current policy framework. The province provides information flows to the national government that has the ultimate responsibility of the youth care sector. The exact information responsibilities in the youth care sector are captured in the youth care policy information format document (Stuurgroep BAM 2009). An object oriented overview of the actor relations, budget, process and information flows in presented in Figure 2-2.

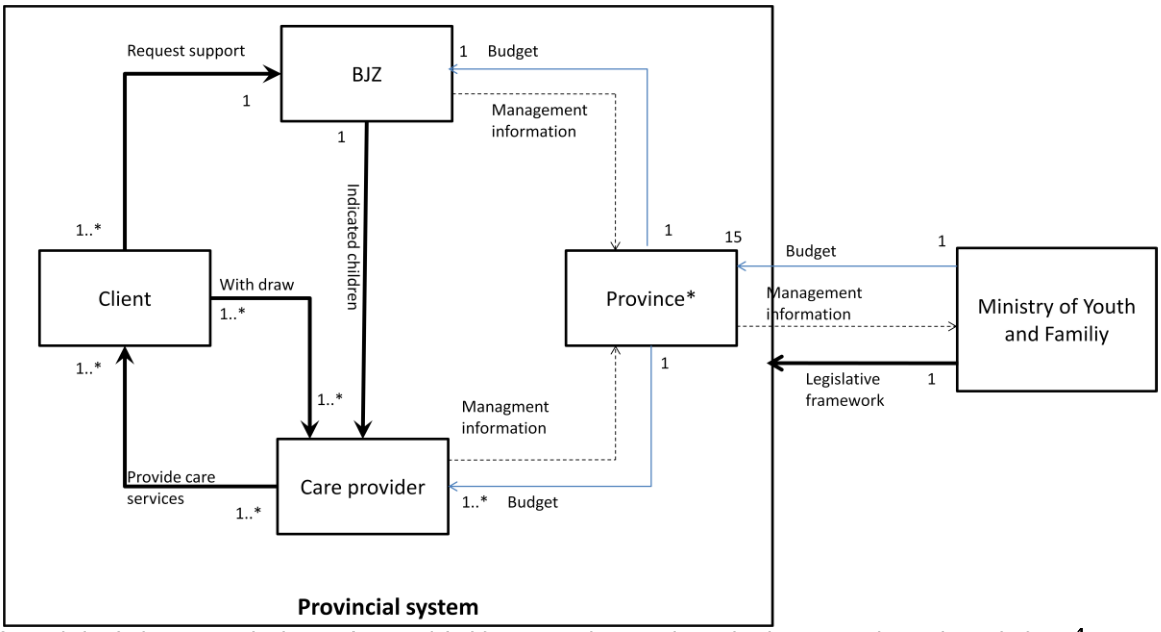


FIGURE 2-2 ACTOR RELATIONS, BUDGET, PROCESS AND INFORMATION FLOWS IN THE YOUTH CARE SYSTEM[4]

The following section further demarcates the information and performance control responsibilities in the youth care sector.

2.1.5 Information hierarchy, budget allocation and performance control

It is argued by Leeuwen, Naborn et al. (2008) that the information provision and performance control in the youth care sector is complex and non transparent as a result of the multiple aggregation layers of management information. This section makes the different aggregation layers of management information transparent and couples the information layer to the information responsibilities and control functions of the different actors in the youth care system.

Trajectory information: The trajectory information measures the amount of trajectories in the different states of the youth care sector. The trajectory layer information is the operational information used by the care providers to evaluate their capacity investments in order to align the demand for care services with the available capacity. Trajectory information is analyzed further, aggregated to the four main care types presented in subsection 2.1.2. The different nature of the three care types makes the trajectory information between different care types incomparable. The budget allocating methods used by the provinces to the different care providers is becoming increasingly based on trajectory output financing aggregated to the different care types.

Child information. The trajectory layer does not provide a clear inside in the exact amount of children in treatment or on the waiting list. Furthermore, the trajectory layer does not provide insight into the time a child needs to wait before receiving the first treatment. The child information layer is introduced to allow unambiguous steering from a national level. The national government objectively allocates macro budget to the provinces and care providers based on the anticipated child demand.

[4] The youth care sector distinguishes 12 provincial systems and 3 urbanized regions. The urbanized regions follow the same structure as the provincial systems; expect the role of the province, which is covered by the urban authorities in the urbanized regions.

An important performance criterion in the youth care system is the performance agreement between the former ministry of Youth and Family, in the person of former Minister Rouvoet and the actors in different provincial and regional systems, which states:
"Every child should receive youth care in less than nine weeks after the assessment of care needs at the care provider" (Rouvoet 2009).

A summary of the introduced information layers in relations to the informative and control responsibilities of the different actors is presented Figure 2-3.

FIGURE 2-3 INFORMATION LAYERS

Aggregation layer	Information level	Reported by	Controlled by
Child	Management	Province BJZ	Ministry
Trajectory	Operational	Care provider	Province

2.2 Waiting lists in health and youth care

Over the last few years, the Dutch youth care sector has faced long waiting lists and long waiting times, a problem that received a lot of media attention. Youth care waiting times became an important issue on Dutch political agenda. A policy that combined a individual maximum waiting time of nine weeks with additional government funding to reach these targets was implemented. Although the policy resulted in an initial decrease of overall waiting lists, shortly after the policy implementation unexpected increases in waiting list occurred. The provincial and regional systems did not manage to guarantee the maximum individual waiting time target of nine weeks. In individual cases the youth care sector is not able to provide the entitled care within the nine weeks target. In the context of the youth care sector, which has a high intolerance to failure, this is perceived unacceptable.

Hospital and general health care face similar problems with regard to waiting lists and the high intolerance to failure. Waiting lines in the health care sector have received little attention in scientific literature. A common approach taken by governments to tackle these problems is the injection of capital which is used to increase capacity. It is argued that this provides a short term solution, as available capacity and queue lengths reach a new equilibrium after a short period of time (Hurst and Siciliani 2003; Postl 2006). Saulnier, Shortt & Gruenwoldt (2004) identify the main approaches to decrease waiting times: monitoring of procedures, using priority scoring and setting waiting time targets. Rachlis (2005) argues that such methods do not work by themselves in the complex health care setting with an inherent dynamic character caused by political influence, patient withdrawals and uncertainty. Waiting lines in health care face withdrawals when clients have to wait for an extended period of time. Several studies have shown that the amount of time that a client is willing to wait for care is related to the urgency of the problem (Goodacre and Webster 2003). Problems that are more urgent genuinely require attention, and are difficult to treat elsewhere. These cases will therefore accept longer waiting times before withdrawing from the waiting lists. Rising (1977) states that many health care systems can be viewed as some form of a stochastic random network. Furthermore, he addresses the importance of accounting existing process variability when analyzing health care queues, whereas management by averages can yield radically inaccurate results if significant variation exists.

2.3 Decision support model requirements

This section introduces the generic factors that determine the success of decision support models, after which these factors are taken into account in the formulation of requirements for a successful decision model in the context of decision support in the care provider capacity negotiations.

2.3.1 Sound and successful models

It has been identified in literature that the development of a sound model, for the purpose of solving a particular problem needs a fit between three dimensions: system dimension, problem dimension and methodology dimension (Pidd 2004; Lorenz and Andreas 2006; Chanal and Eldabi 2008). The fit between these dimensions is presented in Figure 2-4.

System dimension (what?) [5]. Refers to the nature and the structure of the real world system under investigation. A model refers to the selected aspects of the real world, examining the characteristics of these real world objects provides important indications for the selection of an appropriate modelling approach.

Problem dimension (why?). Refers to the simulation objective, which can include solving a given problem or optimizing a given behaviour or to gain insight into a broader not yet understood problem context. This is also important for the identification of adequate modelling boundaries.

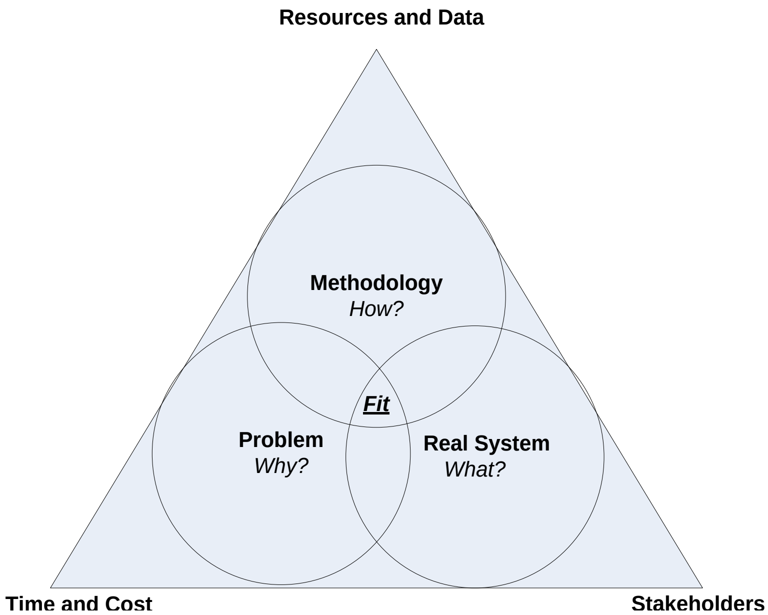


FIGURE 2-4 FIT BETWEEN MODELING METHODOLOGY AND A PARTICULAR PROBLEM SOVLING PROCESS (CHANAL AND ELDABI 2008)

Methodology dimension(how?). The aspects and capabilities of the modelling or simulation[6] method. Through this set of concepts and methods a methodology defines how the object is approached in order to achieve the intended purpose. Since all methods have strengths and weaknesses the application of a certain method already presents a tendency to which aspects are associated with the real world problem.

It is generally recognized in the information system community that successful solutions to complex problems do not only require technically sound deliverables. A modelling project is not considered successful before it is implemented successfully, which requires much more than technically sound models. Chanal and Eldabi (2008) recognize that modelling time and cost, stakeholder trust and data availability are the main barriers for uptake of simulation in industries such as health care where quick and affordable decisions are required (Lowry 1992; Carter and Blake 2005). Based on these findings additional to the soundness of the model stakeholder trust, resource and data dependency and modelling time are introduced as parameters that influence that success of a model study, as visually presented in the corner of Figure 2-4.

2.3.2 Model requirements

Requirement analysis involves defining customer needs and objectives in the context of planned model use, environment and identified system characteristics to determine requirements for system function (Defence Acquisition University Press 2001). The complexity of requirements necessitates to analyze the world from different points of views and to make connections between these different points of views (Robertson 2001). Keen and Sol (2005) argue that the effectiveness of a decision support system can be expressed in a combination of three factors: *Usefulness, Usability and Usage:* *Usefulness.* The usefulness of a decision support tool expresses the value a simulation model adds to decision making or problem solving process and is closely related to the afore mentioned soundness of the model (Chanal and Eldabi 2008). It relates to the analytical model, the embedded knowledge and the information resources available in a model or tool. It serves as the synthesis between the soundness of the model and the data dependency.

[5] The definition of a system : *A system is a part of the world we choose to regard as a whole, which contains a collection of objects and underlying relations (Holbaek-Hansen 1975).*
[6] A clear distinction between modelling and simulation is provided in following chapter.

Requirement 1: Accurate insight into performance indicators
The model is required to provide insight in the behaviour of the important performance indicators and internal variables in the youth care, necessary to evaluate the state of the youth care system and the impact of possible policy options.

Requirement 2: Data availability or collectability
The necessary data to initialize the model is required to be accurately collectable from the care provider system or accurately determinable by assumptions or analytic methods.

Usability. Usability expresses the stakeholder trust and understanding of the simulation model. Usability mainly depends on the interface between users and the decision support technology. It expresses, the responsiveness, flexibility and ease of interaction with the tool in de decision making process. In other words, it expresses the communicative quality of the model in the decision making process. The usability serves as a synthesis between the conceptual view and technical aspects of the methodology at one side and the stakeholder or sector worldview on the other.

Requirement 3: Low distance between stakeholders and model worldview
The problem owners and stakeholders should be able to relate the real world to the abstraction of the system model in order to provide trust and understanding of the decision support model.

Requirement 4: Clear and intuitive interface.
The model interface is required to provide a clear and unambiguous overview of the important performance indicators and interval variables. Furthermore, the decision support model should be intuitive.

Requirement 5: Easy experimental set-up.
The SD model is currently used during negotiation and scenario analysis workshops between the province and the care provider. The model is required to be quickly adaptable to experiments, which can include different policy options or scenarios.

Requirement 6: Low experiment run-time
Furthermore, the experiment outputs are required to be analyzed during the workshops a short experimental time is required to ensure efficiency of those workshops.

Usage. Usage expresses the flexibility, modularity and suitability of the decision support model for the organizational, technical or social context. It refers to the time and costs of adapting the model to changing environments and objectives. Characteristics of influence or modularity, flexibility and the ease of initialization.

Requirement 7: Generalizability
From a problem owner perspective, the model is required to be generic for different care providers. From a care provider perspective the model should not provide the province with insight in the exact organisation and procedures of the autonomic care provider.

Requirement 8: Flexiblity.
The decision support model is required to be adaptable to the introduction of new care services, procedures and performance indicators. The flexibility of a decision port model is strongly related to the concept of modularity.

Requirement 9:Low time and costs of model initialization
The time and cost to re-initialize the model for a different care provider are new data set. It is related to the data dependency and the ability to automate the pre-processing of data sets to model inputs

2.4 Problem and system delineation

The preceding parts of this research formulated the objectives and requirements for a decision support model in the context of the youth care sector. To satisfy these requirements and reach stated

objectives a decision support model should sufficiently represent the real system. It should allow the adaption of possible policy instruments of the relevant actors and incorporate the possibility to experiment with the possible future scenarios to evaluate the effect and robustness of care provider capacity strategies on the value of the relevant performance indicators. This section takes a system perspective to demarcate the relevant variables to sufficiently abstract the real system in a simulation and forms the foundation of the conceptualisation of the SD and DES simulation model. The structure of this section is visualized in
Figure 2-5.

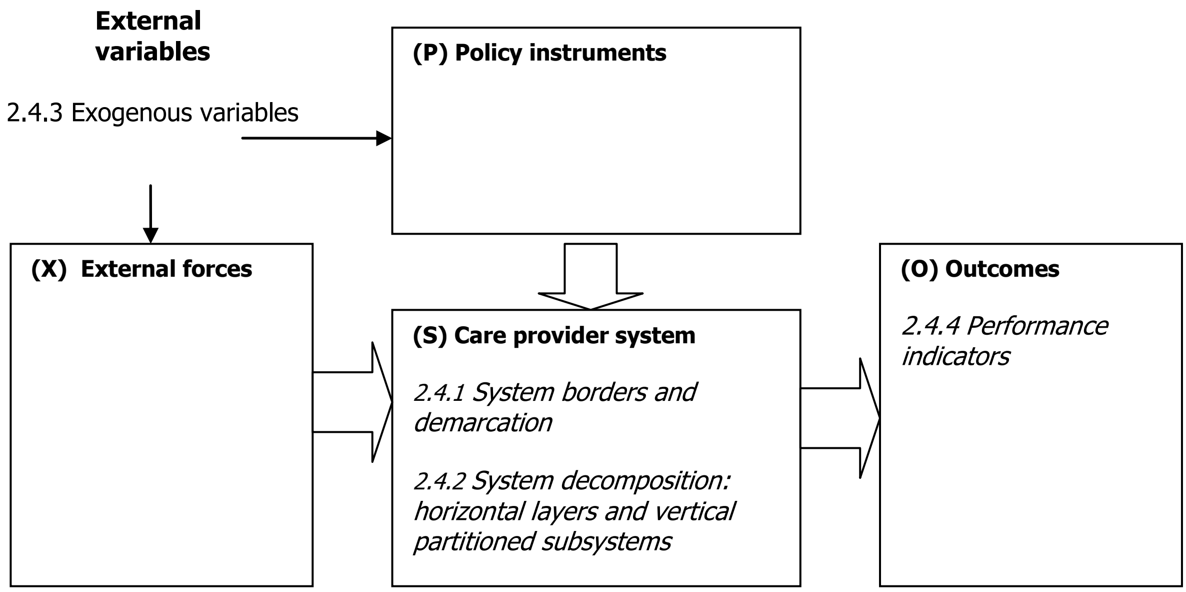


FIGURE 2-5 SYSTEM PERSEPCTIVE STRUCTURE 2.4

2.4.1 System borders and demarcation

A first step in determining the system borders is the demarcation of the part of the youth care sector under study. Taking into account the objective of the decision support model, which is to align the care providers capacity with the anticipated care demand in order to reach the performance agreements made between the actors in the youth care sector, the system is bordered by the process of one care provider. To be more specific the processes with determine the logistic children flow and waiting time in the care provider system. The system borders are presented by the red dotted box in Figure 2-6.

The demarcation of a simulation model determines the complexity and validity of a model. Model demarcation decisions are always a payoff between validity and complexity. The model should abstract enough of the real system to reach the model objective, without becoming too complex to be used or understood. The system is further delineated taking into the account the necessary scalability between care providers. Different care providers broadly have similar structures and processes, the system should capture these common processes, but distance itself from detailed differences in the process of different care providers. The system delineation is based on the following considerations:

- *Simplicity*. Keep the model as simple as possible, given the objective, without detracting from its completeness and its value as a reflection of reality.
- *Influence.* Keep the part of the system which cannot be influenced as much outside the system boundary as possible.

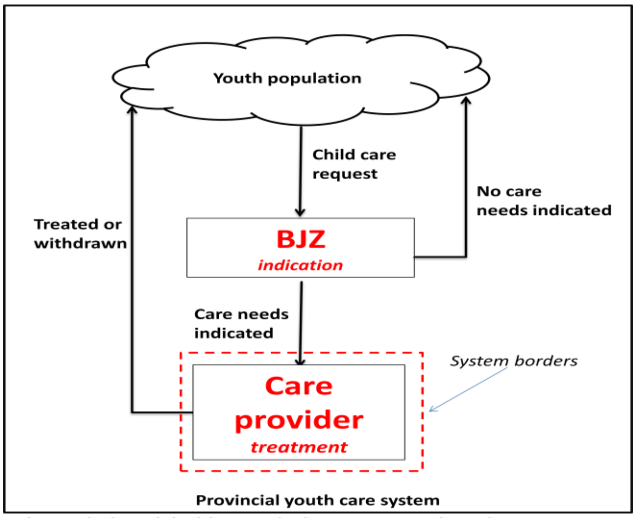


FIGURE 2-6 PROCESS AND SYSTEM DEMARCATION

The following system boundaries form the foundation for both the currently used system dynamics as for the to be developed discrete simulation model.

1. *Care demand*. The demand faced by a care provider can be measured by the amount of children requesting care and by the amount of care trajectories these children request. While the care provider has influence on the amount of care trajectories delivered to a child for a certain care claim, the choice is made to treat both the child as trajectory care demand as exogenous variables. First, because the care demand is dependent on the allocation policy of the BJZ. Second, because the Youth Care Act takes the clients care needs and the quality of treatment as a starting point. A child deserves the care trajectories it needs, the amount of care trajectories is not seen as a policy instruments to control the waiting lists.

2. *Care services.* Previous section introduced the taxonomy of care services. All care services can be subdivided in four care types, which can be further subdivided into seven claim types by the BJZ and 20 detailed product types used by the care providers. The four claim types separate the care services according to their resource usage and are therefore currently used by the care providers for their capacity forecasts (Giesen 2008; Westerflier 2008). The system under study will be aggregated to these four care types because of the importance of capacity forecasting in the youth care policy.

3. *Care provider.* The system under study is demarcated to the logistic flow of children through the care provision process of the care provider. Only the actors, documents and variables that directly influence the logistic flow of children are considered.

4. *Care provider capacity.* Care provider resources are bordered to the trajectory capacity of each care type. Employees, treatment rooms, beds etc. are not explicitly modelled. This demarcation is made because the model serves as a communication tool between the province and the care provider. The care providers compete in a free market, information with regard to their work processes, personal management and budget allocation is perceived confidential.

5. *Costs and benefits.* An important decision criteria for the care providers, in addition to the performance indicators related the dynamic children flows, are the expected financial benefits of possible capacity strategies. The author argues that these benefits dependent on a static cost function, which uses both the care capacity and the care production as a function. Taking into account the purpose of the current research, two compare the application of two dynamic simulation methods; this static cost function is perceived to lie outside the scope of current research. However, the importance of costs and benefits is translated by the emphasis on the care production as an important performance indicator. In addition to the performance

indicators related to the dynamic children flows, care provider capacity costs and care provider incomes, which are based on the outflow of treated trajectories

2.4.2 System decomposition: horizontal layers and vertical partitioned subsystems

Jacobs (2005) argues that separation of concerns is at the core of system engineering, it refers to the ability to identify, encapsulate and manipulate those parts of a system that are relevant to a particular concept, goal, task or purpose. The next step in further analyzing the care provider system is a further decomposition of the system into horizontal layers and vertical partitioned sub-systems. A graphical overview of this decomposition is provided in Figure 2-7

Horizontal layers: information separation
The information hierarchy introduced in the first chapter, distinguished two layers of management information. Namely the measurements related to unique children and the measurements related to the different care services a child receives in the care trajectory layer. These vertical layers are clearly distinguished in the decomposed system diagram presented in Figure 2-6.

Vertical partitioning: process separation
The vertical partitions of the trajectory layer are clearly visualized in the system model. The four parallel subsystems, aggregated by the four care types, are independent parallel care systems. The performance of these subsystems does not influence the performance of other subsystems and is not inter comparable because of the differences between the provided care types. The care provider performance measures, at trajectory level, are also vertically partitioned and aggregated by the care types.

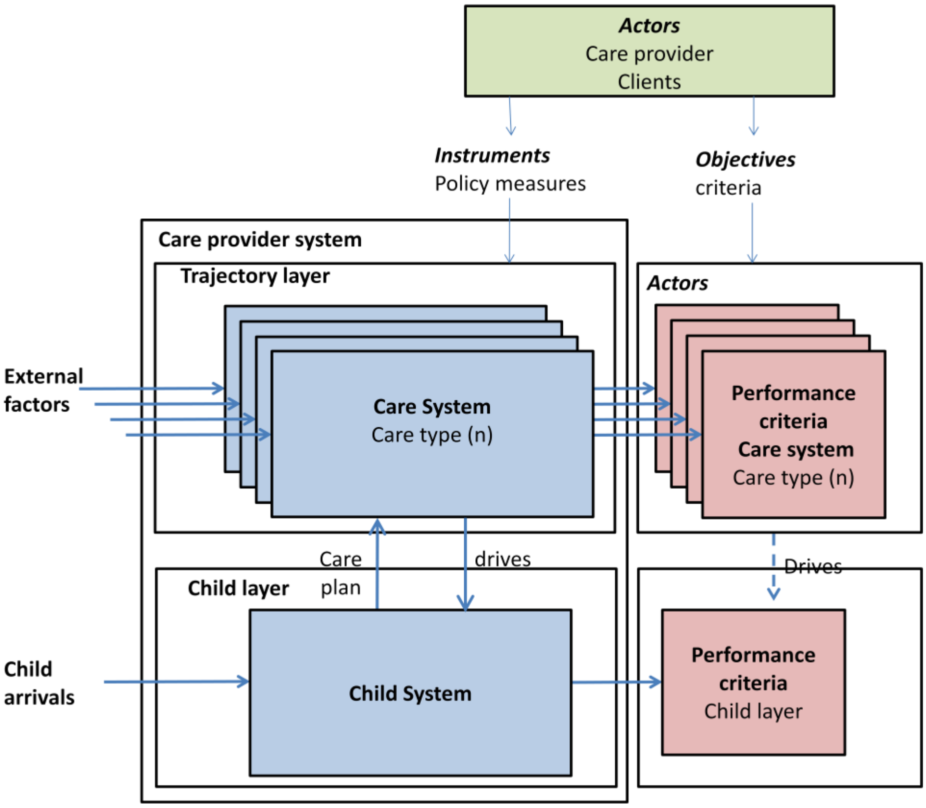


Figure 2-7 System diagram: decomposition of the youth care sector in horizontal layers and vertical partitioned sub-system.

2.4.3 Exogenous variables

The exogenous variables, which influence the system under consideration, can be subdivided into two subcategories, external variables and instrumental variables:

External variables. Variables that cannot be influenced from within the system. Also referred to as the scenario variables.
Instrumental variables. Variables that can be influenced by the decision makers. Also referred to as the policy variables.

Policy variables: The decision makers in the context of the care provider model are the province or regional system and the care providers. While there are many variables the care providers can influence, for most of the variables their influence is bounded by a payoff between care quality and system productivity. An example of such a variable is the patient treatment time. A decrease of treatment times would increase the system output and potentially decrease the waiting time. However, such a policy is likely to decrease the care quality provided to children. For this research the instrument variables are those variables completely controlled by the scope of management control of the care provider, without negatively influencing the care quality. This decision has been made on the basis of the following considerations. First, taking into the account the simulation objective to provide a negotiation tool in the future capacity negotiations between the care provider and the province based the anticipated future demand. Second taking into account the main objective of the youth care sector introduced in subsection 1.1.1 which states: "the need of the client comes first", a pay off which jeopardizes care quality is considered in contradiction with this main objective of the youth care sector. Based on these considerations the following policy variables are considered:

Care capacity. The available care resources at the four independent care systems.

Scenario variables:
The other variables which are perceived uncontrollable and beyond the scope of the care provider management, may still be subject of analysis of *what if* scenario's. Selection criteria for these variables are observed dynamics in these variables and the sensitivity of the system to variable change. The arrival of children in the system is perceived the main scenario variable. Other possible scenario variables are the variables, which determine the link between children arrivals and trajectory demand and the trajectory treatment time. Data analysis of historical case study is necessary to determine which variables are relevant to study possible future scenarios.

Children Arrival. The inflow of new children into the care provider system.
Treatment time. The duration of trajectory treatments for the different care types.
Care profile variables. The set of variables which together determine the link between children and trajectories.

2.4.4 Performance indicators

Law and Kelton (2000) define the state of a system to be that collection of variables necessary to describe a system at a particular time, relative to the objectives of the study. This sub-section beholds an analysis of the collection of variables that describes the logistic children flow through the care provider system at a particular time. The objective of the simulation model is to provide insight into the development of the system performance indicators as a communication tool between the province and the care providers. The performance indicators are selected with regard to the current political focus and the sector performance agreements. A distinction is be made between the operational performance measures used by the care provider measured at the trajectory layer and the performance indicators used by the ministry to control the youth care performance measured at the child layer. The performance indicators are determined by analyzing the managements products provided by INITI8 to the youth care sector and the format of the policy steering rapports used in the control of the youth care sector (Stuurgroep BAM 2009).

Trajectory layer
Literature tells us that the typical measures for queuing systems include server utilization, length of waiting lines and delays of customers (Banks, Carson, Nelson, & Nicol, 1999). The negotiations

between the province and the care provider result in a common youth care policy, which should be a robust pay off between waiting times, costs and efficiency. Figure 2-8 presents the performance indicators measured for each independent care system.

FIGURE 2-8 PERFORMANCE INDICATORS TRAJECTORY LAYER

Performance indicator	Unit	Description
Waiting list	Trajectory (trj)	The number of trajectories on the waiting list
Waiting time	week (wk)	The time children have to wait before the treatment of a trajectory starts.
Production	Trajectory a month (trj/month)	The outflow, of the number treated trajectories each month. It serves as an important input for the care provider income, which is based on output financing.

Child layer
As introduced previously in 2.1.5, the child layer provides unambiguous insight in the child and is used by the national government to objectively allocate the macro budget to provinces and urbanized regions. Furthermore, the child layer allows to objectively control the care provider and provincial performance, without aggregating to specific care types. The child layer performance indicators, currently applied by the ministry, are presented in Figure 2-9. The applied child layer performance indicators have been frequently changed in recent years. In addition to the currently used performance indicators new plans include monitoring the waiting time for the heaviest care type assigned to each child.

Performance indicator	Unit	Description
Children in the system	child	The number of children, which have trajectories in the care provider system (in care or on the waiting list)
Children Waiting list	child	The number of children in the care provider system waiting for one or multiple trajectories without having care trajectories in care.
Children In care	child	The number of children in the care provider system of which on or multiple care trajectories is in care.
Waiting time	Week (wk)	The time children spend on the waiting list without receiving treatment.

FIGURE 2-9 PERFORMANCE INDICATORS CHILD LAYER

2.5 Conclusion

The youth care sectors aims to provide care to children on demand. Care provided in the context of the youth care act is voluntary care, children receive youth care at their own initiative. The care needs of the clients come first, because every child is unique, the care services provided to the children need to be flexible. To achieve this flexibility in care services different care types are distinct and each child can receive a suitable combination of those care types. A high level composition of youth care services divides the youth care services according to nature service distinct are: *Youth assistance and residential care.* These two main categories can be further subdivided to four care types. Youth assistance has the care type ambulatory care (AH), residential distinct three care types day care (DH), foster care (PZ) and residential care (RH). These four care types can again be further subdivided into a multitude of care services. For this research the care provider is analyzed aggregated to the four care types.

The national youth care system is subdivided into 15 autonomic regional systems that cover the 12 provinces and the urbanized regions of Amsterdam, the Hague and Rotterdam. The national government has the formal responsibility of the regional systems and provide the means to the authorities of the provincial and regional systems. Each regional system consists of a BJZ and a set of care providers. The authorities of the regional system have to formal responsibility to align the resource availability at the care providers with the care demand.

Effectiveness of decision support model are not only dependent on the usefulness of the model outputs. In addition to the usefulness of the model, time and cost of modelling, data availability and stakeholders are introduced as important parameters that influence the success of decision support model in the health and youth care sector.

The system delineated in current research describes the logistic children flows through a care provider. Only actors, objects and documents that directly influence this logistic are considered in both currently used SD and in the to be developed DES model .The care services are aggregated to four care types; ambulatory, residential, foster and day care. The model serves as a communication tool between the regional authorities and the separate care providers to create a commonly supported capacity strategy. The care provider capacity resembles the number of trajectories that can receive care at the same moment of time. Accommodations, employees, treatment rooms and beds are not explicitly modelled. In addition to the children flow related indicators, financial considerations serve as an important criterion for possible policy options. Taking into account to objective of current research, two compare two dynamics simulation approaches, the cost function is lies outside the scope of current research.

Figure 2-10 presents a system diagram of delineated system. Distinct are two information layers; the child and trajectory layer. The trajectory layer distinguishes four parallel care systems, each with their own in and outputs.

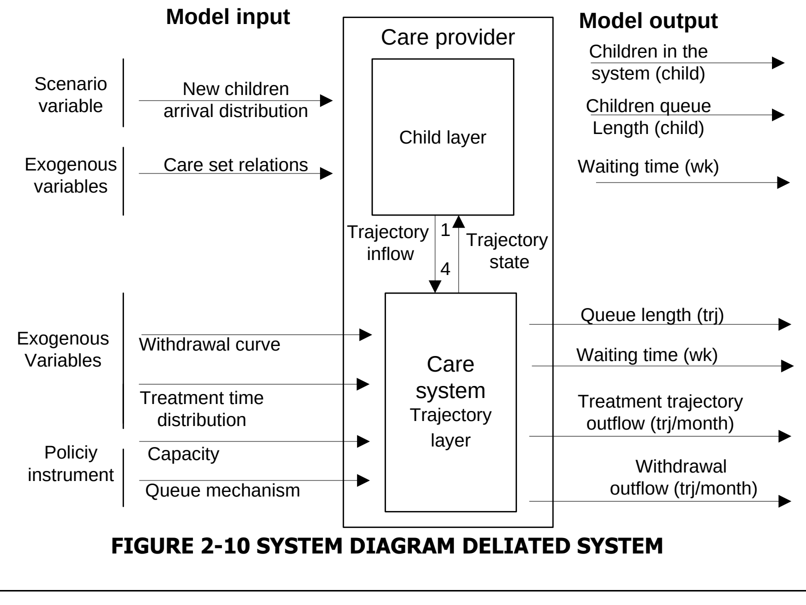


FIGURE 2-10 SYSTEM DIAGRAM DELIATED SYSTEM

Chapter 3

Theoretical and methodological foundation: Modelling and simulation

Modelling and simulation are becoming increasingly important enablers in the analysis and design of complex systems. Vangheluwe and de Lara (2002) mention that simulation modelling as a paradigm increasingly integrates system theory, control theory, numerical analysis, computer science, artificial intelligence and operational research. This chapter serves as the theoretical and methodological foundation of the research. First, the role of modelling and simulation in the system engineering toolbox is demarcated. After which, the SD and DES methodology are introduced and their application in health care is analyzed.

3.1 Conceptual and simulation modelling

This section serves as an introduction of system engineering and a demarcation of the role and function of modelling and simulation in the context of system engineering for complex system and systems of systems. There are several definitions of a *system* in the field of system engineering. In the current research the following definition is employed:

A system is a part of the world we choose to regard as a whole, separated from the rest during a period of consideration, which contains a collection of objects, each characterized by a selected set of attributes, operations and relations (Holbaek-Hansen 1975).

The real or actual system is defined as those parts or aspects of reality we want to investigate as a whole with the intent to know or eventually to control (Holbaek-Hansen 1975). Law and Kelton (2000) discuss when varying modelling techniques may be employed when studying a system as presented in Figure 3-1.

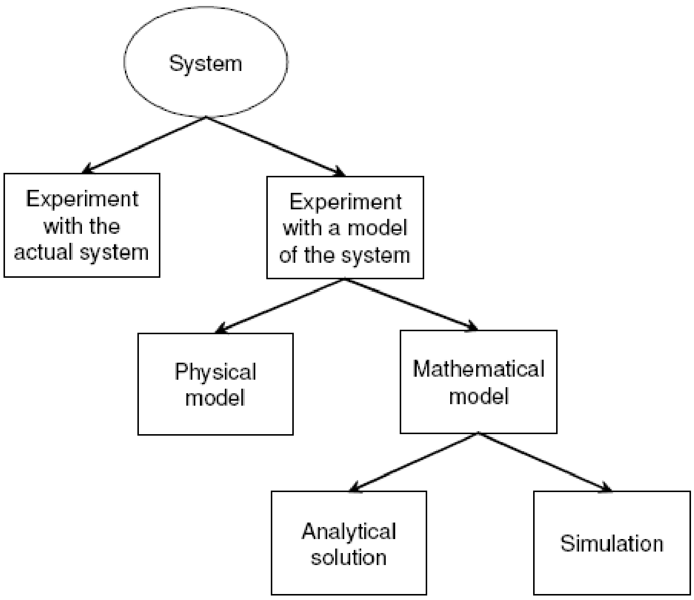


FIGURE 3-1: WAYS TO MODEL A SYSTEM (LAW AND KELTON 2000)

If the system can be altered, if it is cost-effective to do so, and it is safe (for the system and its environment) to use the system, it's desirable to use the real system. Because a model is always a purposeful abstraction of reality, which means that every model has constraints and assumptions which in practice set limits to its validity and applicability. When it is not possible to conduct experiments with the real system a model which captures an abstraction of the real system and its environment can be used. Such a model can be a physical model or a quantitative mathematical model. Two mathematical modelling approaches are distinguished, analytical solutions and simulations. A non-trivial real world system can easily become too complex for a analytical solution to be attempted if randomness and temporal elements are of interest (Banks 1998; Law and Kelton 2000). Simulation modelling is the preferred method of inquiry when the system is too complex to be evaluated analytically. The computer becomes the laboratory for the system engineer (Shannon 1975; Sol 1982).

Sargent (2001) presented a framework to demarcate the role of the real system, the conceptual model, the simulation system and the system objectives in a decision making process, presented in Figure 3-2. A distinction has been made between the real world and the simulation world. The simulation world presents the processes of creating a meaningful abstraction of the real system by using system theories.

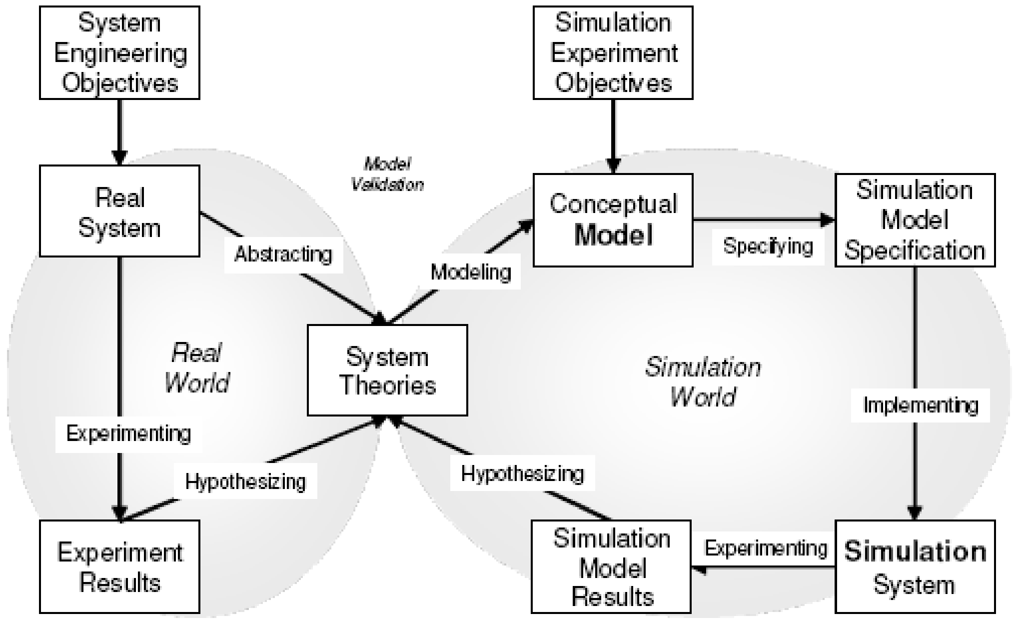


FIGURE 3-2 REAL SYSTEM, MODELLING AND SIMULATION (HESTER AND TOLK 2010)

The figure presents a clear distinction between the conceptual model and the simulation model. The following distinction between the activities of conceptual modelling and simulation modelling is made by Hester and Tolk (2010).

- *Conceptual Modelling* is seen as the process of abstracting, theorizing, and capturing the resulting concepts and relations in a conceptual model.
- *Simulation modelling* is seen as the process of specifying, implementing and executing this model.

Conceptual modelling resides on the abstraction level, whereas simulation modelling resides on the implementation level of the system. The available conceptual and simulation modelling methods and techniques are introduced in section 3.2 and section 3.3

3.2 Conceptual modelling strategies

Modelling concerns the abstraction of a real system by a conceptual model (Banks 1998). The system boundaries, objects and attributes are all subjectively chosen and selected. Modelling is thus considered to be a subjective procedural rational activity (Jacobs 2005). Shannon (1975) refers to modelling as an art instead of a science. This section will first introduce the main principles, methods and viewpoints of system analysis, followed by an introduction of the available methods to make the body of knowledge communicable.

3.2.1 System decomposition

The Systems Engineering method recognizes each system as an integrated whole even though composed of diverse, specialized structures and sub functions. Jacobs (2005) argues that separation of concerns is at the core of system modelling, it refers to the ability to identify, encapsulate and manipulate those parts of a system that are relevant to a particular concept, goal, task or purpose (Tarr and Ossher 2001). Guided by this principle of decomposition, modelling paradigms and languages exist to make the body of knowledge of these decomposed systems communicable.

Jacobs (2005) discusses strategies to divide systems into modular sub-systems. The concept of sub-systems is defined as:.

- *A subsystem is a system that is a part of a larger system.* The usefulness of this concept is entwined with the concept of *modularity*.

System decomposition results into subsystems. Among separation of sequencing activities there are other strategies for dividing systems into subsystems which are applied in this thesis. An important distinction between strategies is:

- *System decomposition into vertically partitions and into horizontally layered subsystems.*

Both introduced decomposition strategies are illustrated in Figure 3-3. A *horizontally layered system* is an ordered set of subsystems in which each of the subsystems is built in terms of the one below it. A *vertically partitioned system* divides a system into multiple autonomous and therefore loosely coupled subsystems, each providing a particular service. Noticeable, the orthogonal decomposition of systems into either vertical partitions or horizontal layers is non-exclusive. Partitions can be layered and layers can be partitioned.

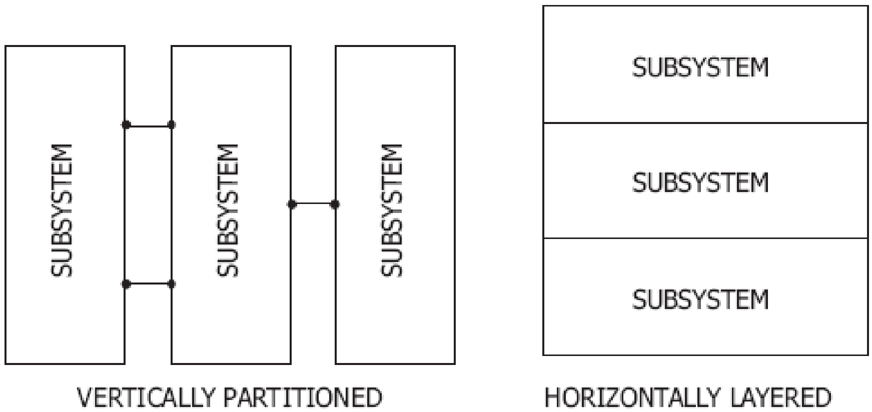


FIGURE 3-3 DECOMPOSITION OF SYSTEMS INTO SUBSYSTEMS(JACOBS 2005)

Different decomposition strategies are applied when decomposing a system from different system viewpoints. For each of these system viewpoints a distinct set of modelling methods has emerged to analyze the system. The three distinct viewpoints are.

1. *Functional view.* The functional view presents the data flows through the system. It defines the processes in the system and the dataflow between the processes. Changes in system functionality result in changes of the function system structure.

2. *The dynamic view.* Made up of state transition diagrams, the dynamic view defines when things happens and under which conditions the happen.

3. *Object view.* An object orientation is made up of entity relationship diagrams; it is a record of what is in the system, or what is outside the system being monitored. It represents the static structure of a system.

Object orientation has emerged as the de-facto modelling paradigm in system engineering (Booch, Rumbaugh et al. 1999). Because information system development has been influenced so heavily by this paradigm, the next subsection introduces the concepts and consequences of the object orientation paradigm in modelling and simulation.

3.2.2 Object Orientation

Object orientation decomposes the system by describing the separate objects and underlying relations. The concept of object orientation can be used both in the conceptual model as well as in the programming of the simulation model. The fact that the first concepts of object orientation appeared in Simula (Dahl 2002), a simulation language, is probably the best argument for the suitability of object orientated in both conceptual as simulation modelling (Panagiotis, Vlahos et al. 1995).
In object orientated system description and programming, the system is divided into objects and relations. Each object is characterized by a selected set of attributes (Booch, Rumbaugh et al. 1999). Three primitive object characteristics are distinguished; identity, state and behavior.

- *Identity.* The ability to identify and distinguishes objects from other objects.
- *State.* The state of an object is defined by its attributes (i.e. age, speed, weight, size, etc.)
- *Behavior.* Objects invoke methods on themselves and on other objects.

A class is a template for a set of objects that share the same attributes (defining their state), operations, relations and semantics (Booch, Rumbaugh et al. 1999). Characterizing object behaviour requires thinking about objects of particular class in relation to objects of another class. In general system relations can be grouped into three categories:

Generalization ↔ Specialization.
Class A is a generalization of class B if and only if every instance of class B is an instance of class A, and there are instances of class A which are not instance of class B. Equivalently, class A is a generalization of B if B is a specialization of A.

Association
Where generalization specifies a relationship between classes, association refers to the structural relationship between objects (or instances of objects).

Aggregation ↔ Containment.
A special form of association specifies a whole-part relationship. An object is an aggregation of another object when it contains attributes that are objects from other classes.

Object orientation distinguishes the following key principles to incorporate this relationships in a model as described in (Booch, Rumbaugh et al. 1999; Eckel 2000):

Classification. Classes capture commonalities of a number of objects. A class can be viewed from different perspectives: modeling, design, implementation and compilation. From a modelling perspective, a class is a template for a category of objects. It defines the attributes, operations and relations of category and thus of all objects belonging to the category. From an implementation perspective a class is a global object with globally accessible attributes, relations and operation.
The object instances of each class form a hierarchy in which the highest level is the root of the system. A visual example of such a model is presented in Figure 3-4.

Inheritance. Classes can be organized in a hierarchical structure. In such a structure the child inherits the protected and public attributes and methods from its parent. The child is referred to as subclass, the parents as *super class*. Inheritance allows the construction of new objects from existing ones by extending their functionality. On implementation level inheritance provides a high level of software reuse (Panagiotis, Vlahos et al. 1995).
Figure 3-5 provides an illustration of the concept of inheritance.

Encapsulation. Attributes and methods uniquely belong to an object; object can encapsulate other objects and keep their services internal, useful to form abstractions. Objects are encapsulated in components and components are encapsulated into systems. In the implementation phase encapsulation is a technique for minimizing interdependency among modules by defining strict external interfaces. The external interface serves as a contract between the module and its client modules. The implication of data abstraction is achieved. In conclusion a client does not need to understand how operations are implemented, so a module can be re-implemented without affecting its clients (Blaba, Premerlani et al. 1988). It also enables the concept of information hiding.

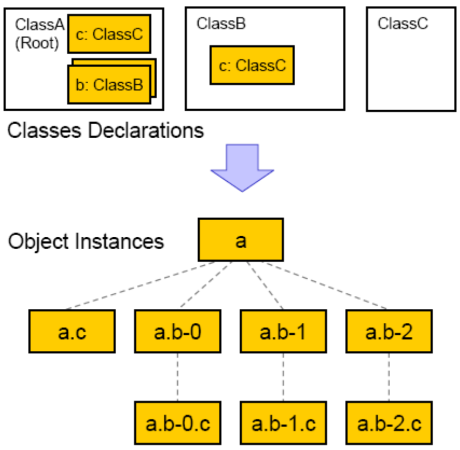


FIGURE 3-4 OBJECT ORIENTATION, CLASS, INSTANT, ENCAPSULATION AND HIERARCHY

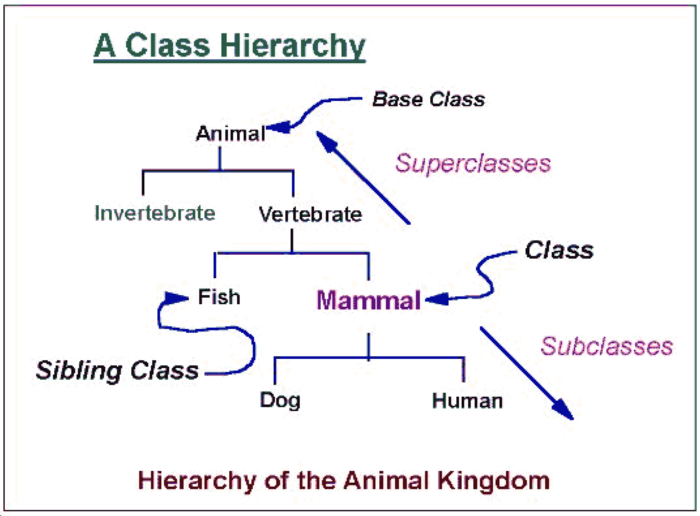


FIGURE 3-5 ILLUSTRATION OF SUPERCLASS ANDSUBCLASS ADAPTED FROM BURNS AND MORGESON (1988)

Message passing is the way in which objects communicate. In order for one object to affect the state of another object, the object sends a message that initiates the second object to execute one of its methods. This is what is called a client-server relationship.

Polymorphism is the ability to take several forms. In the implementation of system by object orientated programming, different objects can understand the same message, but react in different ways.

In general, system relations can be grouped into three categories (Blaba, Premerlani et al. 1988, p. 416): generalisations, associations and aggregations. All three relation categories are identified in the object oriented paradigm. Pracht (1990) points out that the functional and dynamics system view are essentially concerned with association relations, through their emphasis on influence modelling. Object oriented generalization relations (A is a kind of B) and aggregation relations (A is a part of B), serve the purpose of forming hierarchies. Consequential hierarchic relations are difficult to capture and communicate from a functional or dynamic viewpoint. The behaviour of a model over time, which involves the representation of the sequencing activities and states, is on the other side difficult to interpret from an object oriented system representation.

3.3 Classification of simulation

Simulation modelling is the preferred method of inquiry in the context of ill structured problems, when the system is too complex to be evaluated analytically, the computer becomes the laboratory for the system engineer (Shannon 1975; Sol 1982). As aforementioned, Shannon (1975) defines *simulation* as *the process of designing a model of real system and conducting experiments with this model for the purpose of either understanding the behaviour of the system or evaluating various strategies for its operation.* A simulation model is a system description, either object oriented or mathematical, of a real system. This chapter will categorize simulations methods in order to provide a clear understanding of the formal differences between continuous and discrete modelling.

3.3.1 Dynamic simulation vs. static simulation

This is of interest when the temporal element is not relevant to the analysis. Typical examples of static models are deterministic spreadsheet models and stochastic Markov and Monte-Carlo models (Hester and Tolk 2010). All static simulation models represent a system at a given point in time. Static simulations are often simplifications of dynamic real world systems; if the evolution of a system state over time is required a dynamic simulation is more suitable.

Current research is focused on the dynamic simulation methods, these specify both the relations and the behaviour of the system as a function of the system time (Jacobs 2005). Having discussed a framework for modelling the structure of a system in the previous sections, a concise way to represent time and the system behaviour as a function of the system is provided in the following subsection.

3.3.2 Definition of time and state in simulation

A dynamic simulation model may be considered as a set of rules that define how a system being modelled will change in the future given it present state. In other words, dynamic simulation is the execution that takes the model through state changes over time (Borschchev and Filippov 2004). A set of basic definitions in which time and state relationships are carefully distinguished, is introduced by Nance (1981). Starting point is considered to be that a simulation model exists of objects described in terms of their attributes and values. The assignment of a value to an attribute of an object in a system description is based on observations. These observations may change over time the state of an object.

In time based simulation, *simulation time* is used to distinguish different observations of the same attribute. Nance (1981) presents the following concepts concerning simulation time: *instant*, *interval* and a *span*, the definitions of these concepts are illustrated Figure 3-6.

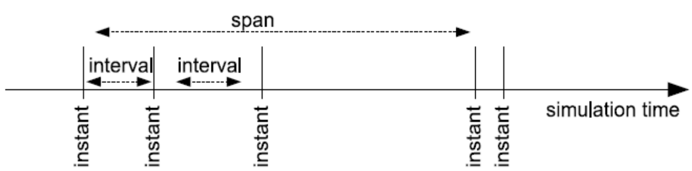


FIGURE 3-6 CONCEPTS RELATED TO TIME(JACOBS 2005)

- *Instant*. A value of a simulation time at which the value of an attribute can be altered.
- *Interval.* Duration between two successive instants.
- *Span.* The contiguous succession of one or more intervals.

The state of an object is the collection of attribute values of an object at an instant. Nance (1981) introduced the following time and state relations: *event, activity and process.* As illustrated in Figure **3-7.**

- *Event.* A change in the state of an object at an instant.
- *Activity.* The actions performed over time in order to create the state change.
- *Process.* The succession of activities of an object over a span.

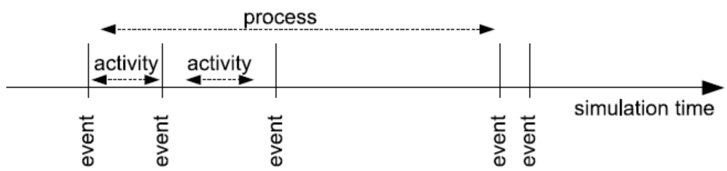


FIGURE 3-7 STATE RELATED CONCEPTS (JACOBS 2005)

The independent variable time and the state variables together describe the static structure of a simulation model; the dynamics of the state variable as a function of the time is described by transition functions that capture the behaviour of a systems. The simulation approaches used to describe this behaviour of a system over time are introduced in the next section.

3.3.3 Taxonomy of simulation

The approaches used to describe the behaviour of a simulation model are referred to as formalisms. The evolution of a formal description for these formalisms started with the categorization introduced by Zeigler (1976). The formalisms were categorized based on the continuous or discrete nature of their time advancing and state transition functions. The following fundamental formalisms are distinguished and visualized in
FIGURE **3-8**.

Differential equation system specification (DESS). This formalism represents systems with a continuous state time advancing function and a continuous state transition function.

Discrete time system specification (DTSS). This formalism represents systems with a continuous state transition function and a discrete time advancing function.

Discrete event system specification (DEVS). This formalism represents systems which operate on a continuous time function with a discrete state transition function.

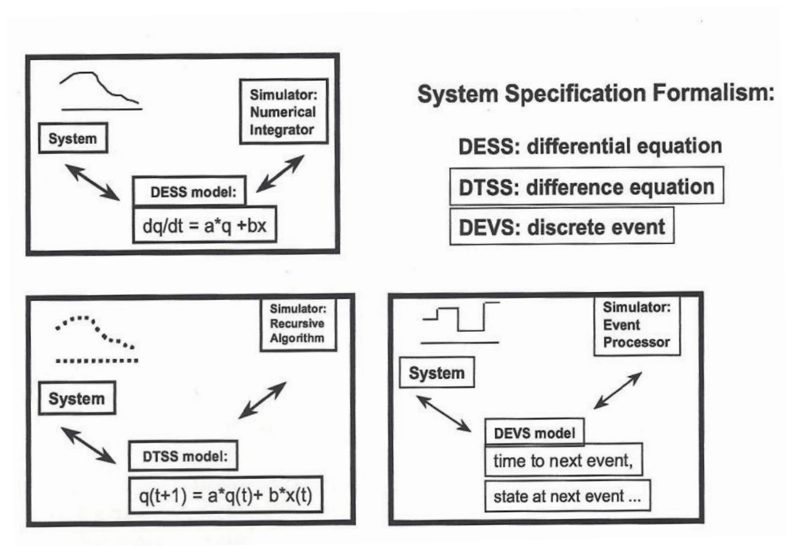


FIGURE 3-8 CONTINOUS VERSUS DISCRETE FORMALISMS(ZEIGLER, PRAEHOFER ET AL. 2002)

The remaining part of this subsection, further sub categorises the DESS and DEVS specification. The introduced formalism classification shows how different time and state transitions functions lead to different simulation formalisms. Commonly used simulation taxonomies in literature categorize simulation to either the discrete or continuous of state or time transitions. The remaining of this subsection presents the taxonomy made by Vangheluwe and the Lara (2002) which categorises formalisms by the nature of their state formalism and the categorizations according to the nature of time advancing set out by Borshchov and Filippov (2004)

Categorization according to state formalism
Vangheluwe and the Lara (2002) present the formalism space in what is known as a formalism graph, presented in Figure 3-9. The different sub-formalisms or methodologies are presented as the nodes of the graph. The vertical dashed line delineates the categorization between continuous state and discrete state formalisms.

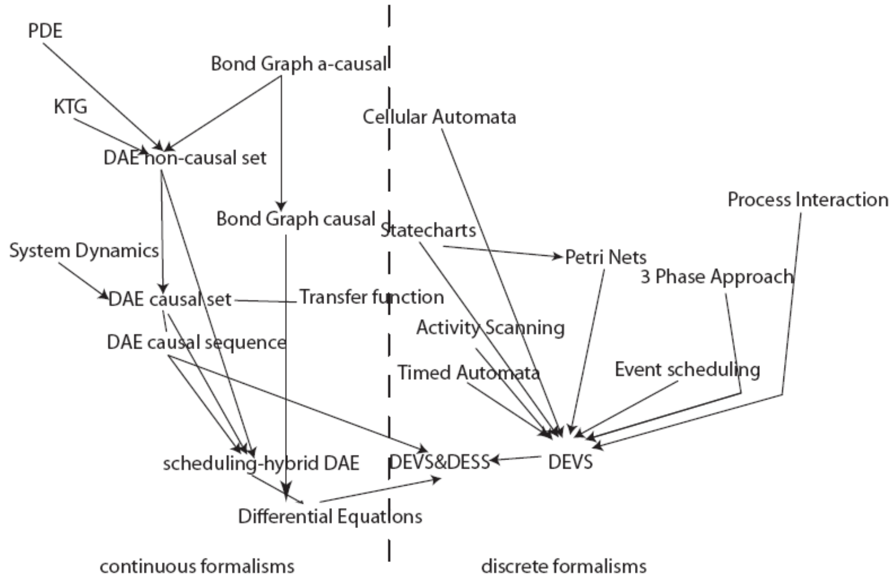


FIGURE 3-9 FORMALISM TRANSFORMATION GRAPH (VANGHELUWE AND DE LARA 2002)

Complex systems often have components and aspects for which the state transitions function cannot be described in a single comprehensive formalism (Vangheluwe and de Lara 2002; Zeigler, Praehofer et al. 2002). For the design and analysis of a simulation model of such a system it would be desirable to express the state tradition functions as a function of multiple formalisms. In the formalism transformation graph, presented in Figure 3-9, the arrows show the possible transformation relations between the formalisms. These relations are also referred as embedded relations in which one formalism is mapped into another (Zeigler, Praehofer et al. 2002).

In the subset of continuous formalisms, these formalisms are related to a specific domain. For example, system dynamics a sub-formalism of the continuous DESS formalisms is targeted at social, socio-economic or ecological topics, while bond graphs are commonly used in engineering systems with a variety of thermal, mechanical or electrical components. The subset of discrete formalisms is not categorized by their specific domain of application. Instead the subset of formalisms is specified by the unique approach or world view followed to specify, or group the behaviour of a simulation model. Overstreet and Nance (1986) refer to the concept of *locality* when they speak of grouping behaviour in a simulation model.

Categorization according to time advancing
The common classification of modelling formalisms is recently adapted to 'time driven' and 'event-driven' modelling formalisms, as can be found frequently in the more recent conference and journal papers from the Winter Simulation Conference and the ACM Transactions on Modelling and Computer Simulation. The difference between both branches lies in the incrementing technique of the simulation clock.

Time driven systems (periodic scan): The value of the simulation clock is incremented by a fixed amount, which is a predetermined uniform unit. After the simulation clock is adjusted by this fixed time increment, the system is examined to determine whether any events occurred during that interval. If any events occurred, they are simulated. The simulation clock is then advanced another time unit, and the cycle is repeated.

Event driven systems (event scan). The simulation clock is incremented at the occurrence of the next event. Thus, the simulation clock is incremented from one event time to the next event time without regarding the interval that separates these events occurrences. After updating the simulation clock, the simulation system simulates the event (implements the resulting changes), and the whole cycle is repeated.

The two distinct time-driven paradigms are the previously categorized continuous state formalisms System Dynamics and dynamical systems distinct by their domain of application. The Event-driven paradigms are distinct by the worldview with which the paradigms specify the behaviour of the system. Discrete Event modelling is a top down approach centred on processes, which may be as logical sequences of activities (Borschchev and Filippov 2004). The emphasis of this research lies on a comparison of the insights produced by SD and DES in the decision making process of the youth care sector. The concepts of these simulation approaches are further explained in the following sections.

3.4 System Dynamics (SD)

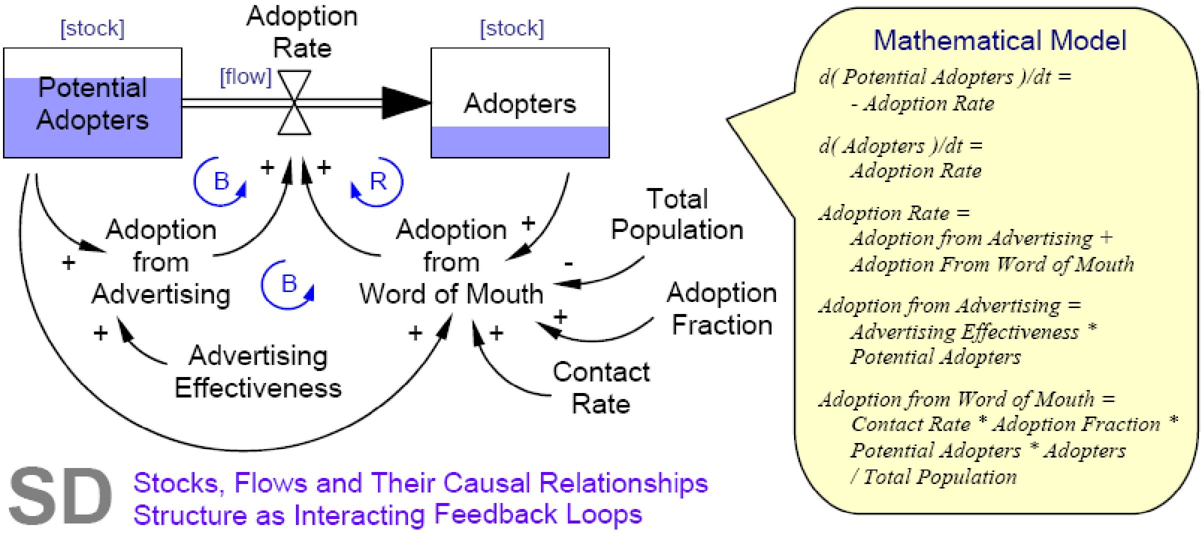
System dynamics (SD) is a methodology and computer simulation modelling technique for framing, understanding, and discussing complex issues and problems. SD is develop by Jay Forester at the Massachusetts Institute of Technology in the early 1960s (Forrester 1961) to help corporate managers improve their understanding of industrial processes by applying feedback control theories. Forrester frames the SD paradigm as:

> *"The study of information-feedback characteristics of industrial activity to show how organizational structure, amplification (in policies), and time delays (in decisions and actions) interact to influence the success of the enterprise*(Forrester 1961)(Forrester 1961)*"*

The goal of the SD paradigm is to develop an endogenous explanation for problematic dynamics (Sterman 2000). SD modelling concerns influence modelling, it identifies the elements considered fundamental to the systems and those that are likely to generate an influence on the problem situation. A SD model presents all elements relevant for generating a real world's system's pattern of behaviour endogenously. The model is composed of interacting feedback loops. The concept of feedback, where output is again used as an input, makes a system capable of generating behaviour endogenously. Such feedback can be either positive (indicated by the 'R' reinforcing feedback loop in Figure 3-10) or negative (indicated by the 'B' or balancing feedback loop). It can also sometimes result in non-linear behaviour which is often found in complex systems. Such complexity possibly produces counterintuitive behaviour which can confuse problem owners and stakeholders (Lane 2000).

Mathematically, SD simulations concern the representation of the system relations according to differential equations (Forrester 1961). Because of the nature of these mathematical functions, SD is well suited for the modelling of continuous process (Chanal and Eldabi 2008), at the specific domains of urban, social, socio-economic and ecological topics. SD models are mostly used at strategic level due to their problem structuring ability, when the problem owner is more interested in overall performance than in the finite behaviour of particular processes within the system (Sweester 1999; Brailsford and Hilton 2001).

SD is characterised by its modelling of a system in terms of levels (for example stocks of material or knowledge), flows between these level and information (rates, delays) that determine the value of these flows. An example of the SD problem structure, in which the system behaviour is described by interacting feedback loops, is presented in Figure 3-10. The dynamic complexity embedded in SD models arises because variables influence each other in ways that involve non-linearity, delays and accumulative or draining relations. SD is a top-down modelling approach and as such it uses aggregated values to represent stocks and abstracts from single events and entities. It is difficult, but not impossible, for it to model heterogeneous populations where the effect of clustering and individual behaviour may be important. It can achieve this by segregating a large population into smaller and related groups, with homogeneous properties, which are more tightly defined.



Bass Diffusion Model In the classic textbook model of product diffusion (Sterman 2000), *Potential Adopters* become *Adopters* at *Adoption Rate* that depends on advertising and word of mouth promotion. The impact of advertising is modelled as a constant percent of *Potential Adopters* (namely, *Advertising Effectiveness* = 0.011 in this paper) becoming *Adopters* each time unit. Therefore, the corresponding summand of *Adoption Rate* equals *Potential Adopters * Advertising Effectiveness*. For word of mouth adoption it is assumed that everybody contacts everybody else in this population group. The number of contacts per person per time unit is *Contact Rate* (100). In case one of the two people in contact is adopter and another one – not yet, the latter one will adopt with the probability *Adoption Fraction* (0.015). Then, during a time unit, each adopter will convert *Adopters * Contact Rate * Adoption Fraction * [Potential Adopters / (Potential Adopters + Adopters)]* people into *Adopters*. The expression in the square brackets is the probability of another person being not already adopter.

FIGURE 3-10 SYSTEM DYNAMICS MODEL STRUCTURE(BORSCHCHEV AND FILIPPOV 2004)

Literature argues that the SD methodology needs to engage with mental models (Lane 2000). The most important information to include in these systems is not documented; it is embedded in the problem owners and stakeholders mental models. The modelling work should be done in close proximity with the problem owner's mental model. Due to this engagement with the mental models SD generates confidence in the simulation model. Additional to the strict predictive value of SD models is the qualitative aspect, with the aim of enhancing the understanding of an identified problem and improving comprehension of the structure of the problem and the relations present between relevant variables (Brailsford and Hilton 2001). Validation of SD models is done to increase the plausibility of the model as a theory for the causal mechanism generating the behaviour. SD models could be characterized as a collective best guess based on a particular groups understanding of the system at a point of time (Sweester 1999).

Although SD is been used with reasonable success in the understanding of supply chains and logistic networks, it is nevertheless limited by its requirements, that the input variables have inherently uniform properties (Brailsford and Hilton 2001). The models are basically deterministic and they treat simulation objects as a continuous mass. SD does not attempt optimisation or point prediction, but it is capable of modelling very large complex systems and can deliver a wealth of qualitative and quantitative output measures. The paradigm is used to model problems where abstraction is high and details are low. Parameters estimation and validation are less of an issue with SD than with DES. SD is typically used to model problems such as global population dynamics, the macroeconomics of a country, ecological systems, and national health systems.

3.5 Discrete Event simulation (DES)

A discrete event simulation model is a system that changes its states at discrete points in time, at specific instants as recalled from section 3.3. The purpose of discrete simulation is the modeling of systems that are dynamic and stochastic, implementation of these models, and running these models (Garrido 2001). As a modeling approach DES can describe complex system structures, which cannot be described easily by analytical models (Law and Kelton 2000, p.115). The main objectives of these models are prediction, optimisation and analysis of "what if" scenarios. To achieve statistical validity to the performance of a real world system, a DES model requires accurate data on how the system operated in the past or accurate estimations on the operating characteristics of a proposed system (Lane 2000). Statistically significant results taking into account randomness, variability and uncertainty can be obtained as long as enough simulations are made (Brailsford and Hilton 2001). The components of a DES model are presented in
Figure **3-11**, the following subsection provides an overview of the concepts and methods embedded in these components.

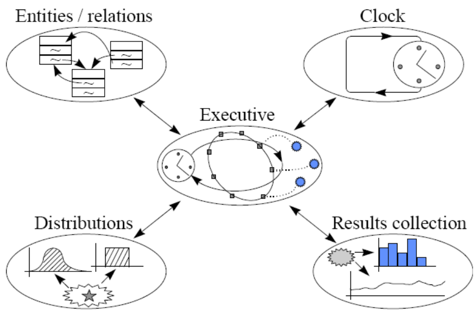


Figure 3-11 Structure of discrete models (Kreutzer 1986)

3.5.1 Passive vs. Active entities

All major components of a system are identified as entities or objects, which have attributes and behaviour. Some of these entities are *active* entities, which have a life of their own. An example of an active entity is a process. Process instances are represented as objects of a thread class. The attributes of such processes are represented as attributes of the class. The behaviour of a process is modelled by the operations that can be performed by the processes; these are implemented as methods in the thread class (Garrido 2001). In addition to processes, a simulation model often includes other entities that do not behave as processes. These entities are modelled as classes that do not define a behaviour (Garrido 2001). A simulation can consist of several active and passive objects of different classes. During a simulation run, all the active objects of the simulation model interact with each other in some way or another. The introduced classification of active and passive objects is presented Figure 3-12.

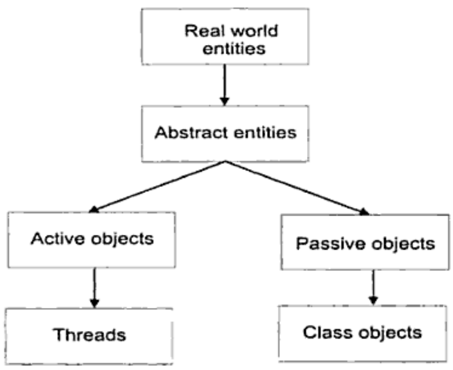


FIGURE 3-12 ACTIVE AND PASSIVE OBJECTS (GARRIDO 2001)

3.5.2 Simulation clock and modeling perspective

The simulation time at which an event occurs is called its event time. The simulation executive, the program that implements and controls the simulation, must carry out time changes in the systems and keep track of the passage of simulation time. The simulation executive of most DES systems use a event scheduling world view.

Event scheduling provides *locality of time*. Each event routine in a model routine in a model specification describes related actions that should always all occur in one instant (Overstreet and Nance 1986). The simulator first identifies all events at which discontinuous state transitions occur. An event can cause state changes, trigger other events, or schedule events at future simulation time (Carson 1993). The strategy for the event scheduling world view is to repeatedly select the earliest scheduled event, to advance the simulation time to the execution time of that event and to invoke the operation specified by that event. The behaviour and thus the processes of the simulation model are grouped in a time sorted event list. The simulation model is described as a time sorted set of scheduled events (Jacobs 2005). Several events may be scheduled to occur at the same moment of time. Simultaneous events may depend on each other or be truly concurrent. As a result of the event executions, the discrete state of the model may change, timers may be activated, events may be deleted from the event and other events may be added.

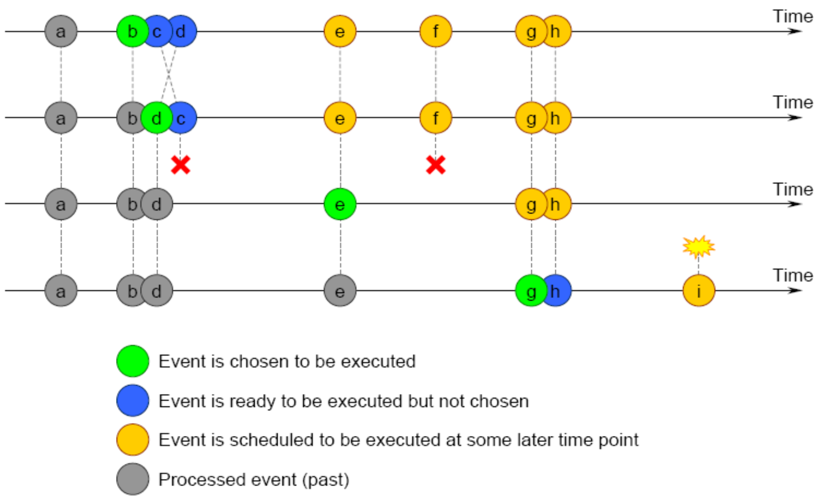


FIGURE 3-13 EVENT SCHEDULING

When analyzing a system, the system can be decomposed from different perspectives as introduced in subsection 3.2.1. For each of these system perspectives a distinct set of modelling methods has emerged to specify the system and system behaviour in a DES simulation model. The following modelling concepts are distinguished:

Object orientation: To specify the relations between objects and entities and to control complexity. Object oriented generalisation relations (A is a kind of B) and aggregation relations (A is a part of B) forms the purpose of creating hierarchies, as introduced in subsection 3.2.2.

State chart (dynamic perspective): State charts define the behaviour of a system from an individual entity perspective by a collection of states and discrete state transitions. Transitions can be triggered by a set of events or conditions and cause a set of actions (Borschchev and Filippov 2004). Hierarchy in state charts permits one state to contain other states. Parallelisms permit multiple states to be active concurrently. Important extensions of this formalism are state hierarchies, parallelism and event broadcasting. Broadcasting of events allows one state to detect changes in other another states and provides the means to trigger a series of actions in one activity depending on transitions that occur in another (Soblev, Harel et al. 2008).

Process orientation (functional perspective). Each process routine in a model specification describes the action sequence of a particular model object (Overstreet and Nance 1986). Process interaction provides a way to represent a system's behaviour from the point of view of the dynamic entities moving through the system. A process is a time ordered sequence of events: activities and delays that describe the flow of dynamic entities through a system (Carson 1993). Each process in a simulation model specification describes its own *action sequence* (Overstreet and Nance 1986). This worldview reflects the autonomy of an individual process, the life cycle and the concurrency in the execution of distinct process (Jacobs 2005).

Implicit focus in most discrete event literature is on process orientation. This could be a consequence of the many commercial tools that support the process modelling style. Therefore, the dominant process orientation worldview is further described in the following subsection.

3.5.3 Process orientation

Process modelling is well known for problems with queuing characteristics. Process model building involves identification and representation of entities, resources, logic and flow of entities (Borschchev and Filippov 2004). An entity is a passive object of interest in the discrete system. An attribute is a property of an entity. An activity represents a time period of specified length (Banks 1998). The process interaction worldview describes systems by a flowchart through which the entities travel. Flowcharts blocks describe among other activities queues, resource seizing and releasing and activities (Owen, Love et al. 2008). The classic view of such a flowchart for a bank kiosk is presented in Figure 3-14.

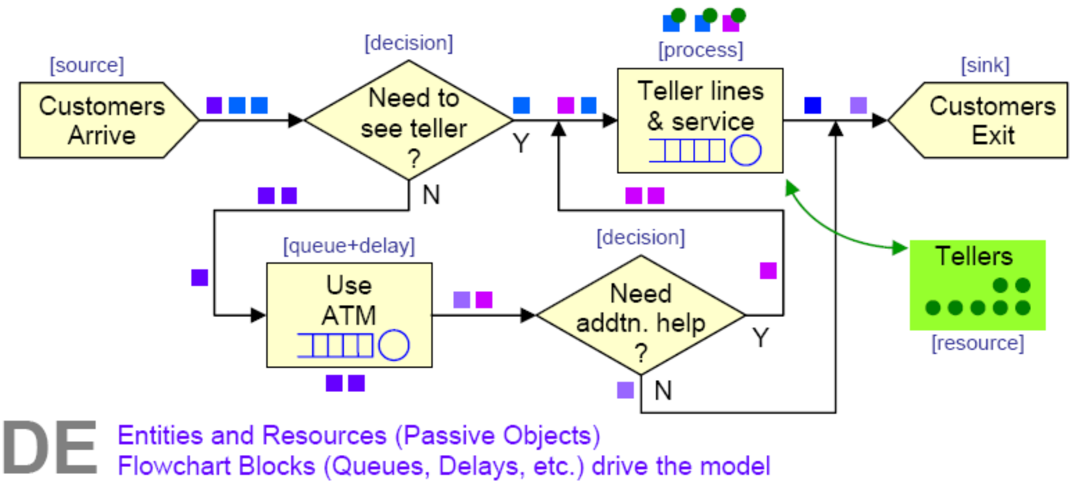


FIGURE 3-14 PROCESS ORIENTATION DISCRETE EVENT VIEW (BORSCHCHEV AND FILIPPOV 2004).

In process orientated models entities have characteristics which determine their pathway through the network. Unlike Markov models, which take no account of history, "service time" can be dependent on individual characteristics and previous history, any parametric or empirical distribution can be chosen to model activity durations. Complex logical rules can be used to determine entities routing through the system.

3.6 Comparisons SD and DES

There is a growing concern in research in understanding which method is better or more suited for a particular problem It has been argued that the choice of modelling methodology is dictated by the modeller's expertise (Brailsford and Hilton 2001; Lorenz and Andreas 2006; Morecroft and Robinson 2006; Chanal and Eldabi 2008). Rather than adapting a tool to the problem, analysts try to adapt the problem to available tools. As introduced in preceding sections, all modelling methods are based on certain concepts, philosophies and assumptions (Lorenz and Andreas 2006). Successful choice between methods depends on understanding the contrasting and overlapping features of the modelling methodology. This section provides a structured overview of the contrasting and overlapping features of the DES and SD model found in previous sections. A distinction will be made between the technical differences and the conceptual differences of the two methodologies.

Discrete Event Simulation	System Dynamics
Systems (such as health care) can be viewed as networks of queues and activities	Systems (such as health care) can be viewed as a series of stocks and flows
Objects in a system are distinct individuals (such as patients in a hospital), each possessing characteristics that determine what happens to that individual	Entities (such as patients) are treated as a continuous quantity, rather like a fluid, flowing through reservoirs or tanks connected by pipes
Activity durations are sampled for each individual from probability distributions and the modeller has almost unlimited flexibility in the choice of these functions and can easily specify non-exponential dwelling times	The time spent in each reservoir is modelled as a delay with limited flexibility to specify a dwelling time other than exponential
State changes occur at discrete points of time	State changes are continuous
Models are by definition stochastic in nature	Models are deterministic
Models are simulated in unequal time steps, when "something happens"	Models are simulated in finely-sliced time steps of equal duration

FIGURE 3-15 TECHINICAL DIFFERENCES BETWEEN DES AND SD (BRAILSFORD AND HILTON 2001)

	Discrete Event Simulation	System Dynamics
Perspective	Analytic; emphasis on detail complexity	Holistic; emphasis on dynamic complexity
Resolution of models	Individual entities, attributes, decision and events	Homogenised entities, continuous policy pressures and emergent behaviour
Data sources	Primarily numerical with some judgemental elements	Broadly drawn
Problems studied	Operational	Strategic
Model elements	Physical, tangible and some informational	Physical, tangible, judgemental and information links
Human agents represented in models as	Decision makers	Bounded rational policy implementers
Clients find the model	Opaque/dark grey box, nevertheless convincing	Transparent/fuzzy glass box, nevertheless compelling
Model outputs	Point predictions and detailed performance measures across a range of parameters, decision rules and scenarios	Understanding of structural source of behaviour modes, location of key performance indicators and effective policy levers

Figure 3-16 Conceptual differences between DES and SD (Lane 2000)

3.7 Simulation experiences in health care

Over the past decades, health care costs have dramatically increased, while health care organisations have been under severe pressure to provide improved quality care for their patients. This situation has compelled researchers and health care professionals to examine new ways to improve efficiency and reduce costs. The synthesis made in this section is made based on the concept of analogy.

Analogy is a cognitive process of transferring information or meaning from a particular subject (the analogue of source) to another particular subject (the target). The concept is based on making useful generalizations. The purpose is to understand and articulate the rules that apply to a specific domain of knowledge and to discover rules that are shared between domains (Robertson 2001).

Based on the concept of analogy, the general knowledge and techniques from the field of modelling and simulation and the experience of their application in the context of the health care sector is transferred to the specific youth care simulation problem under study. In order to provide a justification of using dynamic simulation and to provide insight into the expected strength and weaknesses of the SD and DES modelling methodology in the youth care context.

Static models

Most literature on waiting line management in health care is based on the static mathematical approach described by the Markov queuing theory (Torgenson and McIntosh 2006). These studies focus mainly on utilization of resources and the calculation of the minimum required amount of treatment positions while maintaining a high service rate. Experiences with these studies identify that static queuing theory struggles with the abstraction of phenomena like seasonal effects and the incorporation of human behaviour. These issues are also identified by Brown et al. (2003), who argue that traditional queuing theory in application of health care has a series of shortcomings; the absence of customer withdrawals, time dependent behaviour or customer heterogeneity. Three characteristics, which are all frequently present in healthcare systems. Mandelbaum and Shimkin (2000) made attempts to construct a Markov model which incorporates withdrawal behaviour. They acknowledge that a lot of work needs to be done to achieve practical usability of withdrawals in queuing theory.

Dynamic simulation: SD and DES

Dynamic Simulation is regarded by many as the operational research approach of choice in healthcare modelling. In many respect it is the ideal approach for addressing health care issues, yet the relatively small number of successful implementations would suggest that (outside) academia it has been under used in the health care domain, compared with manufacturing industry or defence (Lowry 1992; Benneyan 1994; Carter and Blake 2005; Brailsford 2007; Kuljis, Paul et al. 2007).

The SD and DES approach, introduced in previous sections, are frequently used in health care modelling. Brailsford (2007) address the application of both modelling approaches in health care. He argues that the SD approach is usually used to address strategic system wide models to answer long-term, broad-brush questions, which are not concerned with individual patient flows through the system. In contradiction, the DES approach is commonly used to address operational or tactical models at the healthcare unit level, which are concerned with modelling the flow of patients through a system in models. These models are used for capacity planning, resource allocation and process redesign. The DES approach seems more appropriate for the youth care problem under investigation, which investigates the children flow through the youth care sector in order to find an optimal pay off between capacity investments and child waiting times. The following subsections evaluate available literature about the application of both methods in health care modelling and abstracts these experiences to their application in the youth care sector taking into consideration the requirements formulated in sub-section 2.3.2. The subsections are categorized according to usefulness, usability and usage factor.

3.7.1 Requirements Usefulness

Requirement 1: Accurate insight into performance indicators (PI's)

Sub-section 2.3.1 introduced the fit between the system, problem and methodology perspective as the basis for sound models. This subsection discusses the fit between the SD and DES methodology and the youth care problem and system perspective, based on past experiences with both simulation approaches in health care modelling.

Problem perspective. The aggregated SD approach, which provides an understanding of the structural source of behavioural modes and the impact of policy levers, provides an aggregated indication of the average of the important performance indicator robustness to variability in the processes of the system. It has been argued in the context of health care systems that basing analysis solely on averages ("management by averages") can yield radically inaccurate results if significant variation exists (Benneyan 1994). Unlike SD models, stochastic DES models are able to provide point predictions and detailed performance indicators. A DES model provides insight into the possible spread of the important performance indicators given the uncertainty in the system (Morecroft and Robinson 2005). Which allows the evaluation of possible policy strategies on other criteria's than expect averages for instance on overall robustness or minimum worst-case scenarios. These criteria are relevant in health care and youth care systems, which both have a high intolerance to failure.

System perspective. Modelling the youth care sector requires the coupling of different political information levels. SD models, in which entities are treated as a continuous quantity rather like a fluid, do not provide the possibility to distinct entities by attributing characteristics (Brailsford and Hilton 2001; Lorenz and Andreas 2006; Morecroft and Robinson 2006; Chanal and Eldabi 2008) . Therefore, it is not possible in the SD modelling approach to abstract realistic child care profiles and their influence on the system behaviour. Unlike, the SD approach, entities in DES models are distinct individuals, each of them can posses characteristics that determine their flow through the system (Brailsford and Hilton 2001; Lorenz and Andreas 2006; Morecroft and Robinson 2006; Chanal and Eldabi 2008). Complex logical rules can be used to determine patient routing through the simulation, or the outcome of a treatment. Randomness, variance, uncertainty and conditionality can be accounted, as long enough simulation runs are performed to obtain significant results. In the context of the youth care sector a DES model allows the abstraction of realistic care profiles and therefore the coupling between the child and trajectory layer. As a general remark the authors argues that the small number of successful simulation implementations in healthcare, in comparison to industry, is likely to be the result of the interaction of complex human withdrawal behaviour and patient priorities present in many health care systems. The youth care system is an example of a health care system, which faces both patient withdrawals and priorities.

Requirement 2: Data availability or collectability

The data dependency of a model is related to its aggregation level. Aggregated SD models are not dependent on large quantities of high quality data, they have the capability of using descriptive or judgmental as well as numerical data (Brailsford and Hilton 2001; Lorenz and Andreas 2006; Morecroft and Robinson 2006; Chanal and Eldabi 2008). Disaggregation of a model requires disaggregation of model inputs, a DES model with the objective to provide insight into the distribution of individual child waiting times requires to abstract the exact distribution of child arrivals and treatment times in parametric or empirical distributions which can be dependent on individual characteristics. Such a model is data dependent ad requires large amount of high quality numerical data sources at which possibly complicated data studies need to be performed.

3.7.2 Requirements usability

Requirement 3:low distance between stakeholder and model worldview

In a SD world view, individual entities are lost and patients become indistinguishable mass which flow around the model like water. Psychologically this creates problems to health and youth care professionals who by training are people-focused and do not like the idea of reducing human being to computer bytes (Brailsford 2007). Brailsford argues that, psychologically DES is appealing in health care systems. It enables the modellers to give the entities all the necessary characteristics for instance age, gender, diagnosis, blood group, disease status, sexual preference, hair colour or whatever ever you please.

Requirement 4: Clear and intuitive interface

The model interface is required to provide a clear and unambiguous overview of the system behaviour. Unlike the SD methodology, the DES methodology allows to animate the entity flows through the system. The author however argues that the movements in the youth care sector are not easy to visualize and an animation would not add much value the DES model.

Requirement 5: Ease of Experimental set-up.
A key difference between the SD and DES approach in terms of their input interface and experiment is the difference in input variables. The variables in a SD model are constants, which represent the average observed values in the real world context. New experiments in a SD models requires deciding about the assumed average value in a possible future scenario. New experiments in a DES model require to decide about the spread of the variable in a possible future scenario and to translate this spread into a distribution. Stakeholders, which are not skilled in quantitative data analysis, usually have a perception of an observed average of important variables in their sector. Determining a valid distribution implicates considerably more difficulties.

Requirement 6: Low Experiment run time
A key advantage of the SD approach is that models runs fast and do not require multiple replications, so it can run interactively with decision makers (Brailsford and Hilton 2001). Unlike SD, a DES model run requires more processing time and CPU memory, furthermore multiple replications are necessary to obtain statistically significant results (Morecroft and Robinson 2005).

3.7.3 Requirements usage

Requirement 7: Generalise ability.
SD models, which do not allow to model individual entities and their characteristics, result in homogenous, holistic models in, which a general system view is presented without concentrating on unnecessary details. These general models are likely to be the equivalent for related systems with the same structure. The ability of the DES modelling methodology to model individuality and conditionality is likely to result in detailed model. The system details of systems with comparable structures are likely to differ, which makes DES model in practice less general than SD models.

Requirement 8: Flexibility.
Flexibility refers to the ability of the decision support models to adapt to changes in the system or performance indicators. It is strongly related to the concept of modularity:

Modularity is a general systems concept, typically defined as a continuum describing the degree to which a system's components may be separated and recombined. It refers to both the tightness of coupling between components, and the degree to which the "rules" of the system architecture enable (or prohibit) the mixing and matching of components (Baldwin and Clark 2000).

SD models, which are based on influence modelling between variables, are frequently decomposed into sub-models. The author argues that the coupling between these sub-models frequently exists of multiple shared variables. A change in system operations results in a change of model structure. Unlike SD and process orientated models, object oriented DES models can achieve the implication of data. In the implementation phase encapsulation is a technique for minimizing interdependency among modules by defining strict external interfaces. The external interface serves as a contract between the module and its client modules. In conclusion a client does not need to understand how operations are implemented, so a module can be re-implemented without affecting its clients (Blaba, Premerlani et al. 1988).

Requirement 9. Low time and cost of model Initialization.
The time and cost of model initialization is closely relation to the aggregation and data dependency of the model. The general average view of a SD models requires less data studies than the detailed DES view. The ability to automate the pre-processing of large data sets to input into the DES models can minimize the extra time and costs of initializing a DES model (Lowry 1992; Brailsford 2007; Kuljis, Paul et al. 2007).

3.8 Conclusion methodological justification

Overall, the objective of this chapter is to answer the second research question: What are the strengths and weaknesses of the SD and DES approach when abstracting the care provider system in a purpose full simulation model? In order to answer this question, first an overview of the current state of the art in modelling and simulation is provided, followed by an analysis of the fit between the methodologies and the in the first chapter formulated requirements and delineated system under study. The analysis is based on the concept of analogies. The experiences with simulation in the health care sector found in literature are abstracted to the specific requirements in the youth care context of current research. Figure 3-17 provides an overview of the relative expected strengths of both methods in comparison to each other.

Figure 3-17 strengths and weaknesses of SD and DES for decision support in youth care

Category	Requirement	Description	SD	DES
Usefulness	**1**	**Relevant PI's**	**-**	**+**
	2	**Data dependency**	**+**	**-**
Usability	3	Worldview	-	+
	4	Interface	+	+
	5	experiment setup	-	+
	6	Run length	+	-
Usage	7	Generalizability	+	-
	8	Flexibility	-	+
	9	Initialization	+	-

Usefulness. The ability to provide insight in the behaviour and value of relevant PI's is arguably the most important requirement. A model, which does not provide valuable insight in the PI's, cannot serve as a purposeful decision support model. While the DES methodology has advantage over the SD methodology, the validity of the model approach is strongly dependent on the availability of data sources. The disaggregated output of DES model initialized on to small or low quality dataset embeds a high risk of misinterpreting the real world behaviour. Furthermore, human decision making such as the youth care queue mechanism and patient withdrawals behaviour, experienced both in health and youth care are difficult to abstract and quantify in a disaggregated model.
Usability. It has been argued that unlike SD, the worldview of DES models is physiologically appealing for modelling health youth care systems, because it enables to give entities characteristics. The worldview is an important factor in the process of gaining stakeholder trust and understanding. Because of the detailed level of modelling, the experiment set-up takes more time for a DES modelling approach. The increased level of detail of DES models, also results in larger simulation run times and CPU memory usage in comparison to a SD model. Furthermore, stochastic DES models require multiple replications to obtain statically significant results. Which could makes large DES models less appropriate to set up and run experiments real time during workshops with stakeholders.
Usage. The detailed characteristics, which determine the entity flows through a DES system result in less generic models than the homogenous relations do, abstracted in SD models. Object Oriented DES models are perceived more flexible in structure than SD models and process oriented DES models because they can be designed taking into account the principles of modularity. Unlike SD models, initialization of DES models requires an large investment of time and costs in data gathering, data analysis and distribution fitting to the data.

In conclusion, a DES approach can provide valuable insight in addition to a SD model for the modelling of systems, which incorporate a high intolerance to failure for each entity, heterogonous entities and a large influence of process variability. A precondition for this additional insight is the availability or collectability of data to quantify the disaggregated DES mechanisms. Furthermore, the higher level of detail should be worth the additional investments in time and costs of a DES modelling approach. The remaining part of this thesis provides a practical evaluation of SD and DES modelling in the youth care sector.

Chapter 4
System Dynamics: Currently used Model

This chapter describes the abstraction of a care provider system in the system dynamics model currently used by INITI8. The second chapter of this research introduced the problem description, the simulation objective and a demarcation of the system under study. Followed by a description of the delineated system in a continuous differential equation system and the implicit assumptions and reductions made to abstracted the real world system in this model.

The conceptual model and equations of the currently used SD model are presented in Appendix B. The following sections describe the specification and the abstraction of the real world variability in the currently used SD model.

4.1 Specification

Previous section introduced the structure of the system dynamics model and identified the causal relations between the variables. This section first makes the assumptions made to abstract the real world system in a system dynamics model transparent, followed by a description of the model structure and equations.

4.1.1 Model assumption

A model is a purposeful simplified abstraction of reality, which means that every model has constraints and assumptions, which in practice set limits to its validity and applicability. The simplifications are made by the demarcation of what is in the system and on how aspects the demarcated real system are simplified in the care provider SD model

1. *Perfect mixing.* The aggregation level of the SD methodology abstract from single events and entities and takes an aggregated view concentrating on policies (Schieritz and Milling 2003). SD models assume homogeneity and perfect mixing within the model compartment (Rahmandad and Sterman 2004). The implication for the care provider model can be separated to the children and trajectory layer.

   The child layer assumes that the set of care trajectories every child receives is homogenous. A disaggregation is made between two categories of returning children, return after treatment and return after withdrawn. The probability of return and the time between returns are modelled differently for these distinct children categories.

   The trajectory layer assumes that all trajectories, of each care type, are homogeneous. The waiting and treatment times for all trajectories are assumed to be exponential distributed.

2. *Withdrawals.* Withdrawals in the real system are among other factors caused by wrong indications at the BJZ, changes in the care needs of a child and allocation difficulties. Previous statistical researches performed by INITI8, found a significant relation between the probability of children withdrawals and the time children have to wait for care. The SD model assumes that withdrawals are dependent on the average child waiting time.

4.1.2 Model initialization

As determined in the model requirements, formulated in Model requirements 2.3.2, generalise ability and flexibility are important requirements. In order to achieve maximum flexibility and reusability the model is initialized from an excel sheet, which creates a separation between the model and its input data. This creates the possibility to quickly adjust the model to different data sets.

INITI8 made the decision to initialise the model in a steady state situation. They argue that this creates an optimal insight into effects of possible policy measures. In a deterministic SD simulation, a steady state implicate that the model stocks and flows do not change over time. INITI8 conceives that the steady state situation does not show insight in the whole system complexity. However, they argue that the communicate value of the steady situation is worth the loss of insight (Sterman 2000). The model objective is to provide insight in the result of policy options, not to provide exact value predications. The steady state calculations can take either the stocks or flows values as input. This results in a situation where the stock values are directly recognizable for the stakeholders. They steady state calculations make all models inflow equal to the model outflows. This decision is made because the outflows experience less variance than the trajectory inflows.

4.2 System variability

While previous chapter introduced SD models as purely deterministic models, previous section described the possibility to initialize the SD model with stochastic input parameters, which results in a stochastic simulation. This section attempts to distinct the real world variance in the care provider system that can be abstracted in the SD model from the variance, which can't be abstracted. First, the abstraction of variability in the SD model is analyzed, followed by an analysis of the variability observed in a real world care provider system that cannot be abstracted in the SD model.

4.2.1 Variability in SD models

The SD methodology allows using stochastic probability functions to parameterize variables. The variability observed in exogenous inflows can be abstracted into the model. Endogenous model flows are often calculated with the help of an aggregation variable, which describe an average attribute of the entity flow. For instance, the number of trajectories assigned a child, the aggregation of this variable translates the heterogeneous children to homogenous entities. Even though these variables can be abstracted by a probabilistic function, this function describes the variability of mean over time, not the individual variability. Furthermore, the variability of the mean over time is more a result of the system behaviour than a system input.

The next limitation can be observed in the stocks. As before introduced SD models do not explicitly model heterogeneity among different elements accounted for in a stock; within each stock it is typically assumed that all entities are perfectly mixed. The flow affecting these stocks are usually formulated using the "mean field" approximations familiar in physics, that is, as the expected or average value of the underlying probabilistic transitions from one state to another (Rahmandad and Sterman 2004). The perfect mixing assumption within compartments makes the probability of exit from a stock Poisson distributed, in other words independent of an individual item's residence time in the stock. This leads to the main approximation in the SD field, which states that the outflow is given by the total stock size divided by the mean residence time. In a perfectly mixed system, the assumed stock delays of individual entities are exponential distributed. While abstracting outflow variables by stochastic function can change the average delay of the stock over time, the assumed delay distribution for individual entity in the stock can only be abstracted by an exponential function. In other words, the impact of individual variability cannot be abstracted in the SD model. The following section analyses the observed process variability in the care provider system.

4.2.2 Variability in treatment time

An primary advantage of stochastic over deterministic methods is that they account for the existence of process variability, whereas basis analysis solely on averages ("management by average") can yield radically inaccurate results if significant variation exists (Benneyan 1994). Based on this statement the process variability of the trajectory delays observed in the care provider stocks, provides an indication of the need for a stochastic (DES) modelling approach. In order to analyse the process variability in the youth care sector the treatment times observed at a case study care provider are analyzed. The treatment times are categorized to the four distinct care types, in order to analyze the process variability in the independent care systems.

Figure 4-1 presents a histogram and a boxplot. The histogram visualizes the foster care treatment time distribution. The presented histogram, which includes a plot of the best fitting exponential distribution, indicates that the foster care treatment time is not exponential distributed. The boxplot visualizes the observed treatment time spread for the four care types. The descriptive statistics of the datasets are presented in appendix C.1. The box plot clearly presents a wide spread and a extremely long tail for residential and foster care, the standard deviation of residential care 11 months and for foster care over 27 months.

It can be concluded that significant variability is observed in the independent care system of residential and foster care of the chosen care provider case study, deterministic analysis on averages, as in the SD model, can yield radically inaccurate results in such a system.

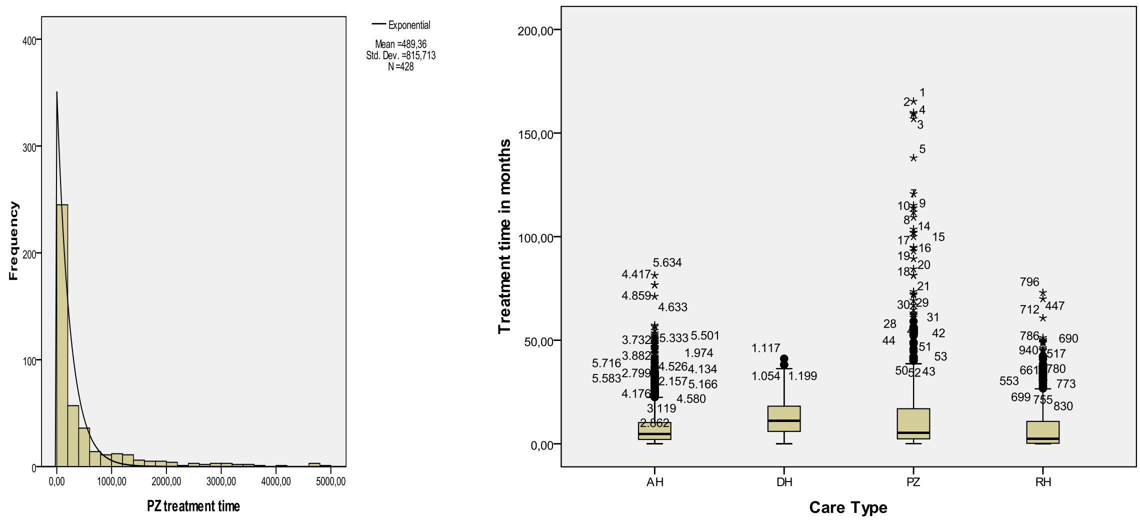


FIGURE 4-1 OBSERVED TREATMENT TIME IN MONTHS (2008-2009)

4.3 SD model outputs and limitations

This section makes the output of the SD model and the insight the model creates in the real system behaviour transparent. A comparison with the required outputs and insights as demarcated in the second chapter provides insight in the limitations of the currently used SD model. First, the measurable performance indicators and the required performance indicators are compared. After which, the level of measurement of the SD output is defined and analyzed.

Measurable performance indicators

The currently used SD model provides insight into the trajectory stocks and flows through the independent care systems. The output of the SD model exists of a set of graphs, which describe the dynamics of the stocks, flows and the expected waiting time. An example set of output graphs for the steady state, base case situation is presented in appendix **Fout! Verwijzingsbron niet gevonden.**. The SD model does not provide insight into the child layer performance indicators. This is a direct result of the homogenous worldview of the SD methodology in which no unique entities are distinct, this makes it impossible to link children directly to trajectories.

Level of measurement

The SD model provides insight in the location of the average values of the key performance indicators in order to find effective policy levers. In the youth care sector, in which every child counts, not only the average is important, but also the exact distribution of child waiting times. A robust policy, which results in a situation in which the spread of waiting times is small, can in many cases, be favourable above a policy with a lower average waiting time but with a larger spread in waiting times. Robustness of the system is especially important for systems which include significant variability. The SD methodology does not provide the required insight into the distribution of the observed waiting time for each child.A practical example of this measurement is the maximum nine weeks waiting time, which cannot be evaluated with the SD model.

Queue mechanism.

The shape of the waiting time distribution of queuing system is a result of its queue mechanism. The queue mechanism in most health systems is based on the First in-First out principle, in many cases in combination with different priority levels. Because of the perfect mixing assumption and the consequential random stock outflow, the SD methodology cannot be use to provide insight into the result of various queue and priority mechanisms. The author argues that in a system in which a child's withdrawal behaviour is influenced by its waiting time, the queue and priority mechanism can have a significant impact on the average waiting time. The queue and priority mechanism influences the waiting time distribution, the waiting time distribution influences the withdrawal behaviour, the withdrawal behaviour the queue length and the queue length the average waiting time. A discrete model can provide additional insight into the result of different queue and priority mechanism.

4.4 Conclusions and implications

This chapter makes the assumptions, structure and limitations of the SD model transparent in order to provide an answer to the third research question.

The core assumption of the SD model is perfect mixing of children and trajectories. Each child, in the SD model, is homogenous and receives the same average set of care trajectories. The care trajectories and care systems are disaggregated to the four care types. The trajectories of each care type are assumed homogenous. The observed trajectory treatment and waiting time distributions are assumed exponentially distributed. The SD worldview, in which no entities are distinct, makes it impossible to attribute trajectories to the children. Therefore, the SD worldview does not allow determining a child's state, based on the current state of its trajectories. Consequently, performance indicators that measure the children states are not measurable in the SD model. The SD model presents an average aggregated view on the measured performance indicators.

While the SD model is able to abstract stochastic variation in parameters, variability observed in endogenous flows and process cannot be abstracted. Consequentially, the robustness of the system to the observed system variability cannot be evaluated with the SD model. Furthermore, the aggregated worldview does not provide inside into the spread of individual trajectory waiting times for different system configurations. An analysis of the observed treatment time variances, for chosen care provider case study, indicates that the treatment times are not exponentially distributed. The treatment time distributions for both residential care and foster care are left skewed with an extreme long tail, which is likely to have a significant impact on the system behaviour.

In conclusion, the SD model cannot abstract the whole impact of heterogeneity and process variance in the care provider system. The following third part of this thesis designs an abstraction of the care provider system in a DES model to analyze the impact of heterogeneity and endogenous system variability on the care provider system behaviour.

Part 3: Design discrete model

Chapter 5
Discrete Conceptualization

The previous chapter abstracts the care provider system in terms of the association and influence relations captured in the SD model. This section presents the concepts and variables of the delineated system from a discrete modelling perspective. The discrete problem view demarcates the most important objects and makes their attributes and state changes transparent. The decomposition of the care provider system into horizontal layers and vertical partitions, as presented in section 2.4.2, serves as the starting point of this conceptual chapter. This section will further decompose the objects, attributes, interrelations and dynamics, which accurately describe the youth care processes with a discrete worldview.

5.1 System structure

DES modelling involves the identification and representation of entities, resources, logic and processes (Borschchev and Filippov 2004). The static view of a system separates entities into their structural components and serves the purpose of presenting hierarchies by presenting the generalization and aggregation relations (Booch, Rumbaugh et al. 1999). Figure 5-1 presents a high level UML class diagram, which identifies the care provider processes, resources and entities of the care provider system categorized to the previously distinguished information layers.

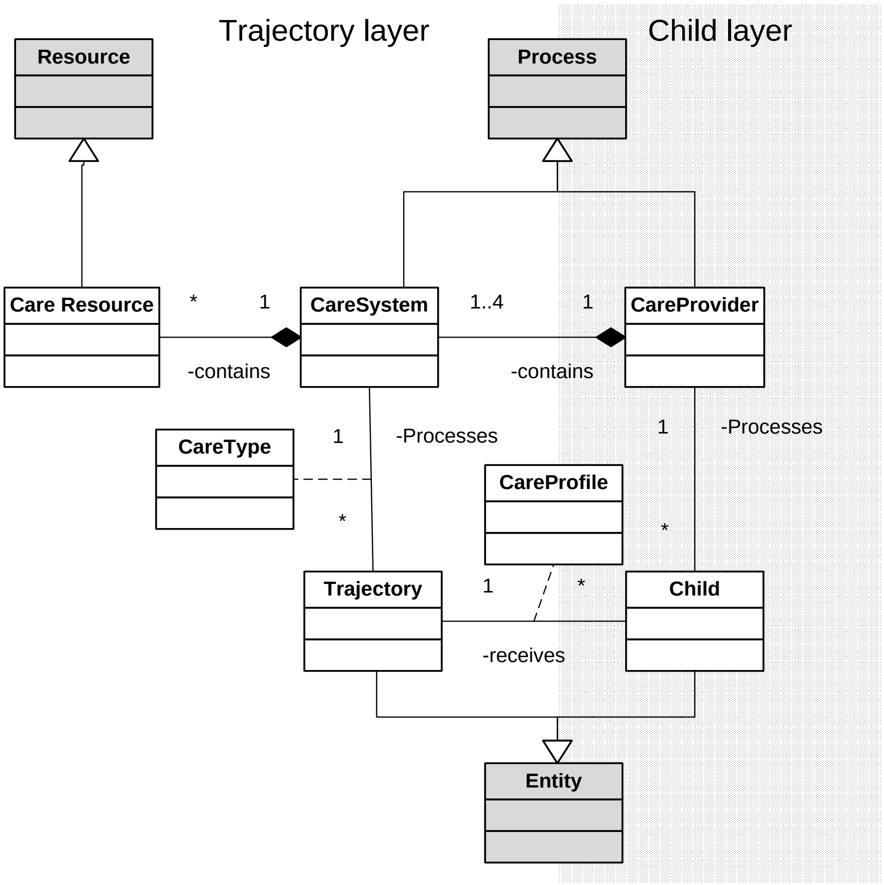


FIGURE 5-1 HIGH LEVEL OBJECT DECOMPOSITION CARE PROVIDER SYSTEM

A first distinction between the embedded objects can be made by separating the *active* objects from the *passive* objects. As introduced in subsection 3.5.1, the DES modelling community refers to active objects as *processes*, while passive objects are referred as entities.

Entities. An entity is a passive object of interest in the DES system, aligned with the distinct information layers in the youth care sector. Two entities are identified, children and trajectories. The definition of a trajectory as provided previously in the SD conceptualization: the execution of a, at the institution of youth care indicated, care service to the child by the care provider.

Processes. The care provider system identifies two process object classes: the care provider object and the care systems. A composition association relation relates the care provider to the care systems. In other words, the care system is a part of the care provider object. The care provider object presents the arrival and state dynamics of the children entities. The care systems describe the flow of trajectories through the care provider system.

Resources. The identified resources class are the care resources of a care system. No resources are distinguished at the child layer. The child layer performance depends on the trajectory layer resource allocation.

Association attributes. Figure 5-1 introduces two classes which serve as a structuring association attribute. The care provider contains a care system for every care type the care provider delivers. The trajectories are matched to the care systems with the appropriate resources by the care type attribute. As such the care type attribute disaggregates the trajectory layer in four independent operating care systems. The second association attribute is the care profile. This document creates a coupling between the distinct children and the care trajectories provided to the children. The care profile document is introduced in the following section.

5.2 Care profile: Coupling of child and trajectory arrivals

The children arrivals and trajectory arrivals are coupled by a care profile. A care profile can be seen as an overview of the trajectories provided to a child over time. A care profile holds one or multiple trajectories possibly of different care types. An overview of the important events and event relations is provided in Figure 5-2.

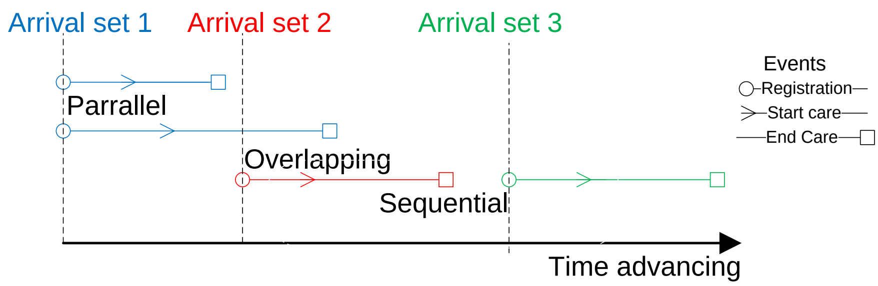


FIGURE 5-2 CARE PROFILE EVENTS AND RELATIONS

Figure 5-2 presents the care profile of a fictive child. The care profile holds four care trajectories and three distinct trajectory arrival sets.

Arrival sets are the events at which one or multiple trajectories start. Trajectories belong to the same arrival set if they register at approximately the same moment in time. In this research the assumption is made that trajectories, which are registered in the same calendar month, belong to the same care set.

Each *trajectory* distinguishes three different events. These are the registration event, the start care event and the end care event. These events and subsequent trajectory state changes are described in the following subsection, which conceptualizes the trajectory layer care system process.

The following relations between the lifelines of trajectories are distinguished: *parallel* trajectories, *overlapping* trajectories and *sequential* trajectories.

Parallel trajectories. Trajectories that share a common arrival set and a common registration time.

Overlapping trajectories. Trajectories, which have a different registration time and arrival care set, but an overlap in their lifetime.

Sequential trajectories. Trajectories with no overlap in lifeline. The lifeline of the first trajectory is finished before the arrival event of the sequencing trajectory.

Figure 5-2 introduced the coupling between children and trajectories from a dynamic perspective. Figure 5-3 presents the static relations which form the foundation for this dynamics by using UML class diagram (Booch, Rumbaugh et al. 1999). It becomes clear that each child can have one care profile, which contains one or multiple arrival sets. These arrival sets contain one or multiple trajectories.

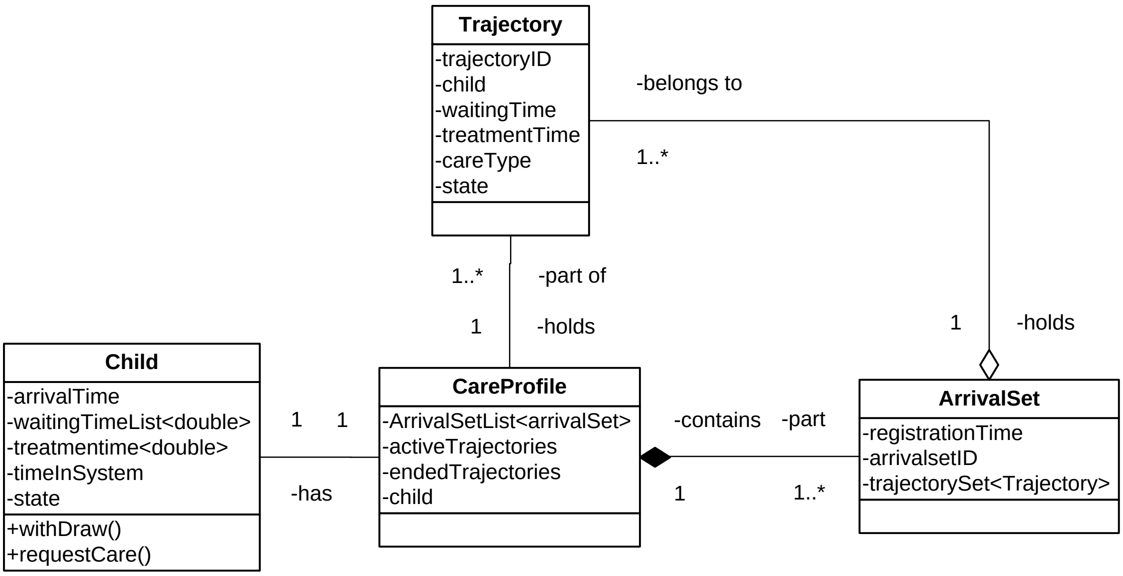


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FIGURE 5-3 OBJECT DIAGRAM CONNECTION BETWEEN CHILD AND TRAJECTORY

The coupling between the children and their trajectories is made transparent. The concepts of the first are outlined in section 5.3, the concepts of the latter in section 5.4

5.3 Trajectory layer

A trajectory can be seen as the execution of a care service indicated to the child at the institution of youth care. As an object a care trajectory can be seen as an administrative document made by the care provider. It holds information about the delivery of a certain care service to a child.

This section first presents the static structure of the care trajectory layer in subsection 5.3.1. A process view is taken in subsection 5.3.2, to analyse the system with a functional view, followed by a description of the dynamic view of the system structure by analysing the state transition diagrams in subsection 5.3.3.

5.3.1 Static structure trajectory layer

The static structure of the objects and relations, which influence the trajectory state, is presented in Figure 5-4. As introduced before, the care systems process the care trajectories in the care provider system. A common care type links the care trajectories to the right care system. The care system can treat the trajectory if a free resource can be seized by the care trajectory. The resource capacity is presented by the resource pool.

Passive vs. Active entities. The static structure presented in Figure 5-1 can be used to distinguish active object classes from passive object classes. Active object classes contain events, which initialize operations. The objects classes, which can actively start operations of influence on the trajectory layer, are the care system process objects and the children objects. The care system class steers the process flow of the trajectories. Youth care is voluntary received care, a child can decide to withdraw from a trajectory at any moment it desires to do so.

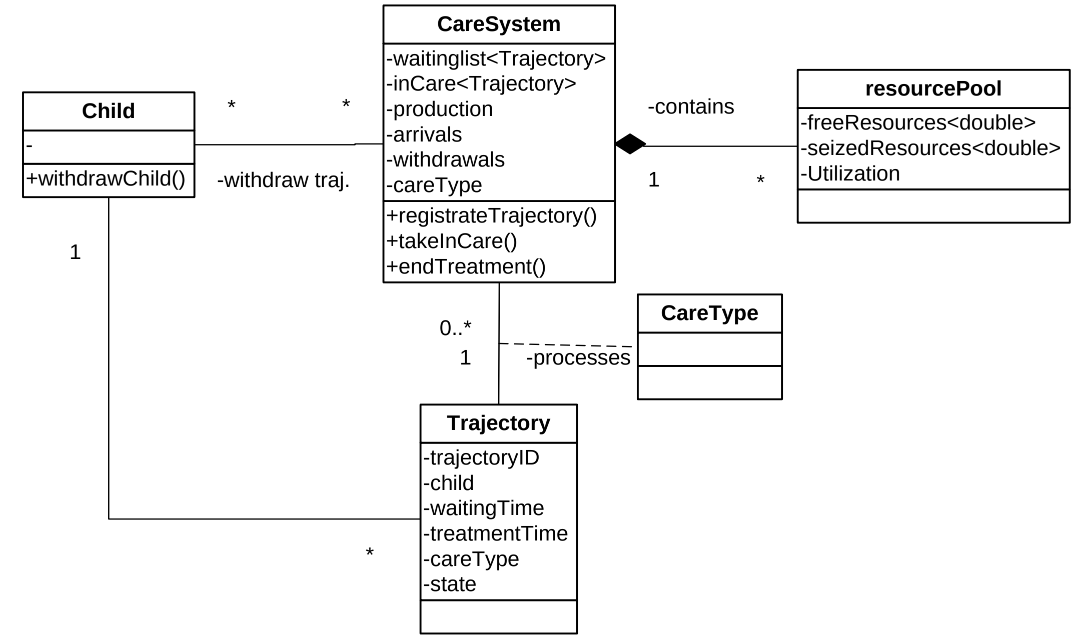

FIGURE 5-4 OBJECT DIAGRAM CARE SYSTEM

5.3.2 Process view: care system

This section presents the structure of the parallel care systems from a functional process viewpoint. As introduced before, the trajectory layer exists of four independent parallel care system differentiated by the four care types. In other words, there are four separate independent care systems sub-models, namely ambulatory care, day care, residential care and foster care. From an organizational perspective, these sub-models are independent systems. Formally, there are big differences between the care processes of the different care types. The basic structure of the processes is however the same. Figure 5-5 provides the graphical representation of the process delivered at the care systems. The simplified process is presented as a basic queuing system.

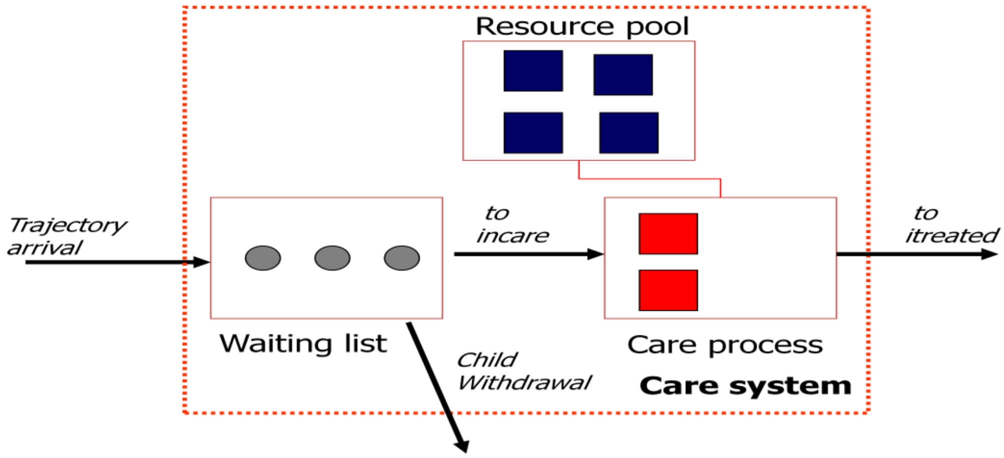

FIGURE 5-5 PROCESS VIEW CARE SYSTEM

Care trajectories arrive from time to time in the care system. After the care trajectory is registered it joins the waiting lists. If there are free resources and the trajectories turn has arrived, the trajectory seizes the desired care resources and treatment starts. After being served, the trajectory is removed from the care system. A child withdraws the care trajectory if the waiting time exceeds the time the child is prepared to wait for the care services.

A discrete queuing system needs a queue mechanism, which determines the logical order of customers in a queue. In the real world system this queue decisions are based on specific attributes of the child and its relative urgency in comparison to other children on the waiting list. Based on this urgencies children receive a priority category. In the youth care commonly two categories are distinct; crisis and regular. Furthermore, the queuing mechanism is considered objective, children with comparable urgencies are selected based on a first-first out principle. Other real world considerations are the fit between children and treatment groups. This fit depends on the group attributes of the other children in the facility and the nature of their problems. The level of details of these attributes is considered to be too detailed for the scope of current research. The queue orders for current research are simplified to either first in first out (FIFO), FIFO with a crisis and regular priority category or service in random order (SIRO).

5.3.3 Trajectory: matching attributes with dynamics

The previous subsection introduced the static structure of the trajectory layer. This section forms a bridge between the trajectory attributes and the trajectory dynamics. Figure 5-6 presents a state chart, which holds the states and state transition mechanisms of a trajectory in a care system. A trajectory is inactive until the arrival time of its care set is arrived. At this point, the trajectories are entered to the waiting list of the care system of its care type. As soon as a resource is available and the queue manager decides it is the trajectory's turn to receive care. The trajectory is taken into care and the child states changes into treatment. When the trajectories treatment objective is reached, the care is ended and the child state turns into the final state treated. A child can decide to withdraw its trajectories at any time. The child state is than changed to the final state withdrawn.

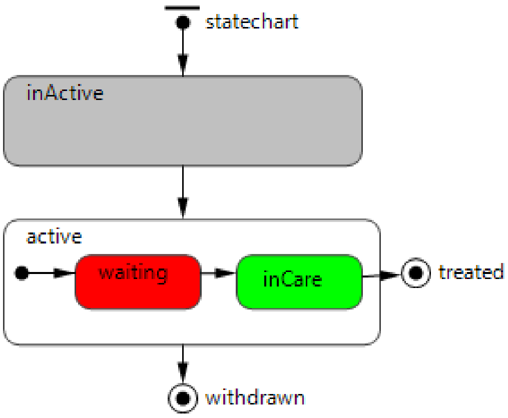

FIGURE 5-6 TRAJECTORY STATES AND STATE TRANSITIONS

Figure 5-7 visualizes the dynamics of two care trajectories, an ambulatory trajectory and residential trajectory. The trajectory flows or state transitions are visualized by symbols explained in the legend on the right of the figure. The trajectory attributes are linked to the events or activities they represent by arrows. The event and activity state relations are previously introduced in subsection 3.3.2.

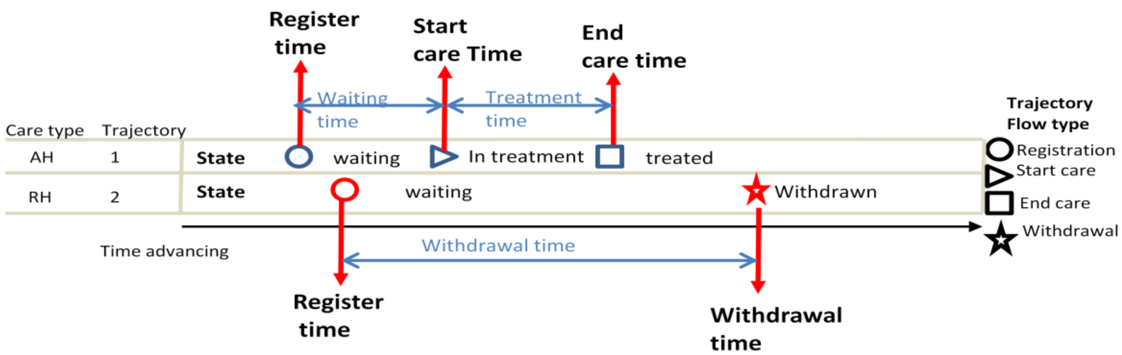

FIGURE 5-7 EXAMPLE TRAJECTORY STATE TRANSITIONS AND ATTRIBUTES

5.3.4 Resources

The separation of independent care systems on the trajectory layer based on care type attribute, as distinguished in both the discrete as the continuous conceptualization, is driven by the difference in resource needed to provide care services of the distinct care types. No exchange of capacity between the different care types is possible. The waiting list of each care system is therefore independent of the waiting list of the other care systems. The care provider capacity for each care type can be further aggregated into different resource types. The main resource types which can be distinguished are *material, personal and buildings*. For this research the choice is made to border the resource allocation process to the capacity level. No differentiation into the different resource types will be made. This choice has been made taking into account the objective of the model to provide insight in to demand and queue behaviour in order to serve as a communication tool between the province and the different care providers in their negotiations to come to a suitable commonly supported policy. From a care provider perspective, operating in a competitive market, it is unappealing to provide the province too much insight into their internal resource and staff policy. Consequently, resource and costs information are expressed at an aggregated level, which helps to keep the model as general, flexible and simple as possible.

5.4 Child layer

The care provider objects steer the arrivals of both children and trajectories. The care provider determines the child's care profile as soon as the child arrives in the system. This care profile links the child arrival to the trajectory arrivals. Furthermore, the care provider administrates the aggregates of the child states of the system over time.

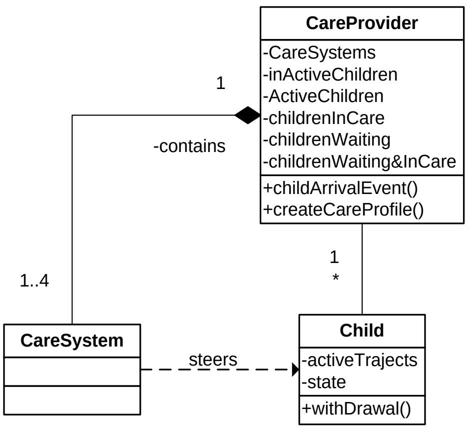

FIGURE 5-8 CLASS DIAGRAM CHILD LAYER

It is important to notice that the care provider provides an aggregated overview of the children process states, but the care provider does not steer the state transitions of the embedded children. The state of child in the care provider system, at every moment in time, depends on the active trajectories of the child at that moment steered by the care systems.

The complex interaction between the trajectory states and children state dynamics are explained by a fictive example care profile in Figure 5-9. If the child has no trajectories in the care systems than the child's state is considered inactive. When a child's trajectory is registered at one of the care systems, it state changes to active. A child is waiting as none of its active trajectories are in care. If one of the child's trajectories is token into care the child's states turns to in care. Two sub-states of being in care are identified. The child is in treatment when all of its active trajectories are in care. If the child has both waiting and treated trajectories the child's state turns to in care.

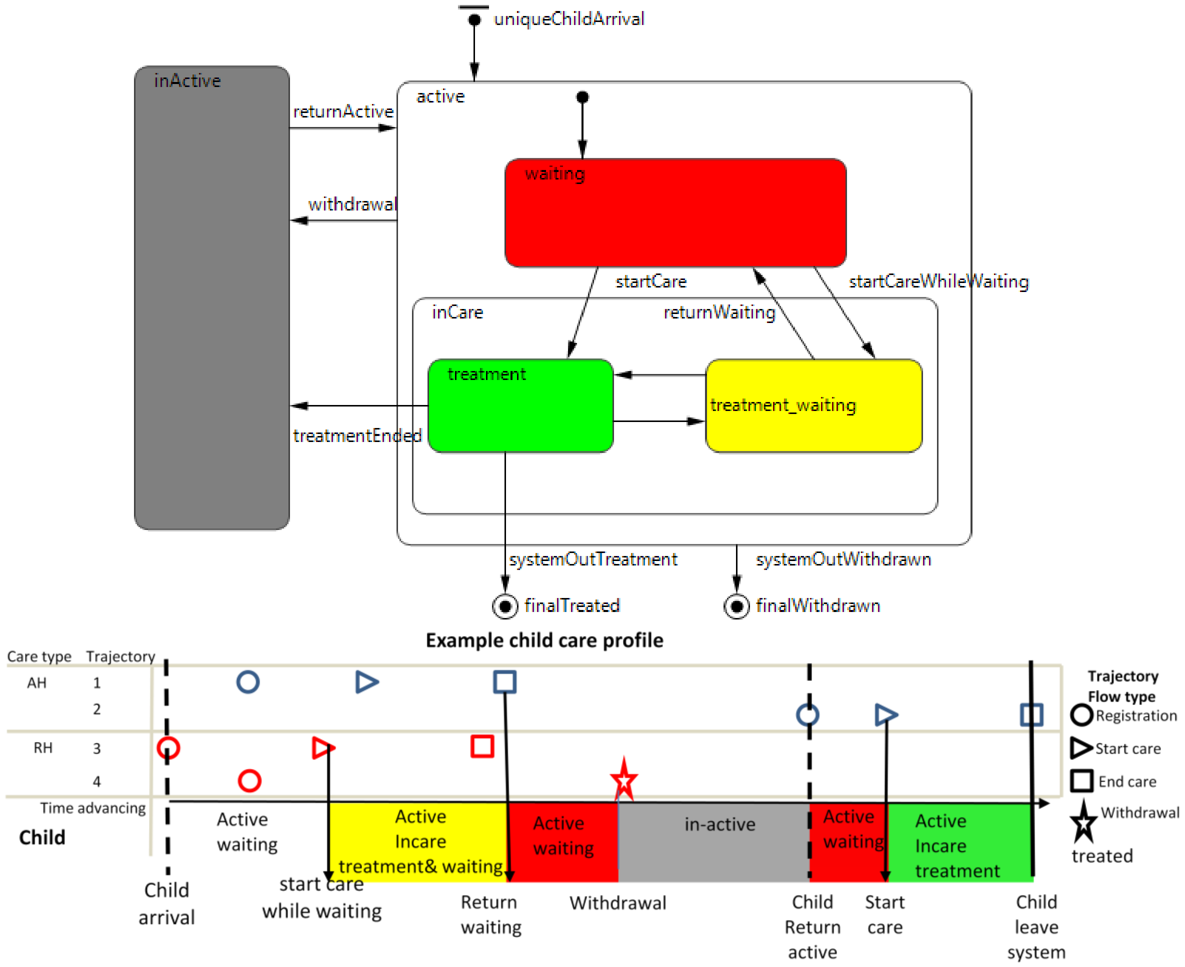

FIGURE 5-9 CHILDREN STATES AND STATE TRANSITIONS

5.5 Conclusion

This chapter answers the fourth research question; a discrete conceptual model of the care provider system is presented. The conceptual model indicates the objects, variables and relations, which accurately and unambiguously describe the problem situation. UML class diagrams, functional diagrams, time oriented dynamic diagrams and state charts where applied to make body of knowledge transparent and communicable.

In order to translate the care provider model in discrete concepts an important assumption is made with regard to the definition of a care set. Trajectories administrated in the same calendar month are assumed to belong to a common care set arrival. This assumption forms an important basis for the data study in the following section. Furthermore, it became apparent that the a DES simulation model requires a queue mechanism. For this research the queue mechanisms are simplified to a FIFO, FIFO with two priority levels or a SIRO queue mechanism.

The following chapter analyses the data of chosen care provider case study, to evaluate the heterogeneity and conditionality relations between the objects demarcated in the presented conceptual model. Furthermore the root of observed system variability will be analyzed.

Chapter 6
Data analysis: variability, heterogeneity and conditionality

The conceptual model presented in previous demarcated the processes, entities and objects in the care provider system. This chapter presents an empirical investigation of the quantitative management information over 2008 and 2009 of a case study care provider. The objective is to rise the insight into the observed system by analyzing the system variability heterogeneity and conditionality. In order to determine which aspect of the real world need to be abstracted in the DES and how these aspect need to be abstracted. For each input parameter, the behaviour over time is analyzed, to determine if it can be abstracted by a stationary input distribution in the following specification chapter.

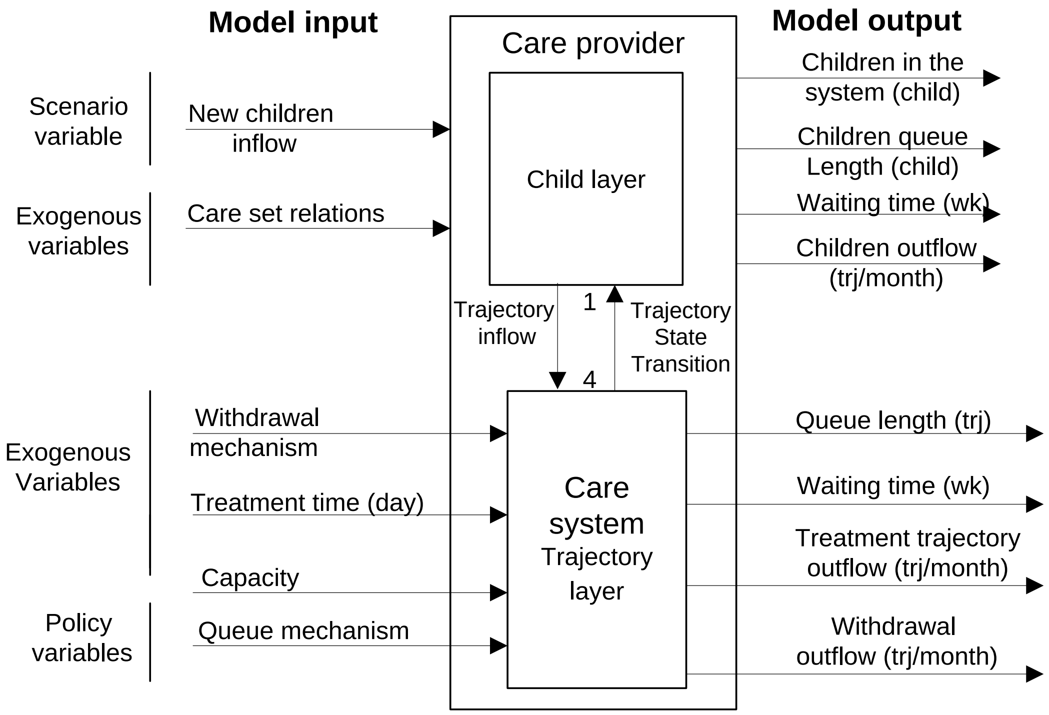

FIGURE 6-1 SYSTEM DIAGRAM CARE PROVIDER

The system diagram presented in Figure 6-1 demarcates the system input variables and the coupling between the child and trajectory layer. The care set relations determine the number and composition of care sets for each child, and thereby the trajectory inflow into the care system after a child's first arrival. An overview of the in the chapter analyzed variables is presented in Table 6-1.

Category	Section	Variable or Relation
Inflow Analysis	6.1	Children inflow
		Trajectory inflow
Care set relations	6.2	Relation arrival type and care set composition
	6.3	Conditionality and dependency in and between care sets
	6.4	Time between a child's sequencing care set arrivals
	6.5	Number of care sets a child
Care system inputs	6.6	Withdrawal mechanism
	6.7	Capacity places
	6.7	Treatment time

TABLE 6-1 OVERVIEW ANALYZED RELATIONS

6.1 Inflow analysis

This section provides insight into the dynamics of care demand faced by the case study care provider. The care provider demand can be analysed from different aggregation layers as presented in 2.4.2. The children layers measure the number of children demanding care services, the trajectory layers present the amount of care services demanded by those children. These care services can be further disaggregated into the demand behaviour at the independent care systems of each care type.

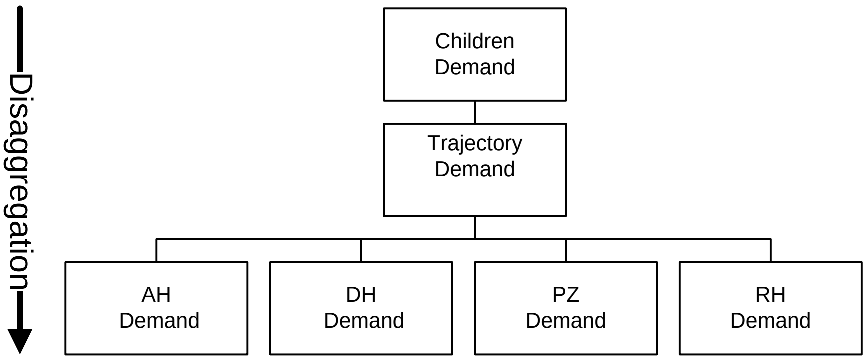

FIGURE 6-2 AGGREGATION OF DEMAND

The demand on each of this aggregation layers is subdivided into *exogenous* demand and *endogenously* arriving demand. *Exogenous* demand is the demand on which the system has no influence; it is the care demand of new children, who never have been registered in the care provider system. The *endogenous* demand is the care demand of returning children, which have been previously registered in the system. They request additional care after previous treatment at the care provider. Section **Fout! Verwijzingsbron niet gevonden.** introduced the distinction between exogenous and endogenous care demand made in the SD model (Westerflier 2008). Figure 6-3 presents the care profile of a fictive child. This care profile will be used to explain the link between the different aggregation layers of demand. The present boxes present the care set arrivals a child level. The red box, presents the child first *exogenous* arrival. The black dotted boxes visualize the child's *endogenous* care demand. It presents the care demand after being served in the care provider system previously.

A care set consist of one or a set of care trajectories with a common registration moment. As introduced before, the trajectories in a common care set are referred too as parallel trajectories. They arrive on the same point of time on the waiting list. A care profile can consist of parallel trajectories, overlapping trajectories and sequential trajectories.

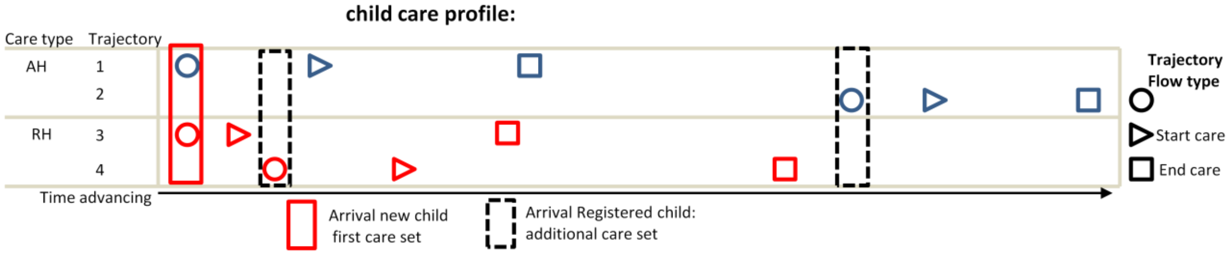

FIGURE 6-3 EXAMPLE CARE PROFILE DEFINITION ARRIVAL EVENTS

Next sub section will analyse the influence of both the exogenous and endogenous arrivals on the total care demand, both measured on the child layer as on the trajectory layer.

6.1.1 Complications, limitations and validation of the demand analysis

The case study data set over 2008 and 2009 contains aggregated children flow data, which distinct the size of the endogenous and exogenous care demands at child level. The data set provides disaggregated data of every trajectory arrival at this trajectory level. No distinction between the two demand types is made. In order to distinguish *endogenous* arrival from *exogenous* trajectory arrivals the trajectory flows of the year 2008 and the children in care at 1 January 2009 serve as a system memory. The children ID's of this flow and level distinguish the trajectory flows from new and registered children over the year 2009. The memory could be too small, which results in a wrong assignment of new and returning children. To validate the assigned memory the new children flow, extracted from the trajectory layer, can be compared to the available child data. Figure 6-4 presents the new children arrival graph, the blue line depicts the extracted child arrivals from the trajectory layer, the red line the new children arrivals from the data.

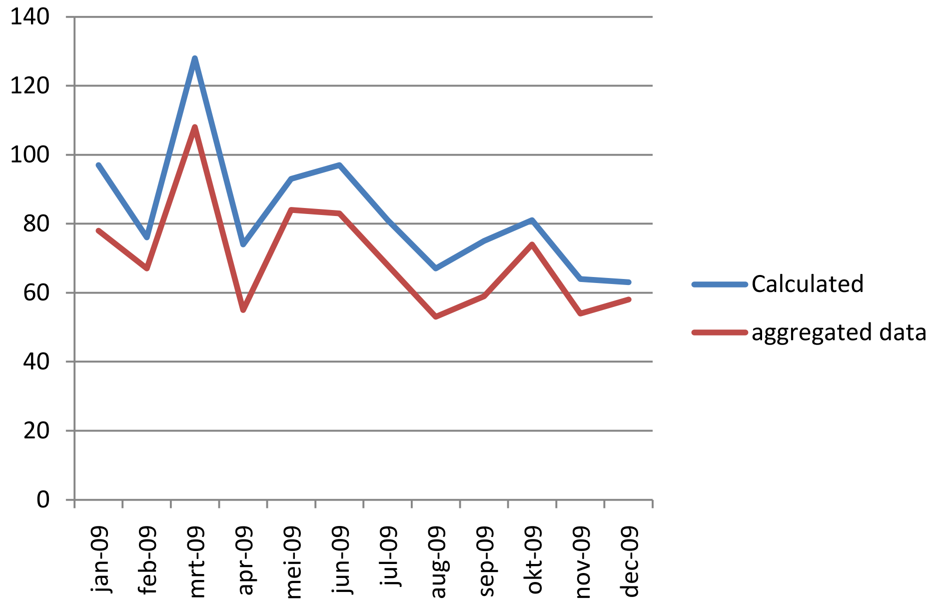

FIGURE 6-4 VALIDATION OF NEW CHILD ARRIVALS A MONTH

The measurement bias, between the calculated and observed, new children arrivals is on average 18%. In other words, 18% of endogenous demand is wrongly interpreted as exogenous demand. The size of this measurement on the trajectory is considered smaller, because endogenous care sets contains less trajectories than endogenous care sets.

6.1.2 Children Inflow

This section contains an analysis of the care demand behaviour faced by the care provider. The behaviour of the external demand of new children, the endogenous demand of returning children already registered at the care provider and the influence of both on the total demand behaviour is analysed. Figure 6-5 presents an overview of the trajectory care set arrivals per month over the year 2009[7]. The blue line presents all child arrivals. The black and red line present a further aggregation of these arrivals to their arrival type. The red line presents the number of first child arrivals, the black line the return of previously registered children.

Trend line and behaviour

The presented graph shows that the peaks and drops of all children arrivals are steered mostly by the variances of children returns in the system. When analysing the trend lines, it becomes clear that the overall number of child arrivals are slightly increasing over the year. The increase is caused by a strong increase of returning children. The new children line is slightly decreasing. The observed increasing trend line increase seems to be steered by one peak of registered child returns in November. time frame captured by the dataset is too small to determine whether or not the increase is caused by a behavioural change or by uncertainty and randomness.

Proportion of exogenous and endogenous arrivals

Figure 6-5 presents a clear inside of the influence of new and return children. Both form a significant proportion of the total number of arrivals. It becomes clear that when forecasting future care

[7] The data set of children arrivals during 2008 and the active children in the care provider system at the first of January 2009 serve as the system memory to distinguish new children arrivals from returning children arrivals.

demands there is a necessity to incorporate both the exogenous demand behaviour as the internal feedback behaviour of returning children in the care provider system.

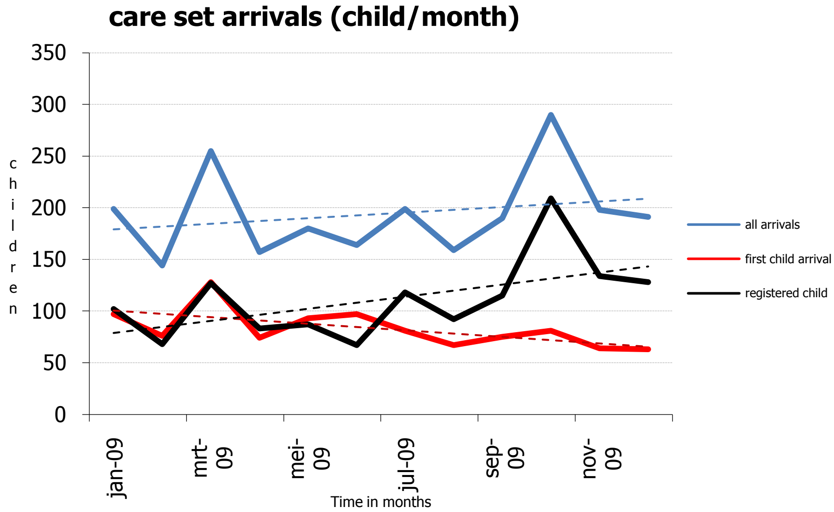

FIGURE 6-5 GRAPH CHILD ARRIVALS DYNAMICS

The presented graph shows that the peaks and drops of all children arrivals are steered mostly by the variances of children returns in the system. When analysing the trend lines, it becomes clear that the overall number of child arrivals are slightly increasing over the year. The increase is caused by a strong increase of returning children. The new children line is slightly decreasing. The observed increasing trend line increase seems to be steered by one peak of registered child returns in November. time frame captured by the dataset is too small to determine whether or not the increase is caused by a behavioural change or by uncertainty and randomness.

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Variance and uncertainty
The system dynamics model analyses the youth care queues as a deterministic system in which the structure determines the behaviour. An important addition to this deterministic behaviour of the SD model in the DES model is the incorporation of uncertainty by modelling probabilistic distributions to copy the variances in the system. The variance of care demand over the months is analysed with the presented care set arrival graph as the starting point. The graph clearly shows that there are big variances in the number of children arrivals per month. Over the year two peaks are distinguished, one in March and one in October. The peak in March is caused by a peak in both the first children arrivals and in the arrival of registered children. The peak in October is caused by a peak of registered children arrivals. In order to provide more insight into the spread of the arrivals and the influence of new and registered arrivals, a visual representation in the form of a box plot is presented in Figure 6-6.

The box plot provides an indication of the median, the range and the inter quartile range of the arrival distributions. It clearly shows the wide spread of the registered child arrivals in comparison to the spread of first children arrivals. It becomes clear that the previously registered child arrivals cause the wide spread and uncertainty of the total arrivals a month. The variance and uncertainty is not produced by external factors, it arises from the inner dynamics of the care provider. The total spread of all arrivals is 146 children, the spread of new child arrivals is 65 children, the spread of registered children is 142 children. Noticeable is the inter quartile spread, the spread of all arrivals is 36 children, which is smaller than the inter quartile spread of registered arrivals which measures 41 children. The inter quartile spread of all arrivals is toned down in comparison to the inter quartile spread of the registered arrivals by the first variance of first child arrivals. If this is a matter of coincidence, then scenarios with even bigger demand spread seem realistic.

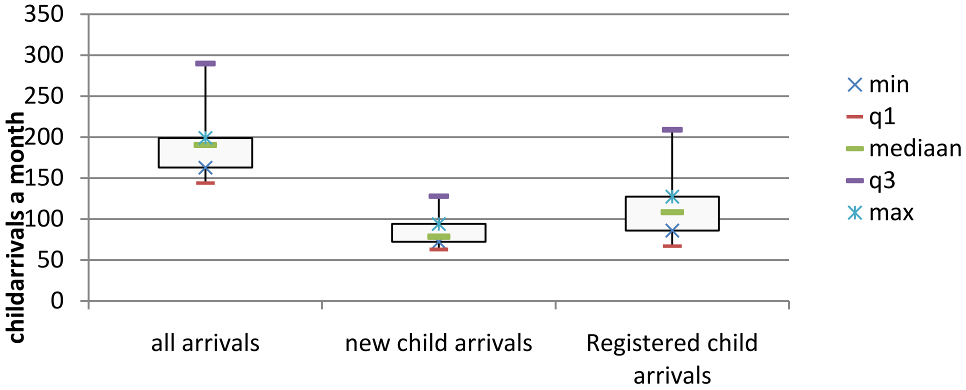


FIGURE 6-6 BOXPLOT CHILDREN ARRIVALS A MONTH

Conclusion and implications

A first conclusion is that based on this dataset, in combination with the variance found in the arrival patterns, no conclusion can be drawn about the behavioural changes over the year. The distinguished trends are likely to be the result of peak values caused by the high variance in monthly arrivals. It becomes clear that both the arrivals of new and the return of registered children form a significant proportion of all demands. It is a necessity for a meaning full abstraction of the care provider system to incorporate both arrivals mechanisms. Remarkable is the conclusion that most of the uncertainty in demand is not caused by exogenous children arrivals; it is caused by endogenous return behaviour of children already in the care provider system. In other words, in order to provide a feasible and adequate forecast of future care demands it is important to take into account the present system state and the internal return mechanisms. Randomness and uncertainty have a big influence on the demand behaviour of the system. The presented analysis provides insight into the demand behaviour measured at the children layer of the system. The next subsection encompasses a similar analysis of the care demand measured on the trajectory of the care provider system.

6.1.3 Trajectory inflow

As before introduced in the conceptual chapter, the children arrivals are coupled to trajectory arrivals through the arrival care sets. The influence of both arrival types, first child arrivals and the return of registered children, at the trajectory layer is dependent on the number of care set arrivals and the number of trajectories per care set. A graph of the trajectory arrivals a month over the year 2009 is presented in Figure 6-7.

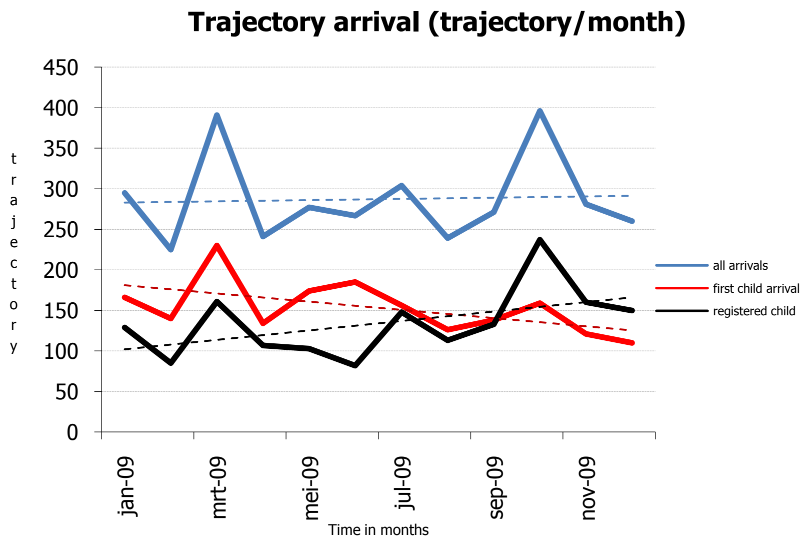


FIGURE 6-7 GRAPH TRAJECTORY ARRIVALS DYNAMICS

Trends and behaviour

When analysing the trend it becomes clear the trend of all arrivals is fairly constant. A slight decrease appeared in the number of trajectory arrivals per month assigned to new arriving children. The amount of trajectories assigned to registered children has an increasing trend. The time frame of this analysis is again too short to conclude if these trends are caused by random peak values or influenced by or the result of behaviour changes over time. Taking into account the fairly constant trend of all trajectory arrivals and the peaks and drops in arrivals, the assumption cannot be rejected that the observed trends are caused by randomness.

Proportion of arrival types

The conclusion can be made that first child arrivals hold a bigger proportion of all arrivals on the trajectory layer than on the child layer. As declared in the conceptual chapter, the amount of trajectory arrivals depends on the amount of arrival sets and the amount of care trajectories embedded in these arrival sets. Combining these definitions it becomes clear that in order to hold a bigger proportion of arrivals on the trajectory layer than on the child layer, the child layer care sets on average embed more care trajectories than the care sets of returning registered children. This forms an indication that in terms of contents there is a significant difference between the care sets assigned to first children arrivals and registered children arrivals. Testing this hypothesis is the subject of the next subsection.

Variance and uncertainty

When analysing the graph, which represents all trajectory arrivals, high peaks in the behaviour are noticed, while the trend line is fairly constant. In order to analyse the variance and spread of the trajectory arrivals, a box plot of the trajectory arrivals is presented in Figure 6-8. The spread of first child arrivals is larger measured on a child level than on trajectory level, the spread of first child arrivals is 120 trajectories. The spread of new arrivals is larger at the trajectory level than measured from a child level; the registered child trajectory arrivals also show a large spread. The spread of all arrivals measured at the trajectory layer is large: the total range is 171 trajectories. The inter quartile range of all arrivals is 42 trajectories, which is smaller than the quartile range of the arrival of registered children which is 47 trajectories. The relation between the variance of the new and registered children weaken the inter quartile spread of arrivals done in this example. If this behaviour is caused by randomness, then scenarios in which both arrivals types strengthen each other are realistic. When testing policy options in this system, robustness to randomness and variance in demand behaviour is considered to be an important simulation objective.

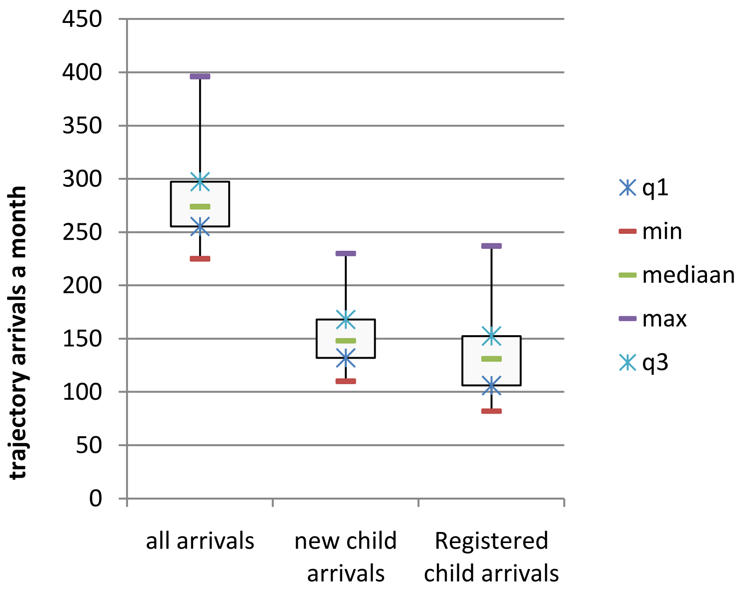


FIGURE 6-8 BOXPLOT TRAJCTORY ARRIVALS

Conclusion and implications

The one year time frame of the examined dataset is too short to determine if the observed trends are caused by randomness or by change in behaviour patterns. The fairly constant trend of the overall trajectory arrivals strengthens the assumption that the observed trends are mostly a result of randomness. The proportion of new arriving children is higher measured at the trajectory than measured at the child layer. This is a clear indication that the care sets assigned to new arriving children on average hold more care trajectories than the care sets assigned to returning[8] children. Next section analyses the difference between care sets assigned to new and returning children, based on this finding. It should be noticed, that the impact of the analysed variance in trajectory arrivals on the system behaviour is hard to predict. The next subsection analyses the trajectory demand behaviour further disaggregated to the trajectories care types. This separation provides the opportunity to analyse the demand faced by the different independent care system sub models.

6.1.4 Trajectory arrivals aggregated to care type

This subsection disaggregates the trajectory arrival demand analysed in previous section to the trajectories care type. This separation of concerns provides insight into the demand behaviour experienced at the independent care provider care systems. The behaviour graphs and the box plot of the demand over 2009, for the four care types, are presented in Figure 6-10 until Figure 6-13. The statistic summary of these graphs is presented in Figure 6-9. The grey line shows the total demand statistics for each care type. The mean total arrivals of the care types provide an overview of the influence of each care type on previously introduced trajectory demand. Ambulatory care demand makes up for 77% of all arriving care trajectories, residential care 10%, foster care 7% and day care 4%.The peaks in the graphs of the behaviour of each care type provide a first indication of the uncertainty of demand behaviour. The behavioural trends are steered by the peaks in demand. For none of the care types a clear behavioural shift can be determined.

The box plots provide a visual indication of the uncertainty of demands resembled by the variance statistics. Furthermore, they provide an overview of the proportion of exogenous and endogenous demand of each care type and the influence of exogenous and endogenous demand on the total demand variance. The endogenous demand provides a significant influence on the total care demand for each care type. The influence of endogenous demand is around 40% for ambulatory care and for the other care types even more than 50%. It should be noted, that the calculated influence of endogenous demand is the minimal influence as explained in subsection 6.1.1.

FIGURE 6-9 STATISTICS CARE DEMAND AGGREGATED TO CARE TYPE

	Arrival Type	mean	Median	Standard deviation	q3-q1	spread
AH	all	223,4	216	35 (16%)	34,8	166
	new	126,8	121,5	22,6 (19%)	32,8	109
	return	96,7	91	25,4 (28%)	37,5	136
DH	All	12,6	13,5	4,7 (35%)	4,5	19
	new	6,9	6,5	1,25 (19%)	1,3	9
	Return	5,7	6	5 (83%)	5	10
PZ	All	22,2	21	7 (33%)	8,3	13,7
	new	8,5	7,5	3,6 (48%)	4,5	12
	return	13,7	13	6 (46)	4,3	24
RH	All	29,2	30	7,8 (26%)	13	22
	new	11,1	11,5	4,1 (36%)	6,5	13
	return	18	15,5	7,37 (48%)	10,3	22

[8] Registered children arrivals exist of children who return at the care provider after being registered before. The term registered and returning children are perceived equivalent and are both used to refer to this type of children.

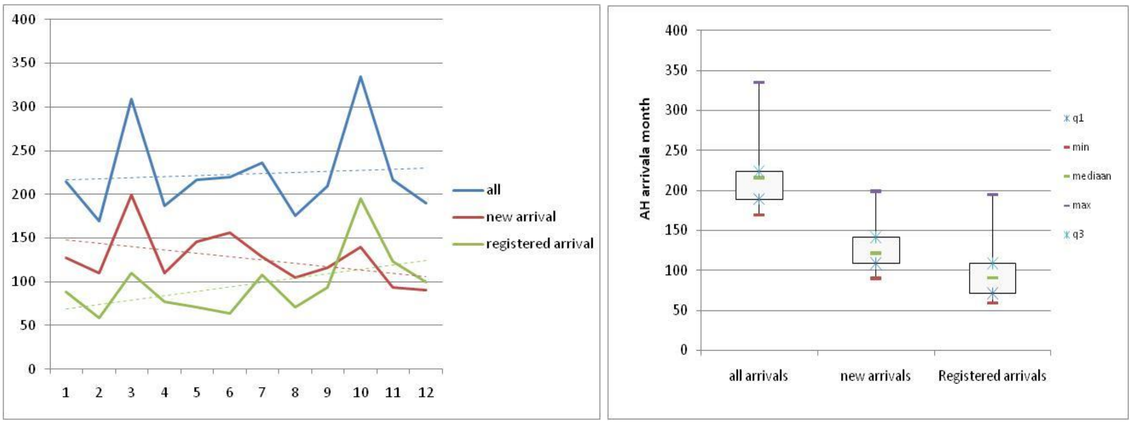


FIGURE 6-10 2008 AMBULATORY CARE DEMAND

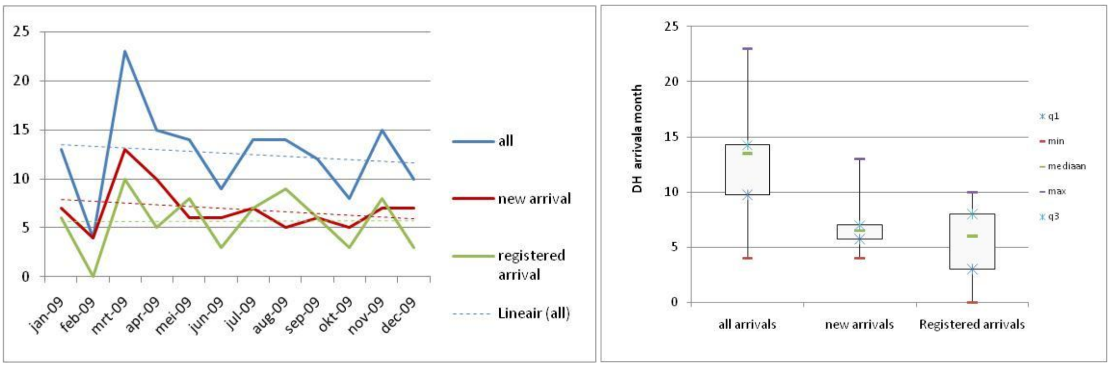


FIGURE 6-11 2009 DAY CARE DEMAND

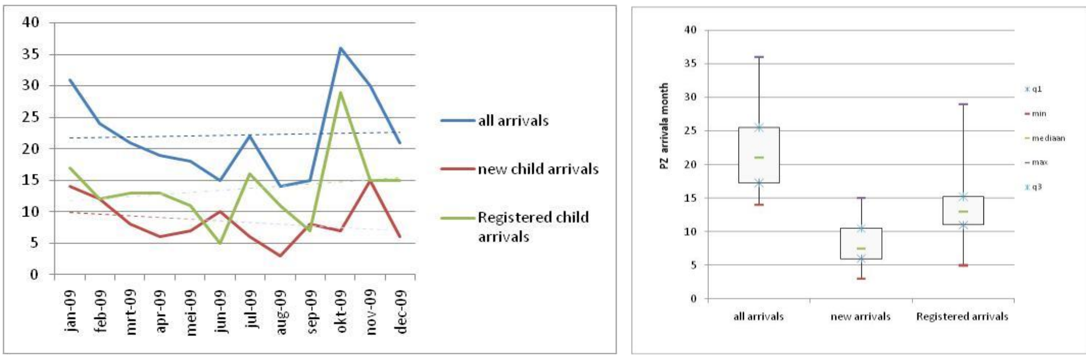


FIGURE 6-12 2009 FOSTER CARE DEMAND

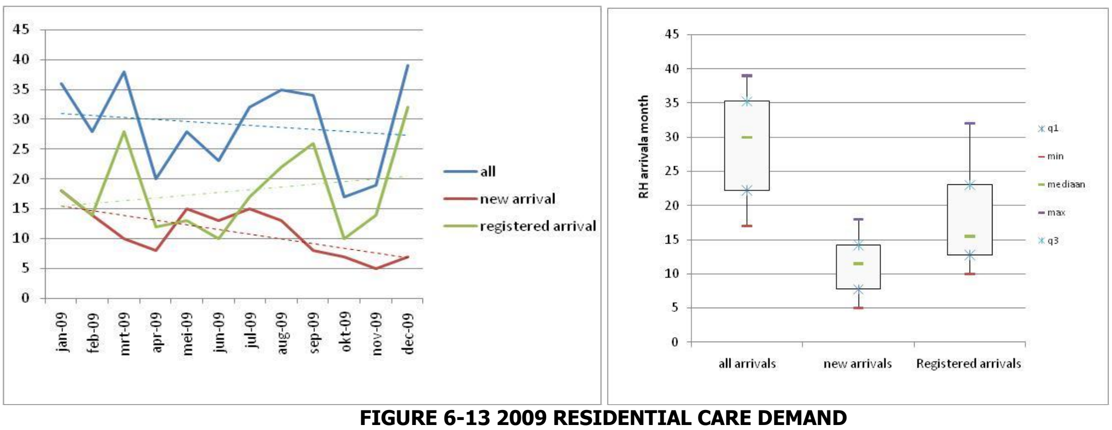


FIGURE 6-13 2009 RESIDENTIAL CARE DEMAND

The standard deviation statistics provide insight into the absolute spread of monthly demand. The influence of this spread on the system behaviour can be analysed by the relative standard deviation, which measures the size of the standard deviation as a percentage of the mean demand. The relative standard deviation of the total monthly demands for the different care types range between 16% and 35%. The box plots provide clear insight into the influence of endogenous and exogenous variance on the total demand uncertainty of the different care types. For each care type, the absolute and the relative variance of endogenous monthly demands are higher than the variance of exogenous demand. Understanding the endogenous demand behaviour is considered essential when forecasting future anticipated demand and when analysing the robustness of policy measures.

6.1.5 Conclusion analysis of demand behaviour

This section analysed the care demand dynamics of the chosen care provider. The total number of new care set arrivals is sub-categorized to the nature of its child's arrival exogenous new children and endogenous demand from children who return after being registered at the care provider for previous care. The arrivals are analysed from the different information levels: the child layer, the trajectory and the trajectory layer aggregated to the four main care types.

The influence of endogenous care demand on the total demand is significant for all information layers. The aggregation to care types showed that most of the variances in the demand of the independent care systems are caused by the variance produced by the endogenous care demand dynamics. The variance in demand is considered to be of large influence on the behaviour of the different subsystems. A simulation model able to incorporate the stochastic behaviour exogenous and endogenous demand behaviour in order to find the most robust policy options would be valuable.

6.2 Relation arrival type and care set composition

The analysis presented in the previous section concluded that both new and registered children arrivals have a significant influence on the system demand. A first indication of differences in the average number of trajectories embedded in new and returning care sets was made. The current chapter will analyse the necessity to model both arrival types differently in a discrete system model. As a whole the analysis will determine the differences between the care sets of both arrival types.

6.2.1 Number of care trajectories a care set

Based on the first indication of the difference between the number of trajectories per care set for new arriving children and returning children, this subsection will analyse the number of care trajectories a care set. First, the behaviour of the number of trajectories per care set will be analysed. Figure 6-14 provides a graph which represents the behaviour of the average amount of trajectories a care set. The presented graph is calculated by dividing the number of care trajectories arriving each month, by the number of children arrivals each month. The children and trajectory arrivals graphs are previously presented in Figure 6-5 and Figure 6-7.

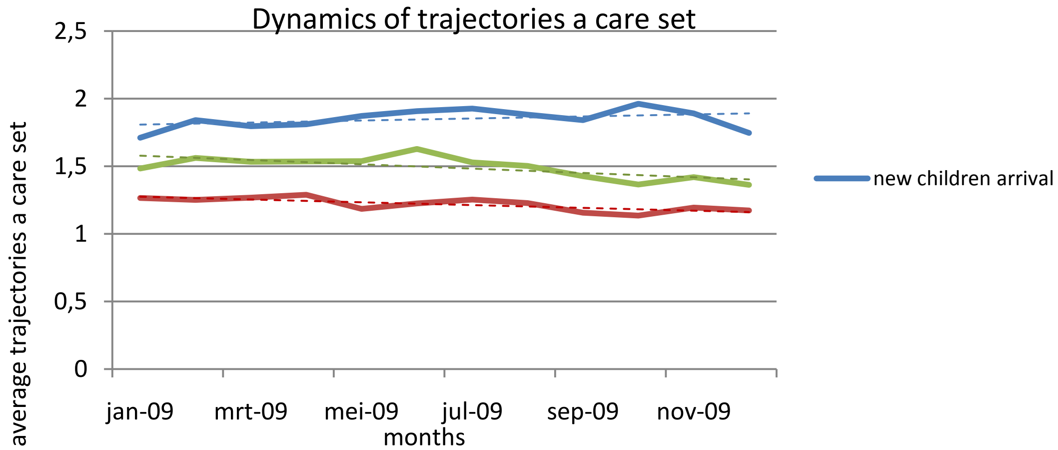


FIGURE 6-14 GRAPH BEHAVIOUR OF TRAJECTORIES A CARE SET

A first observation shows that new children on average have around 1,8 trajectories a care set, while returning children receive on average 1,2 trajectories a care set. Figure 6-14 presents a fairly constant trend for the new arriving children and the returning children. The overall amount of care sets an arrival is slightly decreasing, which is explained by an increase in the proportion of returning child arrivals over time, as determined in previous section. Based on this graph the assumption is made that for both new and returning children arrivals the assignment of the amount of trajectories is constant over time.

The remaining part of the subsection will analyse if the observed difference, in the number of trajectories of exogenous and endogenous arrival care sets, is a significant difference. The research question is the following:

Is there a difference between the number of trajectories a care set of new and returning children arrivals?

This research question will be answered by testing the following bivariate alternative and zero hypotheses:

H_1 : There is a difference between the number of care trajectories in arrival sets of new and registered children arrivals.

H_0 : The amount of care trajectories in arrival sets of new and registered children is the same.

The significance level of this statistical test is determined at α=5%**.** The care provider care set arrivals over the year 2009 are analysed. A total of 996 new children arrival sets and 1330 registered children arrivals are distinguished. Figure 6-15 presents a graphical overview of the distribution of care sets for both new children arrivals and the return of already registered children. The x-axis categorises the data to the number of trajectories in the care sets. The y-axis presents the proportion of that number of care trajectories of all trajectories with that arrival type.

It becomes instantly visual that the mode of registered children arrivals is one care trajectory. The mode of new children arrivals is two care types. The mean is 1,85 care trajectories for new arriving children, the mean for registered children arrivals is 1,21 trajectories. In order to determine if this found difference is significant a Student T-test will be performed. First, an F-test is performed to determine the equality of variance of the two samples in order to choose between the Student T-test for equal variances or the student T-test for different variances. The descriptive summary and the results of the F-test are presented in Appendix C.3.

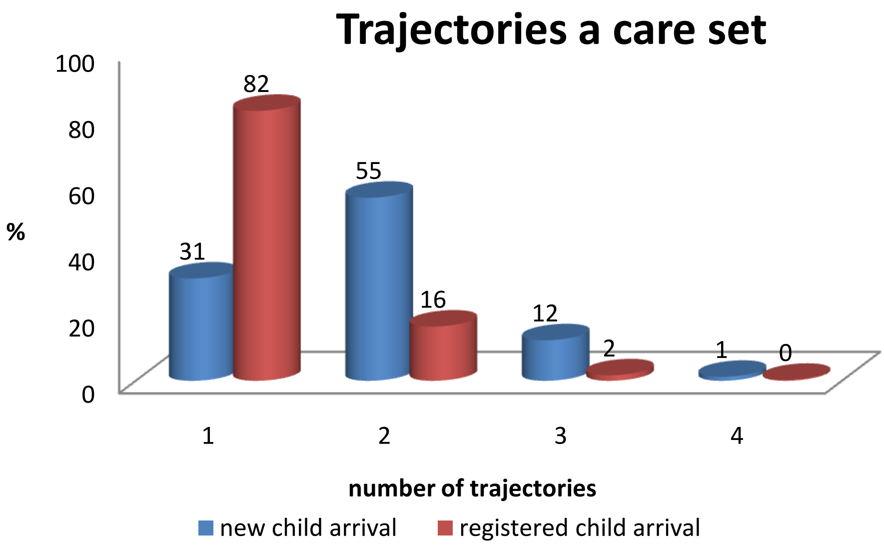


FIGURE 6-15 COMPARISON OF NEW AND REGISTERED CHILDREN CARE SET SIZE

The measured $P(F<=f)=1{,}187*10^{-38}$ is smaller than the α = 0,05, the preliminary test for the equality of variance indicates that the variance of the two groups are significantly different. Therefore, a two sample T-test is performed that does not assume equal variances. The test results are presented in Appendix C.3. The highlighted p-value is less than the chosen significance level of $\alpha = 0{,}05$, this provides evidence to reject the null hypothesis, the number of care trajectories per care set is significantly different for new children than for registered child arrivals.

Conclusion

The average amount of trajectories per care set assigned to new and returning children is evaluated. A plot of the average amount of care trajectories over 2008 and 2009 made the assumption feasible that the average of both categories amount of care trajectories was constant over this period of time. A T-test for unequal variances determined that there is a significant difference between the number of care trajectories of new and returning children. The specification in the next chapter should make a distinction between the distribution of care types to new and registered children arrivals.

6.2.2 Comparison trajectories assigned to new and return care set

Based on the analysis in previous subsection and the interviews with care providers and case managers of the institution of youth care by Giesen(2008), a first assumption of differences in the care type distribution to new and returning children can be made. The assumption can broadly be explained by classifying the care types to their objectives. The care types are subdivided into two main categories according to their main objective. The following two objectives are distinguished: treatment & support and the provision of a stable home situation.

Ambulatory and day care are focused at providing the treatment and education to cure the problems experienced by the child. Residential care and foster care provide a stable home situation if a child's family is for different reasons not capable to provide one. Ambulatory and day care treat the children and improve the faced situation. Residential care and foster care provide an alternative for a home situation. The cause of the problem, the dysfunctional family situation is not improved.

Based on the introduced distinction a hypothesis can be made that the proportion of treating care types for returning children is lower than for new children because their situation is likely to be improved after the initial treatment. Returning children are expected to have a bigger proportion of day and foster care in their care set in comparison to first arrival care sets. Based on the introduced assumption the following hypothesis will be analysed:

H_1 : There is a difference between the trajectories assigned to the care sets of new and returning children.

H_0 : There is no difference between the trajectories assigned to the care sets of n new and returning.

The first step in analysing the relationship between these categorical variables is a contingency table. A contingency table displays the multivariate frequency distribution of the different variables. The theory of probability can be used to calculate the expected percentages under the assumption that the zero hypotheses is true. The theory of probability states, if there is no relation between two random variables X and Y, the following relationship holds: $P(X = x \wedge Y = y) = P(x = x) * P(Y = y)$.

Figure 6-16 presents the contingency table of care set arrivals. The contingency table provides the multivariate frequency of each care type categorized to the arrival type of the care set. If the zero hypothesis is true and there exists no relation between the arrival type and the distribution of care types, than the counted numbers should be equal to the expected numbers.

Cells with a higher observed count than the expected count are yellow highlighted, the cells with a lower observed count than expect are blue highlighted. The table shows that new children arrivals have a higher than expected number of care sets which contain ambulatory or day care. Returning children have a higher number of foster care and residential care than expected, which is in line with the made assumptions. The question remains whether these expected counts differ significantly from the observed counts from the samples or that they are just caused by the sample error. To test this statistically, an overall measure for the difference between all expected and observed counts is defined:

EQUATION 1 OVERALL MEASURE FOR THE DIFFERENCE OF SAMPLES

$$X^2 = \sum_{i=1}^{k} \frac{(o_i - e_i)^2}{e_i} = 17{,}1$$

FIGURE 6-16 ARRIVAL SET CARE TYPE CONTINGENCY TABLE

		new	registered	total
AH	observed	910	1005	1915
	expected	*879*	*1036*	
DH	observed	81	68	149
	expected	*68*	*81*	
PZ	observed	100	156	256
	expected	117	139	
RH	observed	117	195	312
	expected	*143*	*169*	
	total	1208	1424	2632

The chi-square density function can be used to find the upper critical value for χ2. Inputs are the α = 0,05 and the degrees of freedom df =(rows-1)(colums-1)=(4-1)(2-1)=3. The upper critical value is 7,82. The value of the sample statistics is bigger than the upper critical value 17,1>7,82. The zero hypothesis can rejected. There is a relation between the arrival type of a care set and the trajectories in that care set.

6.2.3 Conclusion relation between arrival type and trajectories

Based on youth care domain knowledge collected from the interviews by Giesen (2008) the hypothesis has been made that there is a significant difference in the care type distribution in the care sets of new and registered children arrivals. A contingency table has been made and the significant difference between the care type distributions of both arrival types has been proven with a chi-square test. The contingency table provided inside in the distribution of care types over the care sets of the two arrival types. It becomes clear that new children arrival care sets receive more care types focused on treatment of the child, while children returns receive a higher proportion of care types which provide a substitution of a safe living situation. This can be explained by the difference in objectives between the two care types, the first category is focused on curing the child and thereby improves the situation which causes the problem, the second categories does not improve the problem cause of the care, which is considered the dysfunctional family situation. The analysis in the current and previous sections provide a clear indication that the care set of new registered children arrivals should be distinguished and modelled differently in the DES simulation model to be developed. The next section will analyse the conditionality in and between sequencing care sets of a child.

There is a significant difference between the care sets of new and returning children.

6.3 Care set relations: conditionality and dependency

The previous section proved that a significant difference exists between the first care set assigned to new arrival children and the care sets assigned to children returning for additional care. The objective of this section is to make the important relations between trajectories of different care types in these care sets transparent. Two types of relations between care trajectories can be distinguished: parallel trajectories and sequential trajectories. A visual representation of these relations is presented in Figure 6-17.

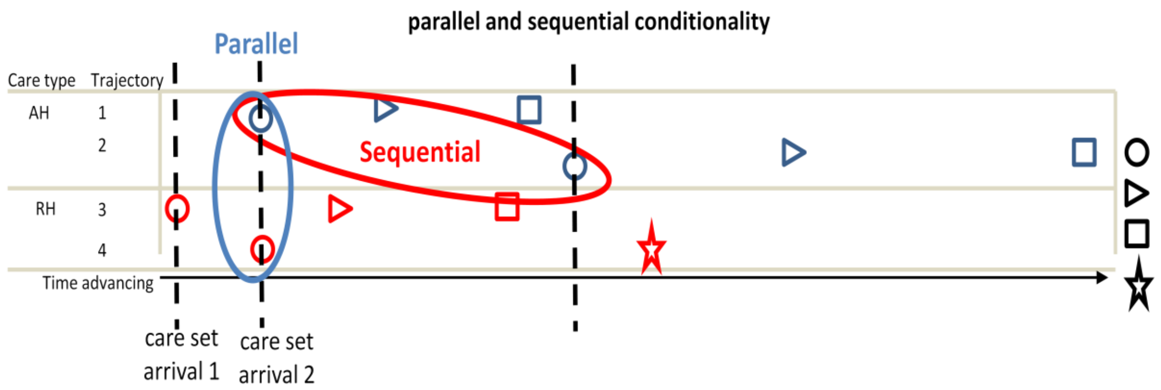


FIGURE 6-17 TRAJECOTRY RELATIONS: PARALLEL AND SEQUENTIAL

Figure 6-17 represents parallel trajectories in an arrival care set with a blue oval, the sequential trajectories are visualized with a red oval. *Parallel* trajectory relations are the relations between the care trajectories in the same arrival care set. *Sequential* relations are the relations between trajectories of sequencing care sets. First subsection analyses the parallel trajectory relations, the second subsection presents an analysis of the sequential association relations.

6.3.1 Parallel conditionality

Discrete event simulation provides the opportunity to model unique entities and relations between those entities. This subsection will analyse the relations between care trajectories in arrival care sets in order to make abstraction and reduction decisions about these relations in the following specification chapter. The analysis of this subsection answers the following research question:

Is there a relation between the occurrence of care trajectories of different care types in a common arrival care set?

The system dynamics models, introduced in Chapter 4, assumes that all children received the same average care profile which contains an average of all four care types. Domain knowledge of the youth care sector, gathered from the care products and programs of different care providers, provides an indication of the parallel relations between different care types (Entrea 2010; Stichting Jeugd formaat 2010). These care programmes indicate that ambulatory care is used frequently parallel to one of the other care types, to monitor the care process and to provide additional support. The three other care types are considered mutual exclusive in the same care set. The following analysis tests the found relations for the chosen case study care provider.

The previous section proves that there is a significant difference between new and registered children arrivals. Based on this difference a separate analysis for the relation in the care sets both arrival types will be performed. The separate analysis, for both arrival types, exists of six relation tests for which the following generic hypothesis can be formulated for the occurrence of parallel trajectories of a two care types in a care set. :
H_1 : There is a relation between the occurrence of *care type 1* and *care type 2 in a common care set.*
H_0 : There is no relation between the occurrence of *care type 1* and *care type 2 in a common care set*

Figure 6-18 provides an overview of the possible conditionality relations to be tested between the different care types.

FIGURE 6-18 PARRALEL RELATION TABLE

relation	Care type 1	Care type 2
1	PZ	RH
2	PZ	DH
3	RH	DH
4	AH	PZ
5	AH	RH
6	AH	DH

An example analysis, in which the relation between PZ and RH in the care sets of already registered children arrivals is tested, is explained in the next part of this section. The analysis for the other relations is presented in appendix C.4 at p. 137.

Example analysis: Parallel relation between PZ and RH registered arrival set[9]

Residential and foster care both provide a home situation for children who for different reasons do not have a save and sustainable home situation living with their parents. The choice between foster care and residential care depends on the age of the children, the availability of foster care parents and the assumed care needs of the child. Because both care types provide the same product, a save home situation, the expectation is that PZ and RH are mutually exclusive care types in the same care set. The relation to be tested is again an association relation between two categorical variables, a contingency is analysed. The contingency table of the parallel relation between PZ and RH is presented in Figure 6-19. The contingency table provides a frequency analysis of the different care sets categorized to occurrence of the two care types under study. Each cell in the table represents a mutually exclusive combination of RH and PH. The left table presents the frequency of the observed care sets. The right table provides the expected frequency under the assumption that the zero hypothesis is true, calculated with the theory of probability. If there is no relation between the two care types, then the observed counts are equal to the expected counts.

When analysing the observed and expected tables it becomes clear the frequency of care sets with parallel RH and PZ trajectories is observed 5 while the expected frequency is 22,87. A chi-square test is performed to test whether these expected counts differ significantly from the observed counts. The overall measure for the differences between the two samples x^2 is calculated. The chi square distribution is used to determine the change P that X^2 coincidentally is at least as great as the calculated x^2 value, assuming in dependability between the two care types. If this change is smaller than the chosen $\alpha = 0,05$, than the zero hypothesis is rejected and a significant relation is proven.

FIGURE 6-19 CONTINGENCY TABLE PARALLEL TRAJECTORY PZ-RH[10]

counted		Pz			expected		PZ		
		yes	no	total		0	yes	no	total
RH	yes	5	190	195	RH	yes	22,87218	172,1278	195
	No	151	984	1135		No	133,1278	1001,872	1135
	total	156	1174	1330		total	156	1174	1330
Chi square P($X^2>=x^2$)		1,66461E-05		< α=0,05					

The calculated chance (highlighted in yellow) is smaller than the α=0,05, the zero hypothesis can be rejected. There is a significant relation between residential and foster care products in the arrival set of first arriving children. This relation decreases the amount of parallel residential and foster care. The care types are however not mutually exclusive, 5 parallel care sets are distinguished. In order to decide between modelling the parallel relations or simplifying the system by assuming mutual exclusiveness, the influence of parallel care sets on the system behaviour should be analysed. A first indication of this influence on the care system of both care types can be extracted from Figure 6-19. From all arrival sets, which contain residential care, 3.2% also holds a parallel foster care trajectory. From all arrival sets, which contain foster care, 2.6% hold a parallel residential care trajectory.

Conclusion and implications

Based on the contingency table and the performed chi-square test it is proven that a significant relation exists between the occurrence of residential care and foster care in common returning child arrival care set. The frequencies in the contingency table can be used to analyse the influence of

[9] The relations between the occurrence of care types in the same care set are tested. The influence of the amount of care trajectories of the those care types are not analysed. This decision has been made in order not to harm the statistical power of the test by over disaggregation the data in categories with low frequencies.

[10] The chi square values are determined with the Microsoft excel 2007 chi-square distribution.

parallel trajectories arrivals on all arrivals of this care type. This serves as an indication of the impact of simplifying the system by assuming mutual exclusiveness of both care types in a common care set. For this example, which tests parallelism between foster care and residential care, it becomes clear that around 3% of the residential care sets hold foster care and vice versa.

Overview results all relations

The presented methodology to test if there is a relation between parallel care trajectories of foster care and residential care is applied to all six possible relations, for both arrival types. The results of these tests are presented in Figure 6-20. The left column presents the results of the first child arrivals sets, the right column presents the results for the registered child arrival sets. For every tested relation the percentage of influence of parallel arrivals on the total of arrival sets for both care types is calculated. As discussed in previous section, these percentages provide a first glance of the impact of assuming mutually exclusiveness of both care types in one arrival set in a discrete simulation model.

FIGURE 6-20 RESULTS PARALLEL RELATIONS TEST[11]

Relation		First child arrival			registered child arrival		
		$P(X^2>=x^2)$	% parallel of all care type arrival sets		$P(X^2>=x^2)$	% parallel of all care type arrival sets	
care type 1	care type 2		care type 1	care type 2		care type 1	care type 2
PZ	RH	0,0111	4	3,42	1,67E-05	3,21	2,56
RH	DH	0,0471	3,42	4,94	0,0016	0,51	1,47
DH	PZ	0,0017	0	0	0,0161	2,94	1,28
AH	DH	0,0132	7,47	83,95	9,70E-20	1,99	29,41
AH	PZ	1,41E-59	5,27	48	2,90E-82	2,09	13,46
AH	RH	0,0001	10,55	82,05	1,10E-20	4,68	40,17

Results parallel relations between care types

The results of the chi-square tests prove that every possible parallel relation between care types is significant. The relation between residential care and day care for first child arrivals is the only relation close to the significance level of the test. The differences in chi square values for new and registered children arrival sets are the consequence of the in previous section proven difference in a number of trajectories a care set and the distribution of care types over the care set. In general the calculated $P(X^2>=x^2)$ is smaller for registered child returns. This is a result of the lower number of parallel trajectories in returning care sets, the probability of a parallel care trajectory between care type decreases if the number of care trajectories in care set decreases.

Now conditionality between the occurrences of different care types in the same arrival set is proven, the question arises how to incorporate the proven relations into a purposeful simulation model. The percentages in Figure 6-20 presented the proportion of the care sets arrivals of the two care types under study that hold the tested parallel relation. The percentages highlighted in red demarcate the parallel relations which hold a proportion of less than 5% of the total care sets of both care types. The demarcated relations are the parallel relations between foster care, residential care and day care, which are considered mutually exclusive in the youth care sector. The green highlighted relations demarcate the relations of these three cares type with ambulatory care. The proportion, of all arrival sets of residential, foster and day care that hold a supporting parallel ambulatory trajectory, is high. Based on these proportion the assumption can be made that the influence of the red highlighted relations are neglect able, while the green highlighted relations are essential to capture the system behaviour. The validity of this assumption will be explored in the next part of this subsection.

Influence of parallel relations between PZ, RH and DH on the system behaviour

[11] The expected counts for all cells in the different cross tables of this analysis are above 5 and all expected counts are larger than zero.

The performance indicators, determined in subsection 2.4.4, indicate that both the performance of the child layer and the care system sub-models of the different care types are of interest. In order to confidentially neglect and simplify system relations, the influence of such a relation on the different parts of the system should be determined. The assumption that the red highlighted relations in Figure 6-20 are neglect able is analysed by determining the proportion of care sets witch hold these relations on both the trajectory as the child sub-models. Figure 6-21 presents the proportion of care sets of the assumed neglect able parallel relations between PZ, RH or DH. The proportion are measured both at the trajectory level aggregated to the different care types and on the child layer which exists of all care sets not aggregated to the specific care types.

FIGURE 6-21 PROPORTION ARRIVAL SETS WITH PARALLEL RELATIONS BETWEEN PZ, RH OR DH

Care type	First child arrival	Registered child arrival	All arrivals
PZ	4,00%	4,49%	4,30%
RH	6,84%	3,08%	4,70%
DH	4,94%	4,41%	3,59%
All arrival sets	**0,60%**	**0,80%**	**0,69%**

The table shows that neglecting parallel care sets between PZ, RH and DH, has the most influence on the residential care submodel. The total influence of the relations on the demand behaviour of the different sub models is presented in the right column and is for each sub-model less than 5%. Interesting is the influence on the child level which contains all arrivals sets and is presented in the last row of the table. While the influence of the relations on the different sub-models is higher for first child arrivals, the influence on all arrival sets is higher for registered child returns. This results seem contradictory at first glance, but can be explained by the higher proportion of ambulatory care in the subset of all first children arrival sets in comparison to the proportion of ambulatory care in the subset of all registered child arrivals. As proven in the analysis of care type distribution over the two arrival types presented in previous section, 0,69 percent of all care sets contains a parallel relation between two of the three accommodation care types.

Implication of assuming mutual exclusiveness between PZ, RH and DH

Based on the observed influence of the parallel relations under study of less than 1 percent on the overall system behaviour, the assumption is made that PZ , RH and DH can be considered mutual exclusive when abstracting the system behaviour in a discrete simulation model. An important notification can be made toward the influence of this decision on care types sub models. While the tables show the percentage of arrival sets which will not be modelled as in real life, the implication on the demand behaviour of the sub models are smaller than these percentages. The observed parallel trajectories in the dataset are taking into account when determining the frequency of the different care types in the following specification chapter. The influence of assuming mutual exclusiveness of these care types on the demand behaviour of the care type sub models is therefore considerably smaller than the percentages in Figure 6-21.

Conclusions and implications

First, six possible parallel system relations between care types in a arrival care set were distinguished, presented in Figure 6-18. These relations have been tested separately for new and returning children arrival sets. A cross table has been made for every relation and the significance of the relationships has been proven by a chi-square test. All six possible parallel system relations between care types were proven to be significant.

The cross tables provide evidence that, although RH, PZ and DH are not mutual exclusive, the probability of occurrence of both in one care set is low. The influence of neglecting this probability and assuming mutual exclusiveness between this care types has been analysed for the different sub-models and information layers of the system. The analysis showed that the proportion of influence of the assumed neglect able relations is less than 5% on the different care type sub models. An important conclusion is that the influence assuming mutual exclusiveness on the abstracting of these sub models will be smaller than this 5%. The influence of assuming mutual exclusiveness between RH, PZ and DH on all arriving care sets measured on the child layer is determined less than 1%. The first simplification for the discrete model to be developed is the assumption of mutual exclusiveness between RH, DH and PZ. This assumption is to simplify the analysis of relations between a child's sequential care sets in the next subsection and to simplify the specification of the model in the following chapter.

There is a significant relationship between the parallel occurrence of care types in a arrival set. *Mutual exclusiveness can assumed between RH, PZ and DH in a common arrival care set.*

6.3.2 Sequential conditionality

An important difference between parallel relations and sequential relations is considered the influence of time. The parallel care set relations, analysed in previous section, determine the care services assigned to children at a specific moment of time. Sequential relations capture relations between care sets assigned to children at different points in time. Sequential relations are dependent on the different states of both the child and child's environment between these points in time. A child's future state is among other factors influenced by the care services delivered to the child during the time span between the two arrivals. There are other dynamics, which could influence these relations, for instance a child's family situation. These dynamics are unknown when abstracting the behaviour of the care provider model into a simulation model. This subsection will analyse the dataset of child arrivals over 2008 and 2009 in order to derive an empirical distribution, which captures the resulting behaviour of these unknown dynamics. Starting points of this analysis is the information derived from the youth care sector, previous modelling attempts by INITI8 (Giesen 2008; Westerflier 2008) and conclusions made in the preceding subsection of this chapter.

In the previous sub section, it is concluded that a valid simplification is to assume mutual exclusiveness between the care types RH, DH and PZ in a care set arrival. Based on this simplification and the care services domain knowledge introduced in the second chapter, the following conceptual representation of the sequential influence relations between sequential care types can be made.
The conceptual representation makes a clear distinction between accommodation services and youth assistance. The same distinction has been introduced previously in section 2.1.2, which introduced the domain knowledge of the youth care sector. The solid black boxes represent the accommodation and youth assistance care sets, which contain one or multiple care trajectory.

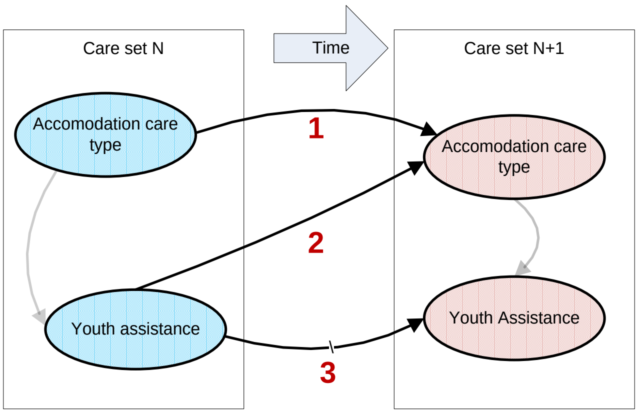


FIGURE 6-22 CONCEPTUAL VIEW SEQUENTIAL CARE SET RELATIONS

Accommodation services. The set of accommodation services can contain one or more accommodations providing care trajectories. Based on the conclusion presented in the previous chapter, mutual exclusiveness between the different accommodation providing care types is assumed. A care set can contain either trajectories of the care types PZ, DH or RH.

Youth assistance services. The set of youth assistance services can contain or multiple care services of the ambulatory care type.

The analysis in previous section proofed the existence of significance parallel relations between the different accommodation services and youth assistance services, presented by the faded black arrows in Figure 6-22. The sequential relations analysed can be decomposed in three sub relations, each presented as a black arrow in Figure 6-22.

6.3.2.1 *Sequential relation1: sequentiality between accommodation services*

The hypothesis of this analysis is that there exists a relation between previously provided accommodation services and the assignment of new accommodation trajectories in a sequential care set. The following hypotheses are formulated:

H_1 : There is a relation between the accommodation care type of sequencing care sets.
H_0 : There is no relation between the accommodation care type of sequencing care sets.

Figure 6-23 provides a cross tabulation (contingency table) which displays the sequential relationship between the occurrence of care services categorized to accommodation care type of the care services. The rows present the category of the previously assigned care set, the column the category of the new care types. The category "None" presents the care sets which hold no accommodation care services. The only care type in such care sets is ambulatory care. The number of distinct categories for each variable determines the size of the table, each cell in the table represents a unique combination of the two variables. If the expected counts are equal to the actual counts, then there exists no relation between the variables.

FIGURE 6-23 CROSSTABULATION SEQUENTIAL RELATION ACCODAMTION SERVICES[12]

			N+1_Accommodation				
			None	DH	PZ	RH	Total
N_Accommodation	None	Count	841	62	56	126	1085
		Expected Count	726,3	56,1	127,4	175,3	1085,0
		% within N0_Main	77,5%	5,7%	5,2%	11,6%	100,0%
	DH	Count	149	11	6	12	178
		Expected Count	119,1	9,2	20,9	28,8	178,0
		% within N0_Main	83,7%	6,2%	3,4%	6,7%	100,0%
	PZ	Count	62	8	127	46	243
		Expected Count	162,7	12,6	28,5	39,3	243,0
		% within N0_Main	25,5%	3,3%	52,3%	18,9%	100,0%
	RH	Count	191	15	29	116	351
		Expected Count	234,9	18,1	41,2	56,7	351,0
		% within N0_Main	54,4%	4,3%	8,3%	33,0%	100,0%
Total		Count	1243	96	218	300	1857
		Expected Count	1243,0	96,0	218,0	300,0	1857,0
		% within N0_Main	66,9%	5,2%	11,7%	16,2%	100,0%

[12] From this point on the presented statistical tests are performed with the help of the statistical software package SPSS statistics 17.0.

The cells with a higher than expected count are highlighted in yellow, the cells with an lower than expected count are highlighted in blue. The distinction between treatment and support and the provision of a save home situation is again obvious. It becomes clear that children who return after main care types focused on treatment (AH, DH) have an higher than expected chance to receive a care set focussed on treatment again. Children who return after receiving day care as the main treatment type have a chance of more than 83,7% to return for a main care type of the lighter ambulatory type. Children who return after receiving a main care type of foster care have a higher than expected likelihood to receive again foster care or residential care. Returns after receiving residential care have a smaller than expected likelihood to receive foster care. This could be due to the age categorization between foster and residential care. Young children are usually assigned to foster care families, while older children are able to adapt to a residential care situation. A chi-square test is applied to analyse if the observed differences between the expected and actual counts are significant different.

The Pearson chi-square, presented in Figure 6-24, tests the zero hypotheses that row and column variables are independent. The lower the significance of yellow highlighted significant values, the less likely it is that two variables are independent (unrelated). In this case the significance value is 0.00, which means that the zero hypothesis can be rejected. There is a significant relation between the main care types of sequencing care sets assigned to a child.

FIGURE 6-24 CHI-SQUARE TESTS SEQUENTIAL RELATIONS ACCOMDATION SERVICES

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	580,231[a]	9	,000
Likelihood Ratio	446,478	9	,000
N of Valid Cases	1857		

a. The minimum expected count is 9,20.

Conclusion

A significant relation between the accommodation services in sequential care set has been found. When abstracting the dynamics of a care provider system into a discrete simulation model this dependency between sequencing care sets needs to be abstracted in the DES model.

6.3.2.2 Sequential relation 2 : influence of previous youth assistance trajectories on new accommodation care services.

Previous part of this subsection proved that there exists a significant relation between the accommodation providing care services in children sequencing care sets. This part analyses the additional influence of youth care services provided in the preceding care set on the provided accommodation service.

A three-way cross tabulation has been made, to analyse the relation taking into the account the previously proven relation between accommodation care services. The care type accommodation categories of the preceding care sets, in this three way cross tabulation, are further subdivided by the occurrence of youth assistance. The occurrence of supporting care type is divided into two categories "yes" or "no".

This categorical subdivision has been chosen because an ordinal subdivision according to the number of supporting care trajectories of each care type would result in a cross table with more than 50% off the cells counts smaller than 20, which would make the chi-square test unreliable. This three way cross table reveals the relationship between the occurrence of youth assistance in a care set and the accommodation providing care type in the sequential care set of a child. This relation is tested controlled for the effect of the accommodation care type in the previous care set. The three way table is presented in Appendix C.5. Noticeable is the group, which received no accommodation services in their previous care set. These care sets do not hold accommodation services and therefore necessarily exist of ambulatory youth assistance trajectories.

A chi square test is performed to test if the counted frequencies differ significantly from the expected frequencies. The results of this chi square test controlled for the previously proven relation between the main care type in the preceding care set, are presented in
Figure 6-25. Noticeable is the first layer, all care sets, which do not receive accommodation care, contain only ambulatory care trajectories.

FIGURE 6-25 CHI SQUARE TEST DEPENDENCY ON YOUTH ASSISTENCE

N_ accommodation		Value	df	Asymp. Sig. (2-sided)
None	Pearson Chi-Square	.[a]		
	N of Valid Cases	1085		
DH	Pearson Chi-Square	5,460[b]	3	,141
	Likelihood Ratio	5,187	3	,159
	N of Valid Cases	178		
PZ	Pearson Chi-Square	6,382[c]	3	,094
	Likelihood Ratio	6,422	3	,093
	N of Valid Cases	243		
RH	Pearson Chi-Square	14,907[d]	3	,002
	Likelihood Ratio	15,071	3	,002
	N of Valid Cases	351		

a. No statistics are computed because N_youth assistance is a constant.

b. 4 cells (50,0%) have expected count less than 5. The minimum expected count is 1,99.

c. 1 cells (12,5%) have expected count less than 5. The minimum expected count is 2,63.

First, the limitations of the derived cross table and the performed chi square test are discussed. Noticeable is the fact that care sets in which no accommodation service always exist of youth assistance, for this category only the “yes” group exist and no statistics between groups can be calculated. The chi square test analyses the relations between the different youth assistance groups of every accommodation category. The residential care category has 4 cells with an expected count of less than, which is 50% of all cells. For this care type not all chi square conditions are satisfied and the results are considered less reliable.

The significance level of this test is 0.05 %. For care sets, which deliver the accommodation services of the type DH and PZ, there is no significant relation between the occurrence of youth assistance in the first care set and the type of accommodation services in the child’s next care set. For children who receive a care set with the accommodation services of the type RH there is a significant relation between the occurrence of youth assistance and the care type of the accommodation services of their next arrival set.

Conclusion
No significant relation between the type of accommodation service in returning care sets and the occurrence of youth assistance trajectories in previous care sets has been found when controlling for the accommodation services of the care types day care and foster care. The accommodation care type when returning after a care set which holds Residential care trajectories has a significant relation with the occurrence of youth assistance in the previous care type.

6.3.2.3 Sequential relation 3: Sequential relations between the occurrence of youth assistance

The possible relations, which influence the occurrence of youth assistance in returning care sets, where previously presented in Figure 6-22. Two relations are distinguished, the parallel relation with the accommodation type of the care set and the sequential relation with the occurrence of youth assistance in the previous care set. The significance of the parallel relation between the accommodation care types RH, DH and PZ and the occurrence of the youth assistance, with care type AH, is proven in subsection 6.3.1. This subsection analyses the relation between the occurrence of youth assistance in sequential care types controlled for the before proven parallel relation between accommodation and youth assistance care services in a care set. The relation is analysed by a three way cross tabulation. The cross tabulation is presented in Appendix C.7.4. A person chi square test proofs that the relation is significant, the test statics are presented in appendix C.7.4

Conclusion
The chi-square test proves that the sequential relation between youth assistance in sequential care sets, when controlled for the care sets parallel relations is significant for care sets with accommodation type PZ. The relation is not significant for care sets of which the accommodation care type is RH or DH.

6.4 Time between care set arrivals

Previous sections of this chapter analysed the necessity to model the endogenous demand behaviour of returning children and determined the care type relations in and between different care set arrivals. This section contains an analysis of the variables, which influence the time between care set arrivals.

Figure 6-26 presents a conceptual view of the influence relations analysed in this section. A first hypothesis is that the time between two care sets arrivals is influenced by the care types of both the first care set (N) as the sequencing care set (N+1). Seven categories can be distinguished at care type level for both care set N as care set N+1. Care sets which only receive youth assistance (AH), three categories of care sets which only receive one of the three accommodation care types (PZ, RH, DH) and three categories for the care sets which receive a combination of accommodation care and youth assistance (PzAh, PzRh, DhAH).

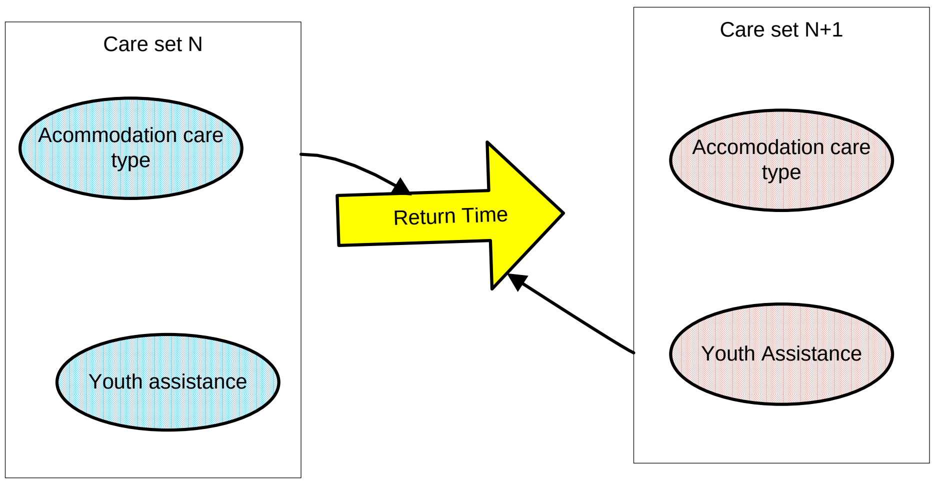


FIGURE 6-26 RELATIONS TIME BETWEEN CARE SET ARRIVALS

The time between care type's arrivals is a variable of ratio level of measurement. A first step in determining the influence of different categories on a variable of ratio level of measurement visually is the creation of a clustered box plot. The box plot is clustered by the seven categories of care set N, the clusters are subdivided by the seven categories of care set N+1. The resulting box plot is presented in appendix C.7. Instantly it becomes clear that the box plot with forty-nine categories is difficult to interpret. The box plot summary table indicates that half of the categories exist of 5 records or less. This indicates that no reliable statistic conclusions can be made drawn from these categories.

After the analysis of box plots of the return time plotted in categories of the accommodation care type for both N and N+1 a clear pattern or relation cannot be found. Based on the separate box plots for each category and the results of previous section the decision is made to first analyze the influence of the accommodation care type of the first care set. The four distinct possible relations are visualized in Figure 6-27. The first relation is tested in the first sub-section, the second subsection provides an overview of the results for the other four relations, controlled for the first relations.

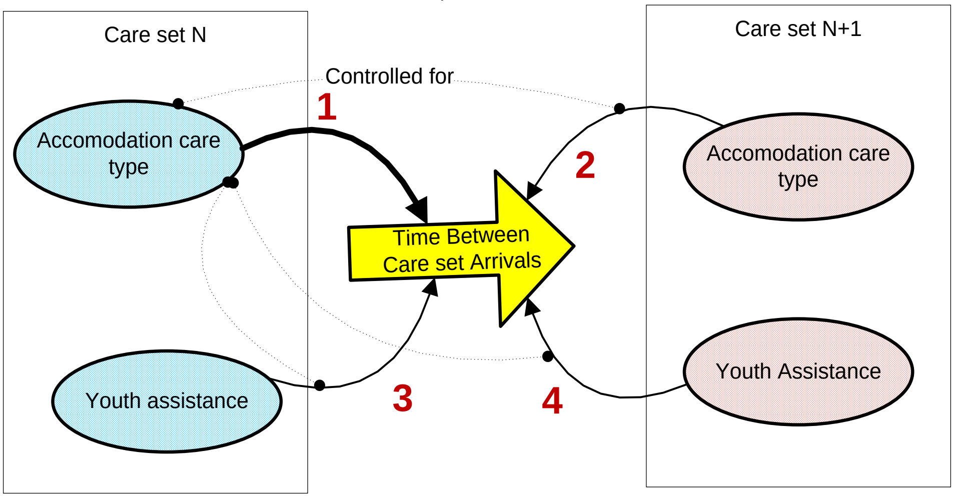


FIGURE 6-27 RESEARCH FRAMEWORK TIME BETWEEN CARE SET ARRIVALS

6.4.1 Relation 1: The influence of accommodation care type in care set N on the time between arrivals

This subsection presents an analysis of the relation between previous accommodation care type and the time before the next care set arrives. The following alternative and zero hypotheses are formulated:

H_1 : There is a relation between the accommodation care type of a care set and the time to next care set arrivals.
H_0 : There is no relation between accommodation care type of a care set and the time to next care set arrivals.

A box plot representation of the to be tested relations is presented in Figure 6-28. It becomes clear that there exist a difference in the median and variances of the time between care set arrivals after a first care set of the different accommodation care types.

A One-Way ANOVA procedure can be used to test the hypothesis that the mean of these groups are significantly different. The ANOVA test assumes that the variances of the groups are equivalent. A Levene test is performed to test these assumptions for the different categories. The Levene statistics rejects the null hypothesis that the group variances are equal. The homogeneity of variances test is presented in appendix C.7. Because the groups of the different categories are not near equal size, a non parametric Kruskal-Wallis test is applied to check if groups are significantly different or not. The

Kruskall-Wallis statistic is 0,015, which is smaller than the significance level of 0,05%. The zero hypothesis can be rejected if there is a significance difference between the inter arrival times of the different categories. The visual representation of these differences is provided by the means graph of the different categories, presented in Figure 6-29. It becomes clear that the mean of foster care differs most from the other categories The mean of ambulatory care and residential care are almost equal and the mean of day care is slightly larger.

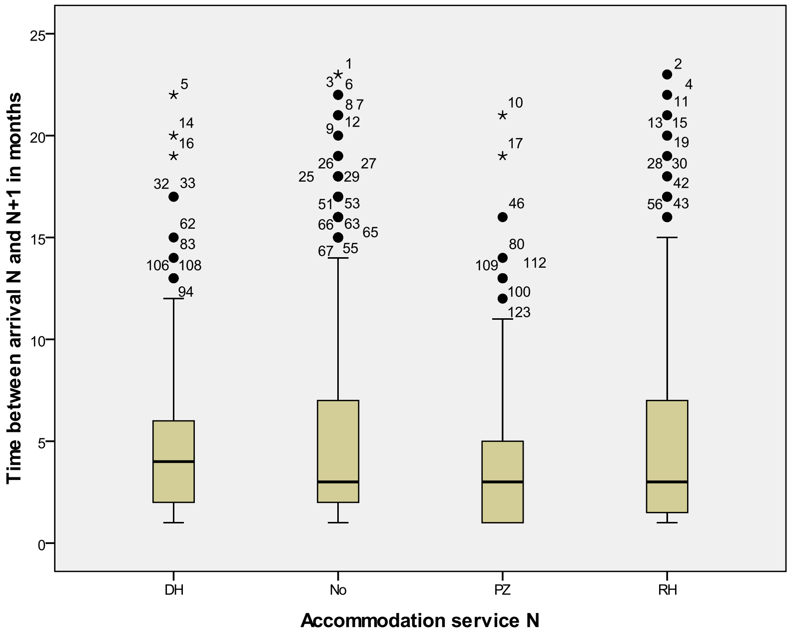


FIGURE 6-28 BOXPLOT RELATION BETWEEN PREVIOUS ACCOMMODATION TYPE AND THE TIME TO NEXT CARE SET ARRIVAL

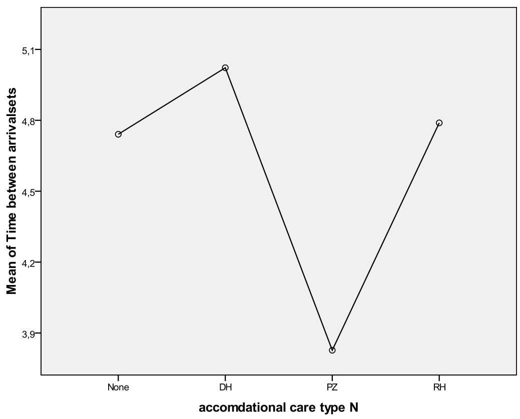


FIGURE 6-29 MEAN GRAPH OF THE TIME BETWEEN ARRIVAL SETS

The Kruskall-Wallis test, presented in Appendix C.7-5, establishes that there is a significant difference between the group means. The mean plot suggests that the return time of PZ differs from the other categories. A Post-Hoc test, which assumes unequal variances, is applied to test which of the found differences between the categories are significant. The Tamhane Post-hoc test proves a significant difference between the return time of care sets which contain trajectories of the accommodation care of the type PZ and care sets which contain accommodation care of the type RH, DH or none accommodation care. Furthermore, no significant differences exist between the return time after care set which contain either RH, DH or no accommodation care. The test statistics are presented in Appendix C.7-6.

Conclusion
A significant relation can be found between the return time in-between care set arrivals and the accommodation care type of the previous care set. A Levene test rejected the homogeneity of the group variance. A Kruskall-Wallis test established a significant difference between the group means. The Tamhane Post-hoc test showed that the return time between care set arrivals is significantly different for PZ than for the other categories. No significance difference between the other categories is found.

The time between care set arrivals does not differ between previous care sets which hold accommodation care of the type RH or DH or no accommodation care. A significant difference can be found between the time until next care set arrival after previous care sets of these categories and previous care sets which contain foster care.

6.4.2 Overview time between care set return relations tests

This section contains an overview of the analysis of relation 2, 3 and 4 visualized in Figure 6-27. Based on the analysis in previous section, the analyses of these relations are performed separately for the two distinct groups. The first group contains all records of the time between care set arrivals of which the first care set exists of all care types except PZ. The second group contains all time between care set records of which the accommodation type of the first care exist of PZ. The second relation is tested with a Kruskall Wallis test for each group, because the assumed equal variances for an ANOVA test are not satisfied for the four distinct care type categories. Relation 3 and 4 are tested with a student T-test for each group. The results of these tests presented in
Figure 6-30, the category column presents which group is tested, the test column the performed test and the results column the calculated found test statistic. The appendix column refers to the appendix where the full test statistics are presented.

As presented in
Figure 6-30, each test statistic exceeds the confidence interval of 0.05%. Neither of the test results allows to reject the zero hypothesis. In conclusion, no significant relation is found between the time between care set returns and the accommodation type of the sequencing care set or the occurrence of youth assistance in either one of the care sets.

FIGURE 6-30 OVERVIEW TESTS TIME BETWEEN CARE SET RELATIONS.

Relation	Name	Category	Test	result	Significance	Appendix
2	Influence of accommodation type return set	No-PZ	Kuskall wallis	0,054	No	D2
		PZ		0,746	No	
3	Influence youth assistance first care set	No-PZ	Student T-test	0,08	No	D3
		PZ		0,068	No	
4	Influence youth assistance return care set	No-PZ	Student T-test	0,068	No	D4
		PZ		0,230	No	

6.5 Limitations and complications care set returns a child

The relations between the composition of a child's care set and the number of care sets a child receives are not addressed yet. This section will perform an initial analysis of these relations and the experienced data complications during these analyses.

A first step of these analyses is to distinct between new and returning children. Counting the number of care set arrivals a child in the time span of the data set without making this distinction could strongly bias the results. It would be possible for the analyzed children to have received multiple care sets before the time span of the available dataset, more precise the perceived amount of child returns from this analysis will be lower than the actual amount.

Sub-section 6.1.1, introduced the complications and limitations of making the distinction between new and returning children in the available data set. First, the data of 2008 was used as a memory to distinct new and returning children in 2009. This reduced the effective time span of the data set to one year, namely 2009. Furthermore, 20% of initially returning children are erroneously interpreted as new arriving children as elaborately discussed in sub section 6.1.1. The reduced time span to one year of effective data is an important limitation for the analysis of the amount of care set arrivals a child.

The spread of return times, visualized in the box plot of Figure 6-28, shows that the median of the return time of the different accommodation categories lies between 4 and 5 months, the third quartile of these categories span from 6 until nine months. Over the one year effective data span, it would at maximum be possible to capture one or in some cases two returns of the new children arriving in the first months of the data sets. The distribution of amount care sets can only be analyzed for the few new children, which arrive in first months of the data time span and for their first or second return care set. In other words, the distribution of total amount of return cannot be found and the sample size is too small to distinguish different categories of influence for further analysis. Taking into account that the bias comes from children arrivals out of the measurement time span, it is certain that the counted number of returns is equal or lower than the actual number of returns.

Based on this knowledge, different care sets configuration that use less than one year as memory can be validated against the above described configuration. These configurations are less valid in terms of of the new and returning children distinction, but they would have a larger time span to count returning care sets. The indicated direction of the bias determines that the configuration that counts the highest amount of return is the most valid representation of the actual amount of returns. It is important to notice that this relative validity provides no indication of the real validity of this best configuration.

The following configurations are cross-validated:

A) Memory: none. Sample: all children arrivals in the first 3 months of 2008. Time span of returns: 2008 and 2009
B) Memory: month 1 till 6of 2008. Sample size: month 6 till 9. Time span of returns. From month nine of 2008 till end of 2009
C) Memory: 2008 and children in care at January first of 2009. Sample: children arriving in the first 3 months of 2009. Time span of returns: 2009.

The found return distribution of the different categories is presented in Figure 6-31 as a bar chart. Configuration A has a lower percentage of zero and one returns after arrivals, and a higher percentage of more than one returns than the other configurations. When looking at the mean number of care sets a child, configuration A has a mean of 1.06 children returns, configuration B has a mean of 1.001 returns and configuration C has a mean of 1.004 returns. A best guess at this moment for the distribution of children returns is configuration A. This distribution, although the best option for now, is likely to result in significantly lower returns than experienced in the real world and with current data there is no possibility to validate the results. Furthermore, the size of current dataset provides no possibility to reliably distinct relations between the composition of a child's care sets and the amount of time a child will return.

In conclusion

The available data set does not provide accurate insight into the number of children care set returns distribution. Neither is it possible to find relations between the care set composition and the amount of care set returns. The following specification chapter presents a none data related strategy to derive the number of care sets return a child.

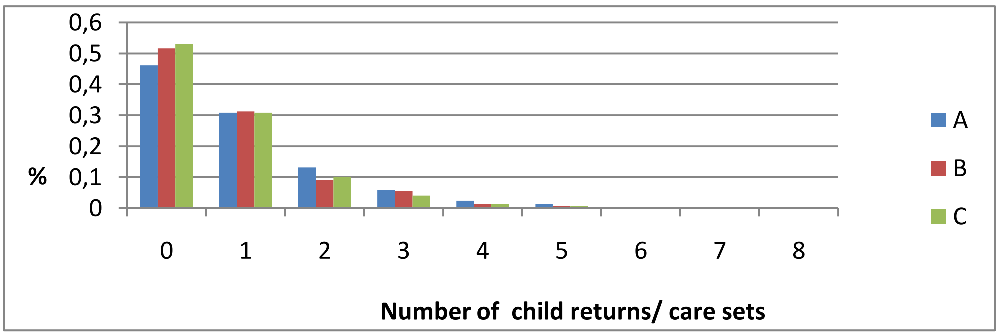


FIGURE 6-31 BARCHART OBSERVED NUMBER OF CHILDREN RETURNS

6.6 Withdrawal mechanism

As previously introduced waiting lines in health care feature withdrawals when clients have to wait for an extended period. Several studies have shown that the amount of time that a client is willing to wait for care is related to the urgency of the problem (Goodacre and Webster 2003). Problems that are more urgent are genuinely require attention, and are difficult to treat elsewhere. These cases will therefore accept longer waiting times. To take the urgency of the problem into account in the analysis, the withdrawal mechanism is analyzed in this section. A first problem arises, because the healthcare waiting lines are not physical waiting lines. The children do not physically stand in a line, from which they walk away on withdrawal. Regularly a child does not notify the care provider when he or she decides withdraws. The care providers do not know about the withdrawal, until it is the child's turn for care and the child is contacted. Consequently, the time a child is willing to wait for a care service of each care type is unknown. A different approach to abstract the withdrawal mechanism is necessary.

Given the available information, an approach is chosen which evaluates the chance of child withdrawal based on the waiting time before a care position is available for each care type. In order to do so, the observed waiting time before a care position became for every child over 2009 are grouped into interval classes. The frequency of observed care starts and withdrawals of children with waiting times in the same interval, are used to determine the withdrawal probability as a function of the waiting time before care resources are available. The class intervals are 30 days wide, except for the maximum class, which also takes into account the extreme values.

For all four care types, a clear relation between the proportion of withdrawals and the waiting time before care resources are available, seem feasible. This mechanism can be abstracted into a DES simulation model by implementing the trend line of these graphs in order to calculate the binomial withdrawal chance for each child, based on their waiting time.

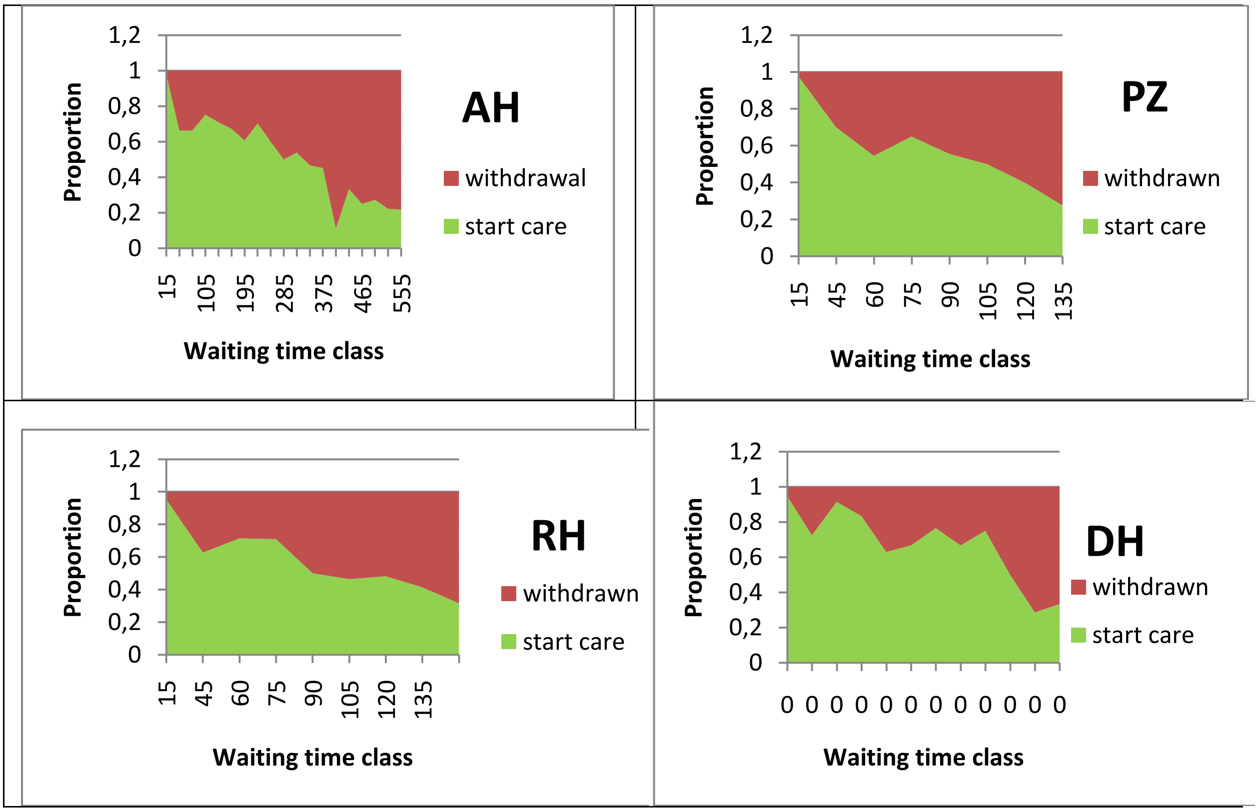


FIGURE 6-32 WAITING TIME WITHDRAWAL PROPORTION PLOTS

6.7 Observed dynamics in policy variables

Dynamic system behaviour is a result of the input into a system, variability and the system structure. While system behaviour changes over time, also policy variables can change over time. This section controls for structural changes and variability observed in the instrumental parameters, which form an important input to the model. Controlled are the number of capacity places and the average treatment time dynamics for each care type.

The behaviour of the weighted average treatment time over six months and of the amount of capacity places is analyzed. The amount of capacity places is assumed to be equal to the amount of children in care, at each moment that there is a waiting lists. The graphs of the average weighted treatment time, the waiting list dynamics and the amount of trajectories in care are presented in appendix C.1 and C.2. Although Some variability is observed in the different graphs, no clear structural changes are found for the amount of capacity places and the average treatment time over 2008 and 2009.

6.8 Conclusion data analysis

The data analysis performed in this section answers the fourth research question, by making the important system relations transparent. Furthermore, the limitations in the available data to quantify these relations are determined.

A distinction between exogenous and endogenous demand was made, by using the data of 2008 and the children in care at 1 January of 2009 as a system memory. In general, the conclusion from the demand analysis was that both measured on the children and trajectory level endogenous demand forms a significant proportion of the total demand. Furthermore, it is concluded that endogenous demand has an important impact on the total demand variability for each care type. Based on the distinction between exogenous and endogenous children arrivals, the care set composition of new and returning children is compared. A significant difference is found between those care sets, both in care type composition and size.

Significant parallel conditionality relations between the occurrences of care types in a common care set where found. It became apparent that the three accommodation care types DH, RH and PZ are mutual exclusive in a care set. Significant conditionality relations between ambulatory care and the three-accommodation care types are found. An analysis of the relations between sequencing care sets indicates that a significant relations exist between the accommodation care type of the first care set and the accommodation care type of the sequencing care set. Furthermore, a significant relation is found for the time between children's sequencing care set arrivals and the accommodation type of the previous care set.

The time span of the data sample is too small to provide accurate and reliable insight into the distribution of the amount of care sets assigned to children. This distribution is there for not quantifiable with the available data sources. A visual presentation of the withdrawal proportions as a function of different time interval indicates a significant relation between the waiting time and the withdrawal probability.

For the children inflow, the number of capacity places and the treatment times the dynamics where analyzed in order to determine if these variables are likely to be stationary over the time span of the data set. It is concluded that the capacity places can be abstracted by a constant, the children inflow and treatment distribution can be abstracted by a stationary distribution.

Chapter 7

Specification: Discrete event simulation model

This chapter describes the specification of the DES simulation model in Any Logic simulation software.

7.1 Model assumptions and reductions

The real world is many times bigger and more complex than can ever be included in a simulation model. The simulation model is simplified, where necessary and possible, to prevent it from becoming needlessly complicated. The following set of simplifications is made:

Resource usage. The demarcated abstraction of resources distracts from employees, treatment rooms and beds. Capacity is modelled as the amount of parallel trajectories, which can be treated at the same moment in time. In the real system, every trajectory has a different treatment intensity, according to the needs and circumstances of the child. For instance, a child can receive a six month trajectory which provides one hour of ambulatory care a week, while another receives for the same amount of time a ambulatory trajectory in which six hours a week ambulatory care is provided. The DES model abstracts from this differences in intensity and assumes homogeneity of trajectory care intensity and capacity usage for every care type. This abstraction has been made because the data sources do not distinct different treatment intensities.

Queue mechanism. The introduced SD model assumes homogeneity and perfect mixing in children and trajectory flows. The DES model picks a distinct trajectory entity from the queue. The queue mechanism refers to the logical order at which trajectories are placed in the queue and determines which trajectory will be served next if a server becomes available. In the real system this selection is made based on the distinct attributes of the child in the queue in relation to the distinct attributes of available capacity. Does a child fit into the current treatment group in terms of age, treatment needs and problem causes? For instance a sexual offender cannot be treated in a group of sexual offended children. In the simulation model, this decision cannot be made based on these unknown details. For this research a first in, first out (FIFO) service mechanism, service in random order or a random priority based queue mechanism is applied.

Care process. The care process of each care trajectory of a certain care type is simplified, our model objective is not interested in the contents of the procedures, the concerns lies on the time the care process takes. The care process is represented by a processing time which the "capacity" resource is kept busy. The process time is drawn from a distribution.

Care profile. In the real world a child's care set is based on a diagnosis at that moment. The development of a child's care needs is among other influences steered by the effectiveness of provided care, developments in the child family situation etc. The employees of the care provider monitor the child and when a change in care needs is diagnosed, an additional care set can be added or one or multiple trajectories in the first care set can be terminated. The DES model makes assumptions of the child developments and their expected care profiles based on the empirical distributions found in the data and the relation between parallel and sequential trajectories, as found in previous chapter. Based on these relations, a child full care profile is determined at the moment the child arrives. Waiting times and withdrawals are assumed not to influence this care profile.

7.2 Anylogic software

The simulation language requirements are defined by the simulation model requirements; the model requirements included usefulness, development cost and time, stakeholder trust and the ability to use the model at other locations.

The AnyLogic simulation software is based on a native Java environment, which provides reusability through a fully object oriented structure. Furthermore, the native Java environment supports limitless extensibility including custom java code, external libraries and external data sources. The included object libraries provide the ability to reuse pre-build simulation elements; including agent based state charts, discrete event process blocks and system dynamic elements. These discrete and continuous simulation elements can be seamless integrated in one model. AnyLogic's extensive statistical distributions function set provides an excellent platform for simulating the uncertainty inherent in all systems.

AnyLogic's visual development environments speed's up the development process and increases the model transparency for stakeholders. The experimental framework includes built-in support for advanced optimization. AnyLogic modes are completely separable from the development environment and can be exported as standalone Java application. This allows users to run the model anywhere, even from websites.

7.3 Model logic

As introduced in previous section, Anylogic supports UML based modelling to utilise all advantages of Objected Oriented modelling. Furthermore, Anylogic enables to model the discrete processes of these objects from different modelling viewpoints. The model logic of each process can be structured by block based state or entity flow charts, while algorithms can be visually captured in action charts. This section will make the abstraction of the in previous chapters analyzed concepts and relations in the developed DES AnyLogic model transparent. The mechanisms and decision structures presented in this section are quantified in the following section.

7.3.1 Static structure Anylogic model

The principles of object orientation are used to create the static model structure. The model classes and the containment relations between those classes are presented in Figure 7-1. The blue boxes represent a class. Six classes are distinguished. The matching between care systems and trajectories is based on their care type attribute. The care type attribute, presented in a white box, is not implemented as a class but as a system dimension. The care sets assigned to a child forms the coupling between a child and its trajectories treated in the care systems. The care provider class serves as the root of the simulation model.

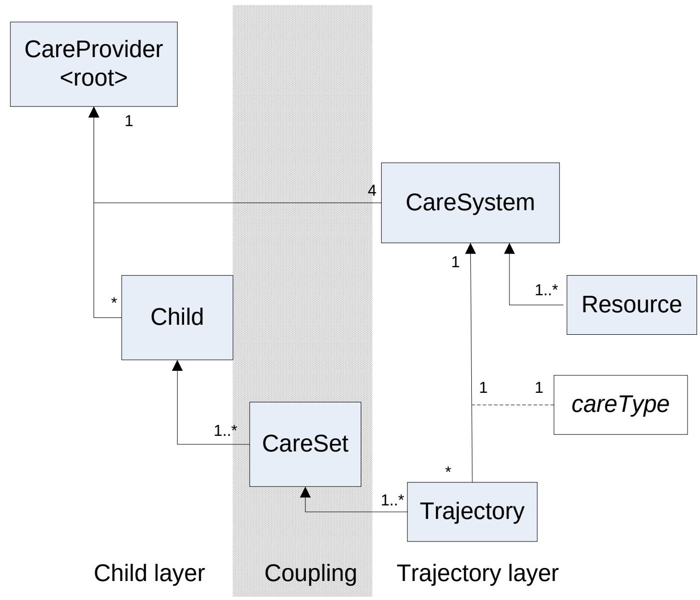


FIGURE 7-1 STATIC STRUCTURE DES SIMULATION MODEL

Now the different classes of the simulation model are introduced following subsections make the important process, algorithms, state transitions, and their initializations requirements transparent.

7.3.2 From child arrival to trajectory arrival

The care provider system is driven by the child care demand. This is abstracted in the DES model by a daily children arrival event. The aggregation level of arrivals a day is chosen taking into account the unit of measurement of the main performance indicator, the waiting time, which is measured in weeks. Abstracting between child arrivals in hours in perceived unnecessarily detailed. Every day the daily child arrival event initiates the action chart presented in Figure 7-2. First the amount of children arrivals for that day are drawn from the amount of children arrival Distribution.

Input variable: *Daily child arrival distribution.*

For each child that arrives a care profile, which consists of a multitude of trajectories with varying arrival times, needs to be created. This done in the blue, create care profile action block, which initiates a sub-algorithm of the daily ChildArrival algorithm, visually presented as an action chart in Figure 7-3.

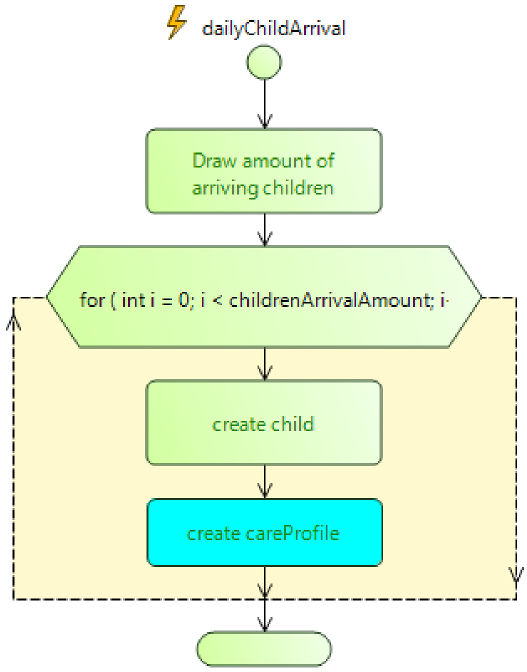


FIGURE 7-2 ACTION CHART DAILY CHILD ARRIVALS

The create care profile sub-algorithm is visually presented as a action chart in Figure 7-3. The child's trajectories, which arrive at the same moment in time are grouped in one arrival care set as previously introduced in chapter 5 and 6. The analysis presented in section 6.2, proved that there is significant difference between the composition a child's first arrival care set and the care sets assigned to previously registered children. This distinction clearly returns in the action chart presented Figure 7-3, which distincts separate sub-algorithms for the creation of first and returning care sets. The trajectories in the first arrival care set are scheduled directly at the time of child arrival in the relevant care system. The createFirstArrivalCareSet sub-algorithm is explained in following sub-section. Dependent on the composition of the first arrival care set a binominal distribution is selected to determine if the child returns for a second care set. Section 6.5 introduced the limitation and complications of determining these return distributions. The made assumptions are defended in sub section 7.4.3.

Input variable set : *Return probabilities (4)*

If the return drawing determines that the child will return for an additional care set, than a while loop is entered. This while loop first initiates the sub-algorithm which draws the return care set based on the sequential care set relations determined in previous chapter. After which, again a drawing of the return distributions determines whether the child returns for another additional care set. The selection of this distribution is dependent on the accommodation care type of previous care set. The while loop continuous until the drawing of the return distributions determines that the child will not return for an additional care set.

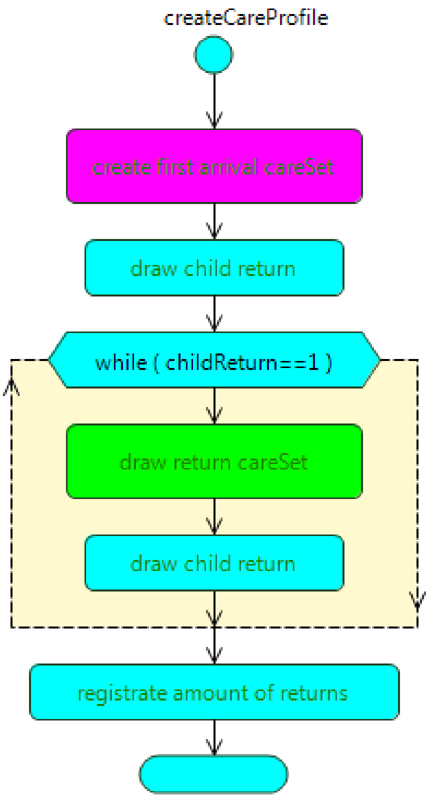


FIGURE 7-3 ACTION CHART CREATE CARE PROFILE

7.3.3 Care set class

Both the new and return care sets are instants of the same care set class, the difference between them lies in the different assignment of trajectories to both. This subsection makes the attributes and sub-algorithms of the care set class transparent, followed by a description of the assignment algorithms of both care sets. A representation of the Care set object Class is provided in Figure 7-4.

The child attribute refers to the child who receives the care trajectories embedded in the careSet. Each careSet has a accommodation key, based on the mutual exclusiveness of parallel accommodation types in a common care set, as defined in sub-section 6.3.1. A care set can hold a set of multiple accommodation trajectories of one accommodation care type, referred to as the accommodationSet. The set of ambulatory trajectories is referred to as the youthAsstistanceSet. The arrival time refers to the simulation time at which the care set state becomes active and at which the startCareSetEvent is drawn.

The startCareSetEvent has two functions, it inputs all trajectories on the waiting list of the care systems, and it schedules the startCareSetEvent of the sequencing care set with a delay of the daysTillNextCareSet variable. The startCareSetEvent of the child's first care set is scheduled directly after the child's arrival time at the care provider.

The care set state transits to active when it has one or more active trajectories in a care system. If all the active trajectories of the care set are waiting the care set state is waiting. When there is one trajectory in care, the care set state transits to in care. The care set state transits to its final state when all of its trajectories finished their treatment.

Object class CareSet
[Attributes:

child	(Child)
accommodationKey	(PZ, RH, DH, NONE)
AccommodationSet	(Set<Trajectory>)
youthAssistenceSet	(Set<Trajectory>)
arrivalID	(int)
arrivalTime	(double)
sequencingCareSet	(CareSet)
daysTillNextCareSet	(double)
state	(StateChartState)

Operations

StartCareSetEvent	*event*
stateChart	StateChart

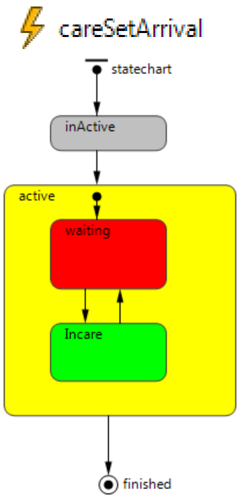


FIGURE 7-4 CARE SET OBJECT CLASS

7.3.4 First care set drawing

The intention of this sub-section is to provide transparency in the procedures and dependency relations abstracted in the simulation model. The high-level structure of these algorithms is implemented in the simulation model by action charts. These action charts provide a clear overview of the sequence of procedures in the system, however action charts do not provide insight in exact procedures and data dependencies of these procedures. A slightly adapted conceptual diagram is introduced, partly inspired by the advantages of IDEF0 diagrams, to make both the sequence of the procedures, the data requirements and the conditionality relations transparent.

First care set drawing.

The procedure of drawing a child's first care set is presented in Figure 7-5. The horizontal line represent the flow through the algorithms, the vertical down oriented arrows presented the system controls or data requirements. The dotted arrows highlight the parallel conditionality relation, determined in previous chapter, namely the conditionality between the accommodation care type, the amount of accommodation trajectories and the amount of youth care trajectories. The accommodation key is used to select the right distribution from the distribution set. The process draws the selected distribution, creates the drawn trajectories and puts them in the care set trajectories lists. The schedule procedure directly initiates the start care set event introduced in previous section.

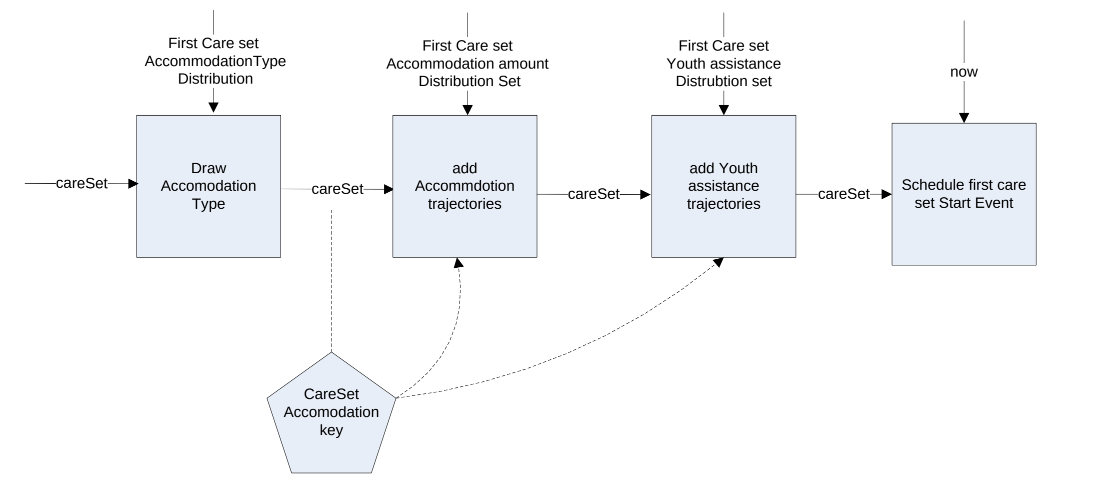


FIGURE 7-5 FIRST ARRIVAL TRAJECTORIES PROCEDURES AND DEPENDENCIES

To initialize the first arrival-drawing algorithm the following data source are required

Input variable: *First care set accommodation type*
Input variable set: *First care set accommodation trajectory amount (4)*
Input variable set: *First care set amount of youth assistance (4)*

Return care set
The main difference between a child's first care set and return care sets is the influence of sequential conditionality between the previous and the new care set. The accommodation key of a previous care set has influence on the probability of the new accomodation care type and on the time between the arrival of the sequencing and previous care set. The data analysis showed that the probability of more than one accomodational trajectories in a returning care set is less than one percent and neglected in the DES model. The parralel relation between the accommodation key of a care set and the distribution of youth assistance trajectories is also abstracted, in the simulation model. The schedule process draws the time between previous care set arrival and the arrival of this care set, further more this variable is assinged to the previous care set. The previous care set uses this variabe to schedule the arrival of its sequencing careset by a timeout triggered event.

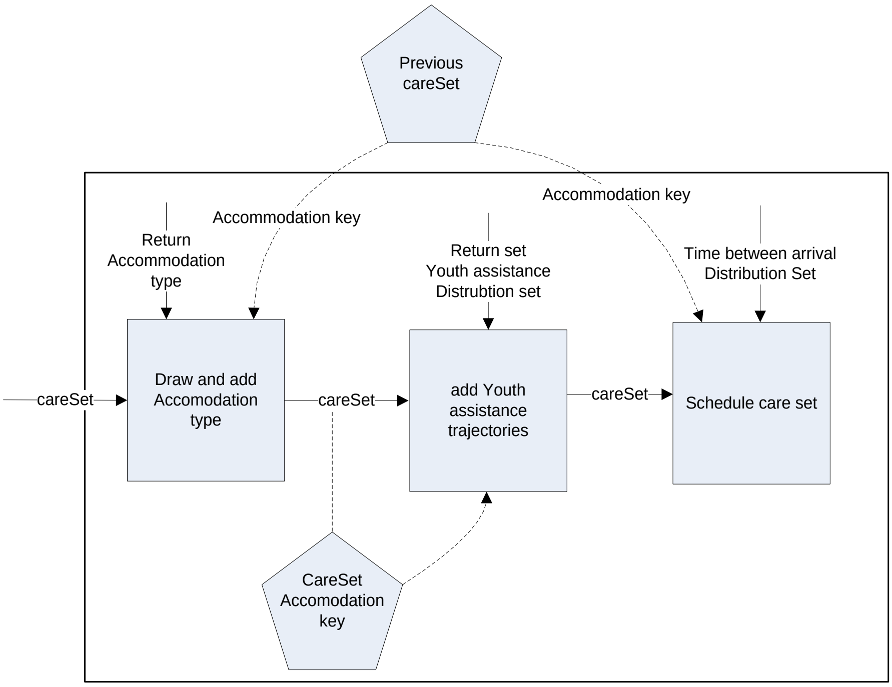


FIGURE 7-6 RETURN CARE SET DRAWING PROCEDURE AND DEPENDENCIES

Input variable set. *Return care set accommodation type (4)*
Input variable set. *Return care set Youth assistance amount (4)*
Input variable set . *Days between sequential care set arrivals (2)*

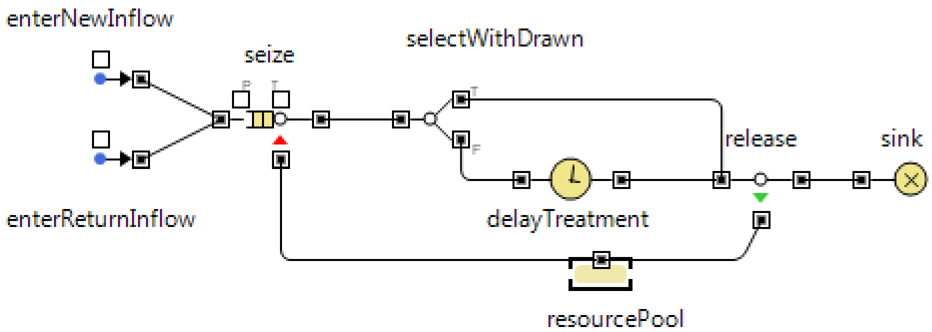
7.3.5 Care system process and trajectory states

The previous section introduced the care set object class, which drives the trajectory demand experienced at the independent care systemss by scheduling the trajectory input. The care system class is presented in Figure 7-7.

The trajectories serve as the entities, which flow through the care system flowcharts. Figure 7-8 introduces the care trajectory class. The match, between the care systems and trajectories, is based on their care type attribute. A trajectory is inactive, before it enters the care system flowchart. The before introduced distinction between new and returning care demand is translated into two enter possibilities, the enterNewInflow and the enterReturnInflow. The distinction between both arrival flows is based on the arrivalID attribute of the trajectories arrivalCareSet. The trajectory state transits to active as soon as the trajectory enters the queue. The trajectory seizes a resource as soon as its turn arrives and there is a free resource available. After which the trajectory flows to the selectWithdrawn block.

Object Class careSystem
[attributes
care Type (DH, PZ, RH, AH)
waiting list<Trajectory>
inTreament<Trajectory>
ResourcePool<resource>

Operations



]

FIGURE 7-7 CARE SYSTEM OBJECT CLASS

Object Class Trajectory

[attributes

careType	(DH, PZ, RH, AH)
waitingTime	(Double)
treatmentTime	(Double)
state	

Operations
]

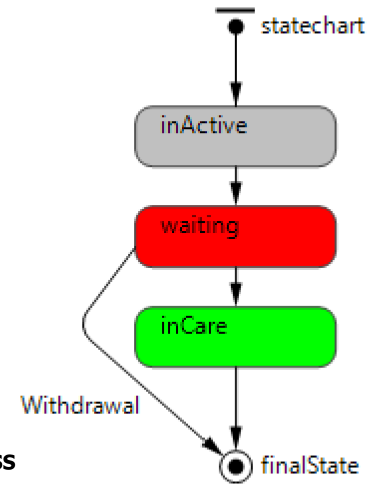


FIGURE 7-8 CARE SYSTEM OBJECT CLASS

The selectWithdrawn block evaluates if the child has withdrawn the trajectory during the waiting time. The withdrawal probability is dependent on the care type and the experienced waiting time, as evaluated in section 6.6. The resource is immediately released if the trajectory is withdrawn which transits the trajectory state to withdrawn. If the trajectory is not withdrawn, the treatment time is drawn and the trajectory is delayed for the drawn treatment time. After which, the resource is released and the trajectory state transits to treated. The following data input is necessary to initialize each care system process:

***Input variable set*.** Withdrawal mechanisme set (4)
Input variable set. *Treatment Time (4)*
Input variable set. *Resource capacity (4)*

7.3.6 Children states

The child's state is dependent on the state of child's care sets. A child turns active when it has an active care set. The child's state is waiting until it has a care set which receives care. The child turns inactive, when it has no currently active care sets and it does have future arriving care sets. The child goes to its final state and leaves the system, if all of its care sets are in their final state.

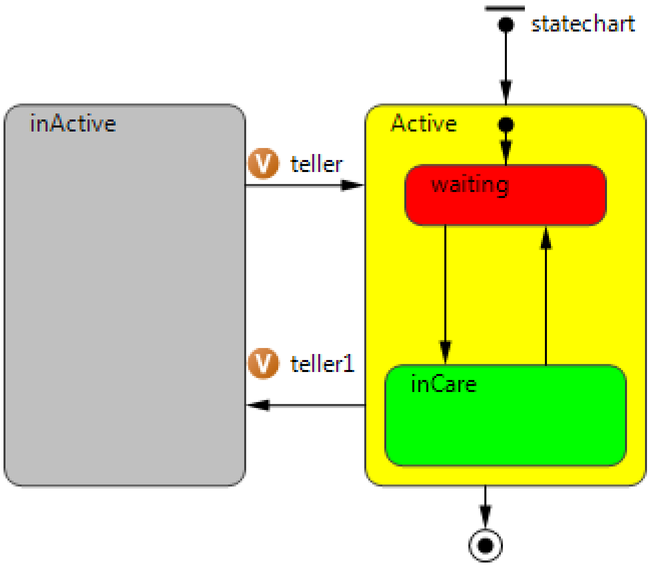


FIGURE 7-9 CHILD STATE CHART

A child's state chart provides an individual view of the child's current state. The actors in the youth care sector are however interested in an aggregated system view. The care provider class therefore provides an aggregated view on the children stocks and flows in the system. This process view is presented in Figure 7-10. It is in important to keep in mind that this process view provides an overview of the children flows and does not steer those flows.

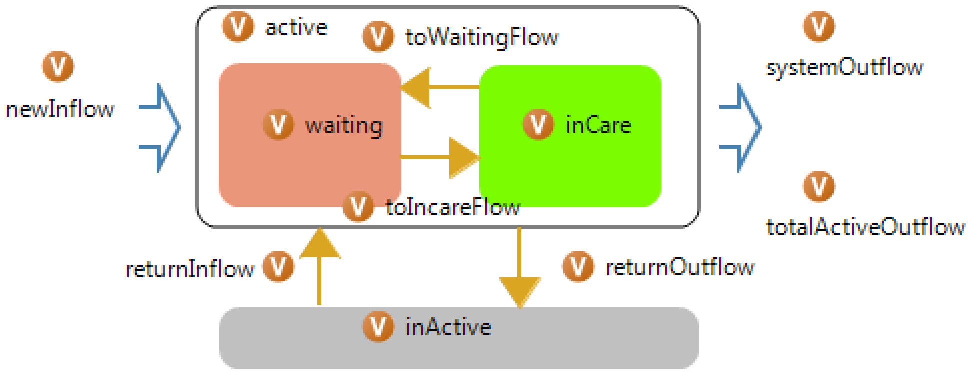


FIGURE 7-10 PROCESS VIEW CHILDREN STOCKS AND FLOWS

7.4 Model Quantification

The explanatory value of a simulation model is among other influences, dependent on the accuracy or reliability of the input data, also referred to as the "*garbage in garbage out*" principle. This section attempts to create insight into the process of transforming the available data and system knowledge into relevant, accurate and reliable input data.

7.4.1 Methods and techniques to quantify input parameters

The general techniques, methods and consideration used during the model initializing process are briefly described in this section to make the body of knowledge embedded in the actual quantification decisions, which are presented in Appendix D, explicit.

Quantification sources and methods
Different information sources and methods to provide the necessary input quantification for the simulation model are available. A main distinction is be made between historical data sources and other methods as visualized in Figure 7-11.

In general, historical data is used when relevant, reliable and accurate data is available. The reliability and completeness of the historical data sources needs to be checked. Therefore, it is desirable to involve field experts in analyzing and collecting the historical data. In this research, field experts of INITI8 collected the historical data. Furthermore, if the data is as sensitive as in the youth care sector, it is important to use objective measurement methods during the data analysis as much as possible. If there is no relevant historical data available to quantify the input parameters accurately, other methods are required. These methods involve expert estimations, parameter calibration and drawing analogies from similar systems.

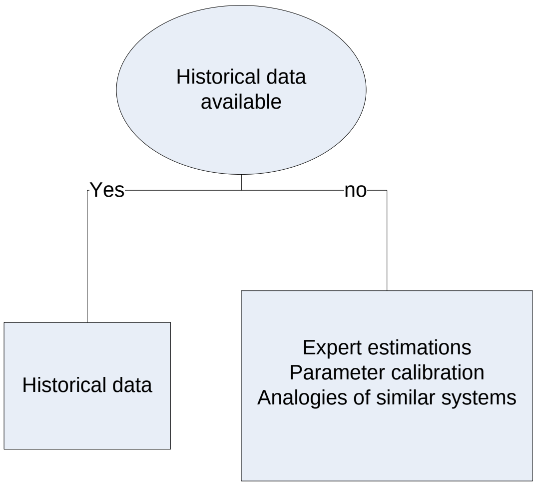


FIGURE 7-11 INPUT QUANTIFICATION DATA SOURCES

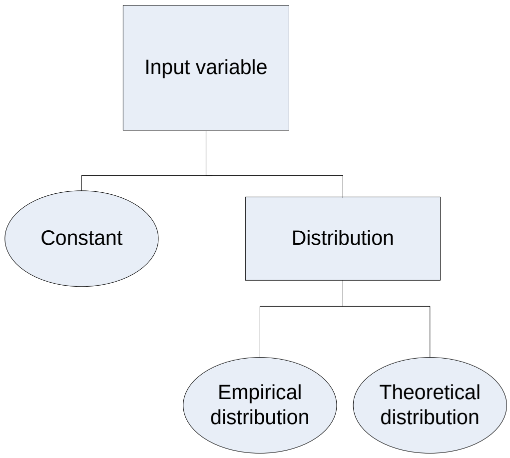


FIGURE 7-12 OVERVIEW INPUT VARIABLE, CONSTANT AND DISTRIBUTION.

Constants and distributions
For each input variable, the decision needs to be made whether to abstract it into the model, by a constant or a distribution, based on the observed or expected variance in the variable as presented in Figure 7-12. Wild (2006) defines:

Constant. An experimental factor or quantity that does not vary or that is regarded as invariant in the specified circumstances.
Distribution. A pattern of variation in an experimental factor or variable.

Empirical and Theoretical distributions.
The distinction between *empirical* versus *theoretical* distributions is between the variation we see in available or collectable data sources and the imagined potential variation in the process in which this variability arises, as presented in Figure 7-13.

Empirical distribution: refers to the empirical frequency of the variables, it contains the variation that is directly observed in the dataset (Wild 2006). Empirical data from the real world is transferred to a histogram. This histogram is used to form an empirical distribution; the input values are periodically drawn from that distribution. There is no inferential component just a description of what exist in the data .

Theoretical distribution. A theoretical distribution, tries to learn wider lessons from the variation seen in the current data set. The unexplained variation is perceived to be generated by a theoretical distribution, which defines the probability in the model and replaces the experimental data.

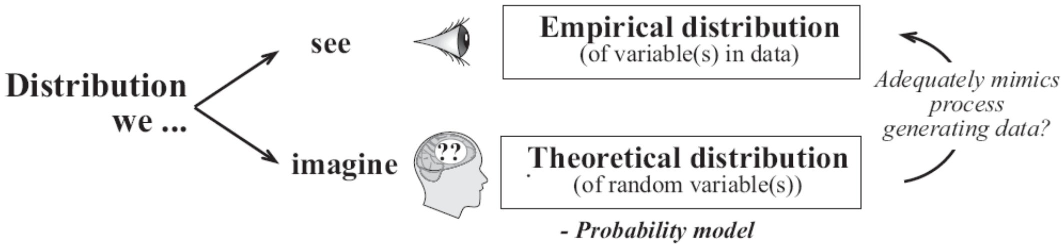


FIGURE 7-13 VARIATION IN EMPIRICAL AND THEORETICAL DISTRIBUTIONS (WILD 2006)

The perceived difference between the explanation value of theoretical and empirical distributions is explained by the difference between the variation in the real world and the variation captured in a data set of this real world. The variation seen in data comes from, the real variation in the system under investigation and from the inevitable overlaid of additional variation induced by the observational process, as presented in Figure 7-14.

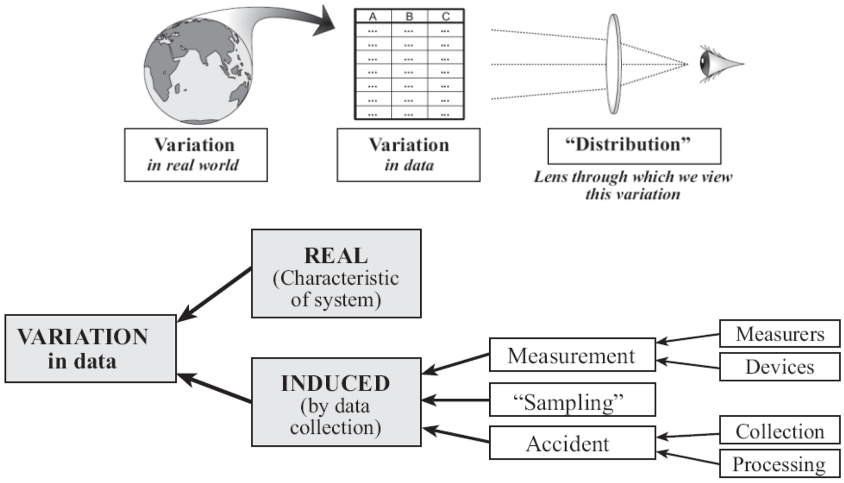


FIGURE 7-14 DIFFERENCE IN REAL VARIATION AND DATA VARIATION(WILD 2006)

Now the difference between the nature and explanation of empirical and theoretical distributions is explained, the question arises when either of the distribution should be used. The choice between both distribution types is dependent on the imagined real world variation, the available data sources, the size of the dataset and the model context. The following guide lines are used to chose between both distribution types:

Empirical distribution. An empirical distribution can only be used, if there is a data set available. The advantage of the method is that it is straightforward and will strongly resemble the observed system data, as drawn values are directly based on the observed frequencies. A disadvantage is the incorporation of variation induced by data collection and the possible discrepancy between the possible real world variation and the variation captured in the dataset. The impact of these disadvantages is a result of the quality and size of the available data sources. An advantage of empirical distributions is the ability to automate the initializing process from the dataset to input sheets.

Theoretical distribution. This method can be used both, if there is no data available or if a theoretical probability distribution corresponds to the empirical probability distribution. If there is no data available a theoretical distribution can be used, based on the knowledge of experts estimations about. If there is data available and a theoretical distribution corresponds to the empirical probability distribution, then a theoretical distribution can replace the experimental data. An advantage of a theoretical distribution is the ability to change it for the analysis of different scenarios. Furthermore, a modeller can decide to use a theoretical distribution if he assumes that the inevitable overlaid of additional variation induced by the observational process of data collection has a large impact on the empirical distribution. The quantification of the care provider model input parameters are described in Appendix D.

7.4.2 Parameter calibration

Previous sub-section introduced the techniques to quantify input variables not quantifiable by the available historical data. This section describes the technique of parameter calibration:

Parameter calibration is the task of adjusting an already existing model to a reference system. This is usually done by adjusting the (internal) parameters of the model according to the input-output sets of the reference system (Hofmann 2005).

The adjustments done by parameter calibrations are necessary because truly reliable data is not available and models are based on abstractions, idealizations and many disputable assumptions. The practical importance of calibration is controversial, critical remarks on calibration with respect to validity where found in Hemez (2004). Despite of these qualifications, the importance of model calibration for practical work is highlighted in many publications. Hofmann (2005) provides an overview of these publications. The calibration process, which exists of the adjustment of model parameters according to the reference system, can be done by hand or automated by an optimization experiment. The following description of simulation optimization is proved by April and Glover et al. (2008):

"The optimization of simulation models deals with the situation in which the analyst would like to find which of possibly many sets of model specification (i.e, input parameters and/structural assumptions) lead to optimal performance. In the area of design of experiments, the input parameters and structural assumptions associated with a simulation model, are called factors. The output performance measures are called responses. In the world of optimization, the factors become decision variables and the responses are used to model an objective function and constraint. Whereas the goal of experimental design is to find out which factors have the greatest effect on a response, optimization seeks the combination of factor levels that minimize or maximize a response (subject to constraints imposed on factors and/or responses)" (April, Glover et al. 2008).

Optimization in the context of model calibration seeks to minimize the difference between the output of the simulation model and the empirical data of the reference system. Commercial implementations of simulation optimization procedures have only become practical, with the exponential increase of computational power and the advance in meta heuristic research (April, Glover et al. 2008). Figure 7-15 shows the black-box approach to simulation optimization favoured by procedures based on the meta-heuristic methodology. In this approach, the meta-heuristic optimizer chooses a set of values for factors (or decision variables) and uses the responses generated by the simulation model to make decisions regarding the selection of the next trail solution.

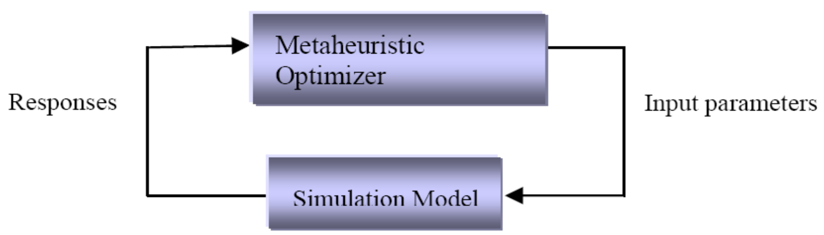


FIGURE 7-15: BLACK BOX APPROACH TO SIMULATION OPTIMIZATION

Following subsection describes among techniques the use of automated and manual parameter calibration in order to fill in the input parameters, which are left blank by the available data sources.

7.4.3 Calibration number of care sets.

The analysis of the number of care sets assigned to each child is hampered by the relatively small time span of the historical data in, relation to the trajectory treatment times and the time between care set returns. The available data set, with a time span of two years, is perceived too small to overlap the total life cycle of children in the care provider system. It is possible to count the number of care sets assigned a child over the year data set. However, the two year time span does not allow to accurately determine the total amount care sets assigned to the children. It is likely, that the counted receive care sets before or/and after the two year data span, which has a large impact on the reliability and accuracy of the analysis. An accurate analysis requires the distinction between new and returning children, which require the use of a significant part of the available time span as system memory. This would further decrease the time span of counted child returns. As described in detail in section 6.5.

The previously presented Figure 7-11, provides an overview of alternative data sources if historical data is not available. The suitability of both optimization and expert estimations are considered. In general, a major problem related to expert estimation as a data collection method is the reliability and accuracy of measurements. Even for experts, it is usually difficult to estimate averages, minimum and maximums of observed variables. Estimating an accurate and reliable of the perceived distribution, for the amount care set a child variable, is impossible. Therefore, the decision is made to derive the amount care set returns by a calibration strategy, the outcomes of the calibration can be validated by experts.

Optimization and assumptions
The optimization experiment optimizes the difference between the average output of the process, which transforms the child arrivals into the system to the trajectory care demand at the different care providers, and the average of the empirical trajectory arrivals of each care type over 2008 and 2009. This approach, based on the average arrivals above the dynamic behaviour of the systems, is based on the assumption that the care provider system is in a steady state situation. An important assumption, which forms the basis for the optimization experiment, is the assumption that the empirical behaviour in child and trajectory demand is the result of system variance, not of structural demand changes. This assumption is based on the conclusion of section 6.1, which analyzes the child and trajectory inflow behaviour. The optimization process requires making founded assumptions about the model structure and the dependency relations in the system. These assumptions, the objective function, the experimental set-up and the results of the optimization are presented in appendix D.2.

7.4.4 Interrelations queue and withdrawal mechanism

The queue mechanism and the withdrawal are not quantified yet. This section provides insight into the difficulties to calibrate these two unknowns. The experienced difficulty is a result of the interrelations between both unknown mechanisms.

Figure 7-16 provides a visual overview of the interrelations between these mechanisms and their influence on the system behaviour. The yellow boxes present the two mechanisms, the grey boxes present an overview of the independent variables and the white boxes are the variables influenced by these relations. It should be noticed that independency of the outflow is a simplification; the outflow can be influenced by the waiting list if the sum of the inflow and the waiting list is smaller than the available capacity places.

Based on the Figure 7-16, it becomes clear that the queue mechanism indirectly influences the number of withdrawals, the waiting lists and the average waiting time by directly influencing the individual waiting time distribution.

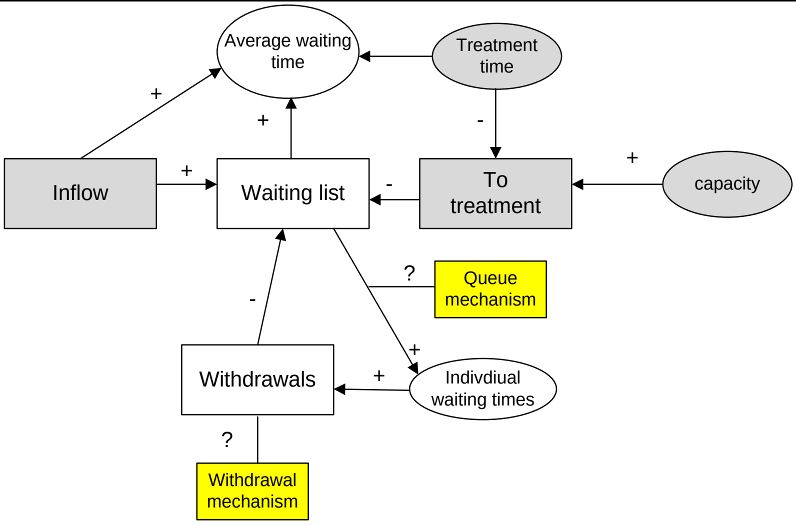


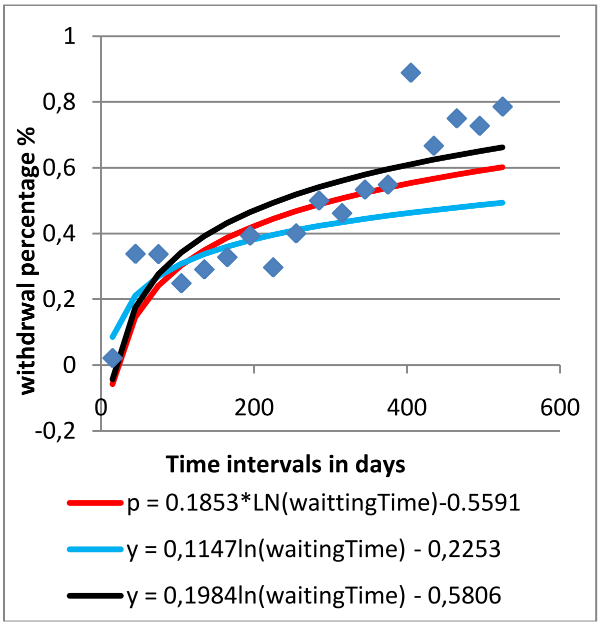
FIGURE 7-16 QUEUE AND WITHDRAWAL MECHANISM INTERRELATIONS

7.4.5 Withdrawal curves

Figure 7-17 provides a graphical representation of the found withdrawal percentages, as a function of the waiting time intervals, for ambulatory trajectories. The blue dots visualize the calculated interval percentage for each interval. The plot visualizes a scattering of the data points. This scattering is arguably due to the low frequency of measurements. Especially the intervals with long waiting times (above 300 days) are hampered by low frequencies. These low frequencies hamper the reliability of those data points. the histogram of the frequencies of each waiting interval is presented at the right in Figure 7-17

The question remains what the best abstraction is for the withdrawal mechanism in a purposeful DES model. The scattering of these data points suggest the best fitting distribution would be an inverted S-curve, however the data points which suggest this S-curve are likely to be biased by the low frequencies over those interval and the expected reality is however a more asymptotic tailing, which is also abstracted in the SD model. The cumulative line in the histogram shows that 97% of all children waits less than 300 days, therefore the impact of tail shape after the inflection point is considered neglect able. Furthermore, a large impact of the first interval on the system behaviour is expected based frequencies. It could even be defended to subdivided the first interval daily intervals for an optimal withdrawal abstraction in further research.

A first indication of the withdrawal curve is made by an analysis in excel. First, the best fitting logarithmic trend line to all observed data points and to the data points with an interval lower than 300 are defined. These two trend lines bound the set of possible withdrawal curves and are presented by the black and blue line. A manual calibration experiment with the simulation model for a set of possible withdrawal curves, which fall in between the range of the two previously introduced trend lines, is performed to find a valid withdrawal function. The calibration objective of these experiments is to minimize the difference between the amount of withdrawals observed in the simulation model and the amount of withdrawals observed in the real system. First broad calibrations are validated on average values, later detailed calibrations are validated by chi-square test statistics. The red line in Figure 7-17 presents the initial withdrawal curve for ambulatory care used as basis for the initial experiments of each queue mechanisms. The initial withdrawal graphs for the other care types are presented in appendix D.6, the validation of these withdrawal functions is presented in the following chapter. To avoid negative withdrawals in the simulation model the amount withdrawals is implemented into the simulation model by a minimum between the minimum interval value and the withdrawal curve.



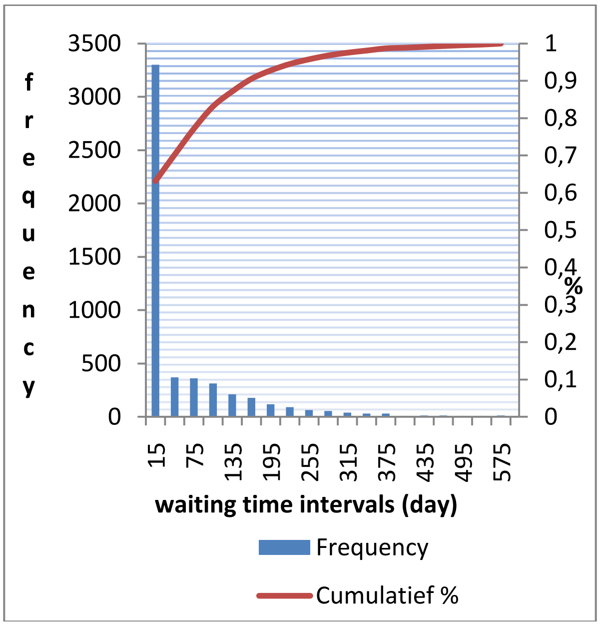


FIGURE 7-17 CALIBRATION WITHDRAWAL GRAPH FOR AMBULATORY CARE

7.4.6 Queue mechanism assumptions and experiments

While there is data available to provide an indication of the withdrawal mechanism, there is no insight in how the queue mechanism should be abstracted in the discrete simulation model. Previous section provides insight into the interrelations between the withdrawal mechanism and the queue mechanisms. Based on these difficulties and the lack of insight into the withdrawal distribution, a basic approach is chosen which tests three commonly used queue mechanisms. The withdrawal graphs of each of this basic queue mechanism will be calibrated, after which all three mechanism can be cross-validated. The following queue mechanisms are considered:

- First in, first out
- First in, first out, with priority category: crisis and normal, 15% percent of the trajectories of every care type is considered a crisis trajectory with priority.
- Service in random order

While these basic queue mechanism are completely based on assumptions, the cross validation provides insight in the best abstraction of the queue mechanism based on the average waiting time and the distribution of waiting times. Furthermore, it allows comparing the best possible DES model in current situation with the currently used SD model and a research direction for future studies.

7.4.7 Care provider input variables

The Previous section, demarcated the model logic and input variables the care provider model. The conditionality relations, analyzed in previous chapter, result in a large amount of care set composition input variables. These variables are abstracted in the model by empirical distributions. Empirical distributions allow model initialization from an input spreadsheet. The input sheet provides the ability to oversee the care set dependency matrixes and to fill the input sheet directly from the data set, which increases the models flexibility and makes initialization less prone to input errors. The input sheet is presented in appendix D.3 The columns and rows of the distinct matrixes refer to the accommodation type and care type dimension in the simulation model. The matrix columns present the dependency categories, the rows the observed frequencies of each category. The simulation model creates a different empirical distribution for each dependency category of each matrix. In total sixteen empirical distributions are created from the data in the care set input sheet.

In addition to the empirical distributions loaded from the input sheet, seven care provider input variables are abstracted by a theoretical input distribution. An overview of those input variables and the theoretical distributions is presented in Figure 7-18. The first column presents the input variable, for dependent layered variables the variable of influence is presented in the second column, the third columns presents an overview of the different categories, the fourth column the chosen theoretical distribution and the fifth column indicates the appendix in which the distribution choice is justified.

FIGURE 7-18 CARE PROVIDER THEORETICAL INPUT DISTRIBUTION

Input Variable	Dependent on	Categories	Distribution	Unit	Appendix
Dailey children arrivals			-0.5 + 13 * BETA(0.701, 2.64)	child	D.1
Return after care set probability	Accommodation type	none	Bernoulli(0.637)		D.2
		DH	Bernoulli(0.436)		
		PZ	Bernoulli(0.772)		
		RH	Bernoulli(0.637)		
Time between care sets	Accommodation type previous cares et	PZ	0.5 + EXPO(4.27)	months	D.4
		No PZ	0.5 + EXPO(3.3)	months	

As extensively discussed in both the SD and discrete conceptualization, a care provider exists of multiple care systems with the same structure. A different care system layer exists for each care type a care provider provides, the difference between those layers lies in the different quantification of constants and distributions. Figure 7-19 presents an overview of the inputs for these variables; each row presents a care system, each column an input variable. The last row present a reference to the appendix in which the quantification is justified.

		Withdrawal mechanism	Treatment Time	Capacity
care type	**AH**	p=max(0.02; 0.2044Ln(waitingTime)-0.6077) Bernoulli (p)	0.999 + WEIB(219, 1.01)	1395
	DH	p=max(0.05; 0.2505Ln(waitingTime)-0.6102) Bernoulli l(p)	Empirical	124
	PZ	p=max(0.02; 0.237Ln(waitingTime)-0.652) Bernoulli (p)	3 + 4.96e+003 * BETA(0.222, 2.04)	173
	RH	p=max(0.047; 0.2798Ln(waitingTime)-0.7565) Bernoulli (p)	0.999 + 2.19e+003 * BETA(0.304, 2.62)	340
	Unit	%	days	traj.
	appendix	D.6	D.5	D.7

FIGURE 7-19 CARE SYSTEM INPUT VARIABLES

7.5 Conclusions specification

This specification describes the abstraction and quantification of the care provider and as such presents an answer to the fifth research question. The discrete conceptual model is simplified and translated into an AnyLogic simulation model. AnyLogic is chosen as simulation software because it is java based, which is an object-oriented language, and because it enables the modeller to mix process oriented flowchart and dynamic state chart elements.

The input variables are where possible quantified by an analysis of the gathered care provider data. In absence of reliable quantification data, an alternative quantification method based on model calibration is applied. A calibration difficulty appeared due to the interrelation of the unknown queue mechanism and the not clearly known withdrawal curves. It became apparent that the chosen queue mechanism, in a system with waiting time dependent withdrawals, is likely to influence not only the individual waiting time distribution but also the average waiting time.

Based on this knowledge and the unknown queue mechanism, the DES simulation model is cross-validated for three different queue mechanisms: FIFO, FIFO with priorities and SIRO. These experimental set-up provides a method to validate the model and provide additional insight into the impact of different queue mechanism on the youth care system behaviour.

Part 4 : Discrete model try out

Chapter 8
Treatment, Verification and Validation

The conceptualisation and specification stages resulted in a simulation model that is ready to run. Now the model must be prepared to make certain statements about the outcome of the model and the corresponding of these outcomes to reality. The simulation model is build with respect to the study objectives presented in the second chapter and its creditability is judged with respect to the demarcated study objectives. First, the experiment specific treatment of the simulation model is determined, after which the correspondence of the simulation with both the conceptual model and the real world is tested by the verification and the validation.

8.1 Treatment

The care provider system is *non-finite* system. A *non-finite* system has a once only start situation and can continue indefinitely. It starts in some state but it is not known at forehand if the simulation will ever be in that state again. The run length of non-finite system in is not uniquely specified. Before we can experiment with the simulation model, first the experiment-specific treatment characteristics must be determined. The treatment constitutes of the system start-up time, the required run length of a simulation experiment and the amount of replications required to find statistically accurate outcomes.

8.1.1 Start-up time

The simulation starts with empty queues and idle resources in the care systems. These conditions differ from the real world condition, which has filled queues and occupied resources. It takes time before the simulation model reaches the steady state conditions to be analyzed. If this transient model condition lasts for a relatively long time, than the observations collected during this time may affect the accuracy of the estimated performance measures. This problem is referred to as the initialization bias or the start up problem. This problem can be overcome by running the simulation for a start-up time; the statistics of this period are not recorded or reset. After this time, the recording of observation starts for the run length of the experiment. The objective of this section is to determine the time at which the effects of the start-up conditions on the system behaviour have become negligible.

A possible method for graphically determining a model start-up time is by plotting the progressive average of the values of the important output variables against the elapsed simulation time (Mahajan and Ingalls 2004). Once the fluctuations in the progressive average have decreased to an acceptable value, the start-up time has elapsed and the statistical observations of the model can start.

Output variable selection
The important output variables to plot are select with respect to the study objectives, the previously demarcated performance indicators are; *waiting time (wk)* and *production.* As presented in the second chapter, the waiting time and the production can be analyzed on the child and trajectory information layer. It is important to recognize the structure, which can be decomposed to the care provider child layer and the four independent trajectory care systems.

Intuitively, a start-up time analysis on the child layer combines the start-up time of the independent sub-systems, which steer the child layer. However, there is a risk to this approach, the child layer can stabilise before the behaviour of a care system stabilises if this care system does not have a large influence on the child layer behaviour. Because both the performance indicators on the child layer and from the independent sub-systems is of interest, a child layer focus could results in an invalid start-up time assessment. Based on these insights the decision is made to analyze the start-up time for both the child layer and for the care system with the longest average treatment, which is foster care (PZ). The maximum start-up time is considered the system start-up time.

The average waiting times before starting care and the monthly outflow of treated children and trajectories are graphically analyzed. The results for a single simulation run is presented in appendix E.1 The black line in each graph presents the smoothed average over a period of two years. The outflow of both treated trajectories and children stabilises in less than eighty months. No clear stabilisation moment is found for the average monthly waiting times of both children and trajectories. The author argues that this lack of stabilisation is due to system variance. In order to determine the start-up time of these performance indicators taking into account the observed variance, the dynamic sensitivity chart of 100 simulation runs, with a random seed, is graphically presented in appendix E.1. The weighted average over two years, for both children and foster care trajectories, stabilises in 100 months. In order to keep the months in the simulation run congruent a start-up time of 108 months, which is 9 years, is considered.

8.1.2 Run length

The run length is the amount of simulated time used to conduct observations of the model. In contrast to the other two treatment characteristics, there are no general methods to determine a correct run length. A rule of thumb is to take three times the longest cycle time that occurs in the model as the run length. Analyzing the longest cycle time on the trajectory layer it is observed, that the maximum foster care cycle time observed over a run of 10.958 months is 4.918 days, which is 13,7 years. The study objectives are to provide insight the currently observed waiting list dynamics and to evaluate the impact of short to middle long-term (2-5 years) policies on the waiting list dynamics. With respect to these objectives, a long run length (<10 years) is potentially confusing for the actors and stakeholders in the youth care sector. Furthermore, based on the extremely long children cycle time in the system, a set-up in which several sub-runs are made in a long simulation run is undesirable. The independency of sub-runs cannot be guaranteed. Taking into account that the confidence interval is determined by a combination of the run-length and the number of replications, and the long warm-up time a relatively long run length is chosen to minimize the number of replications (and warp-up time). Therefore, a then year run length is applied in the experiments. Furthermore, possible bias of a then years run-length on the waiting time and outflow distributions is considered low, based on the 9-year start-up time and the observed waiting time sensitivity graph over a run length of 20 year presented in appendix E.1. Furthermore, no rarely occurring events with a critical impact on the system behaviour are distinguished in the previous specification chapter. Based on these considerations a then year run-length is considered able to gather a representative sample of the output variables and large enough number of results in all categories to calculate statistics with the desired accuracy.

8.1.3 Number of replications

Because of the stochastic distributions used in the simulation model different outcomes can occur within every run, as a function of the random seed numbers. Therefore, multiple replications with different seed values have to be performed to get accurate results within a certain confidence level. The confidence interval for 100 replication runs, with a FIFO queue mechanism, is analyzed for the performance indicators at the independent care systems and at the child layer.

FIGURE 8-1 REPLICATION CONFIDENCE INTERVAL

Observed waiting time (wk) statistics: 100 replications

	DH	PZ	RH	AH	Child
$t_{0.025}$	1.984				
$\bar{X}$	13,23	4,86	12,9	6,8	6,36
S(x)	3,07	1,36	2,075	0,667	0,55
$S(\bar{x})$	0,31	0,14	0,20	0,066	0,055
h	0,6084	0,268	0,41	0,132	0,108

8.2 Verification and validation methodologies

Now the model is specified and the model treatment is formulated, the model correctness can be checked. Model verification and validation is concerned with the questions whether a model and its results are correct. The *model verification* ensures that the model has been correctly coded and transferred from the conceptual model to the computerized model (Sargent 2004). *Model validation* is the substantiation that a computerized model within its domain of applicability possesses a satisfactory range of accuracy consistent with the intended application of the model (Sargent 2004). If the purpose of a model is to answer a variety of questions, the validity of the model needs to be determined with respect to each question.

Verification and validation is not a phase or step in the model development process but a continuous activity throughout the whole process (Balci 1997). Different phases of model verification and validation and the relation of those phases to the modelling process are depicted in Figure 8-2.

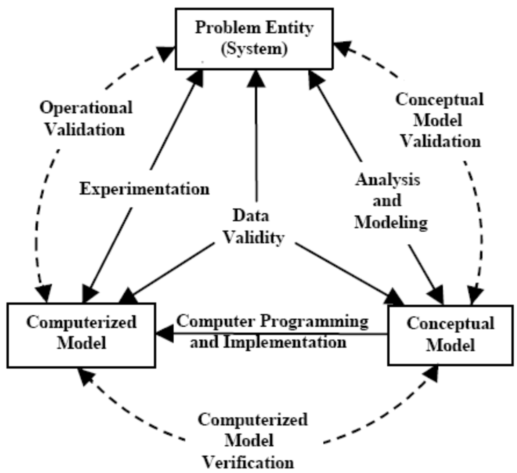


FIGURE 8-2 VERIFICATION, VALIDATION AND THE MODELLING PROCESS

Conceptual model validation is defined as determining that the theories and assumptions underlying the conceptual model are correct and that the model representation of the problem entity is reasonable for intended purpose of the model.

Data validity is defined as ensuring that the data necessary for model building, model evolution and testing, and conducting the model experiments to solve the problem are adequate and correct.

Computerized model verification is defined as assuring that the computer programming and implementation of the conceptual model is correct.

Operation *validation* is defined as determining that the model's output behaviour has sufficient accuracy for the model's intended purpose over the domain of the model's intended applicability.

8.3 Conceptual model validation

This section validates the discrete conceptual model presented in chapter 5. The discrete conceptual model is based on the structure of the currently used SD model; however, major difference occurred when translating the aggregated influence relations and concepts to a model based on individual entities. While for both conceptual models the care system structure is comparable, differences occur in the coupling concept between the child and trajectories and in the transition of child's states.

Because the coupling between children and trajectories in the SD model is based on influence relations, the inflow of children influences the inflow of trajectories and the outflow of trajectories influences the outflow of children. The individual coupling between children and trajectories in the discrete model requires the coupling between individual children and trajectories. This individual coupling between care sets and trajectories is made by the care set objects. The care sets are heterogeneous and composed by parallel and sequential relations. Another conceptual difference can be found in the abstraction of child returns. The SD model abstracts the probability and return time of children as conditional to the type of outflow; withdrawn or treated. The discrete model abstracts the return of children conditional to the trajectory composition of their previous care set. This abstraction is chosen because it enables the modelling of overlapping care sets. The SD conceptual model does not distinct different states of children in the system, the discrete conceptualization disaggregates the children in the care system according to the state of their trajectories.
Domain experts, the consultants of INITI8 who designed the SD model, face validated the discrete conceptual model with a focus on the differences that occurred in comparison to the SD conceptualization.

8.4 Calibration and validation data

Calibration and validation, although conceptually distinct, is conducted simultaneously in the modelling process. Together calibration and validation form an iterative process of comparing the model to the real system data, adjusting the model and comparing again, and so on. A criticism of the calibration process is that the model has been validated only for the one data set used. Just because the model can be made to fit past data does not guarantee that it will fit future data (i.e., data that has not been employed in the calibration process) (Zeigler, Praehofer et al. 2002). In other words, there is no guarantee that parameter assignments that results in best fits actually lead to credible predictions. One way to alleviate this criticism is to reserve a proportion of the original system data for the final stage of validation. The model is than calibrated by one part of the data and validated by the other part (Banks 1998).

The available data sources describe the monthly flow and levels in the system over 2008, 2009 and the first 5 months of 2010. In total, there are 29 observed data points for each stock and flow category. When deciding to subdivide the data in two samples, one for calibration and one for validation, it is important to take into account the expected confidence interval of the mean ofr the two data sources data. However the comparison is not as simple as it might appear, since the output of the care provider systems are *non-stationary* (the distributions of the successive observations change over time) and *auto correlated* (the observations in the process are correlated with each other) (Law and Kelton 2000). The classical approaches to calculate confidence intervals require independency of data and are not applicable for auto-correlated data. The sample mean is still an unbiased estimator; however the sample variance will have a negative bias and is no longer an unbiased estimator. The determined confidence interval of an auto-correlated sample based on the sample standard deviation is likely to by significantly smaller than the distributions real world variance. The 95% confidence interval of the mean queue length based on the sample standard deviation is presented in
Table 8-1.

Care type	mean	Lower bound	upper bound
AH	79,93	71,54	88,3
DH	37,90	34,49	41,30
PZ	352,97	334,84	371,09
RH	28,2	26	34,4

TABLE 8-1 THE 95% CONFIDENCE INTERVAL FOR THE MEAN QUEUE LENGTH (TRJ) OF THE HISTORICAL DATA.

The found 95% confidence interval of the mean queue length of the observed data value influences the reliability of the model validation and therefore model outputs. The confidence interval of the available data, assuming that there is no auto correlation is large, subdividing the data to two samples would make the confidence interval even larger and is therefore non-applicable in the context of current research. To increase the predictive validity of the model, the sensitivity to various perturbations of the calibrations parameters will be assessed. In general, it is recommended to INITI8 to increase the amount of data points of validation set. In practice there are limitations to this recommendation, increasing the time span of the validation set with multiple years will probably bias the validation because the real world system is not stationary over such time spans. Lowering the measures unit to weeks is likely to results in an increased cross-validation of the data source. In conclusion, non-finite systems, with long operation and entity cycle times, such as the youth care sector, face large difficulties with respect to their validation data. Consequentially, the credibility of the system needs to be validated by subjective methods as described in preceding sections.

Another data limitation is observed in the availability of trajectory waiting times. In the context of this research the disaggregated distribution of trajectory times is unknown, only the aggregated mean and median statistic are known. Furthermore, the children waiting list and waiting time are not measured in the considered management data.

8.5 Verification

The verification is subdivided in two parts; specification verification and the implementation verification. The specification verification refers to the translation of the conceptual model the concepts of the simulation software. The implementation verification assures that the defined simulation specification is correctly translated into the simulation model.

The flexibility of the Any Logic software, which includes the ability to combine various simulation worldviews, simplifies the *specification verification* of the conceptual the simulation model. In the conceptual model a combination of object oriented class diagrams, process flow charts and state chart is presented to make the body of knowledge, in every part of the system, transparent and communicable. These methods are all supported in the AnyLogic software. The conceptual concepts and diagrams where directly translated into the simulation model.

The *implementation verification* checks whether the specification concepts are correctly coded into the simulation models. Through the modelling process the inputs, internal variable and outputs of each sub-model are visualized an analyzed to check the correctness of the simulation model and its implementation. The following validation techniques where applied during the model verification process (Sargent 2004):

Extreme condition test. The model structure and outputs where tested for extreme and unlikely combination of input factors into the system

Operational graphics. Values of all important performance indicators and internal variables are shown graphically as the model runs through time to ensure they are abstracted correct

Traces. The behaviour of different types of specific entities in the model are traces (followed) through the model to determine if the model logic is correct and if the necessary accuracy is obtained.

Degenerate tests. The degeneracy of the model behaviour is tested by appropriate selection of the values of the input and internal parameters.

Input distribution. The main and variance of the input distributions where compared to the mean and variance of the historical data to test if the values are correctly generated from the distributions.

8.6 Validation structure

During the validation phase, we check if the model is correct as compared to reality. The validation determines whether the simulation model's output behaviour has the accuracy required for the model's intended purpose over the domain of the model intended applicability. The goal of the validation process is two-folded: (1) to produce a model that represents the system behaviour closely enough for the model to be used as a substitute for the real system (2) to increase the credibility of the model to an acceptable level. Validation is the process by which model users gain confidence that output analysis is making valid inferences about the real system (Banks 1998).

The model credibility is increased by a combination of subjective and objective tests. Subjective tests use knowledge of the system to make judgements about the model and its outputs. Objective tests require data on the system behaviour and statistical procedures to compare aspects of the system with the model data. The validation is subdivided in three phases; the face validation, empirical assumption testing and quantitative comparison of the model to the historical data.

8.7 Face validation

The first goal of the validation is to assure that the constructed models appears reasonable on its face to the model users and other who are knowledgeable about the real system simulated. While the author recognizes the extreme importance for the modeller to interact with the problem owner and domain experts throughout every activity in the modelling cycle and especially during the face validation, no possibility was found to include the problem owner INITI8 or its clients in the face validation phase. While the author gained some system knowledge through the modelling process and data study, an additional face validation with sector experts is recommended to the problem owner. The first sub section visually compares the waiting list behaviour of a single model run to the historical data. The second subsection visually the presents the spread of observed waiting list dynamics observed over 100 replication runs.

8.7.1 Single replication run waiting list behaviour

The waiting list outputs of the real system are compared to a single replication run of the DES model configured with a FIFO queue mechanism and to the stochastic configured SD model. Taking into account the stochastic nature of the real system and both models a direct quantitative comparison cannot be made based on these single replications. A behavioural comparison of a single can provide insight into the step size, variability and stability of the models in comparison the real world system.

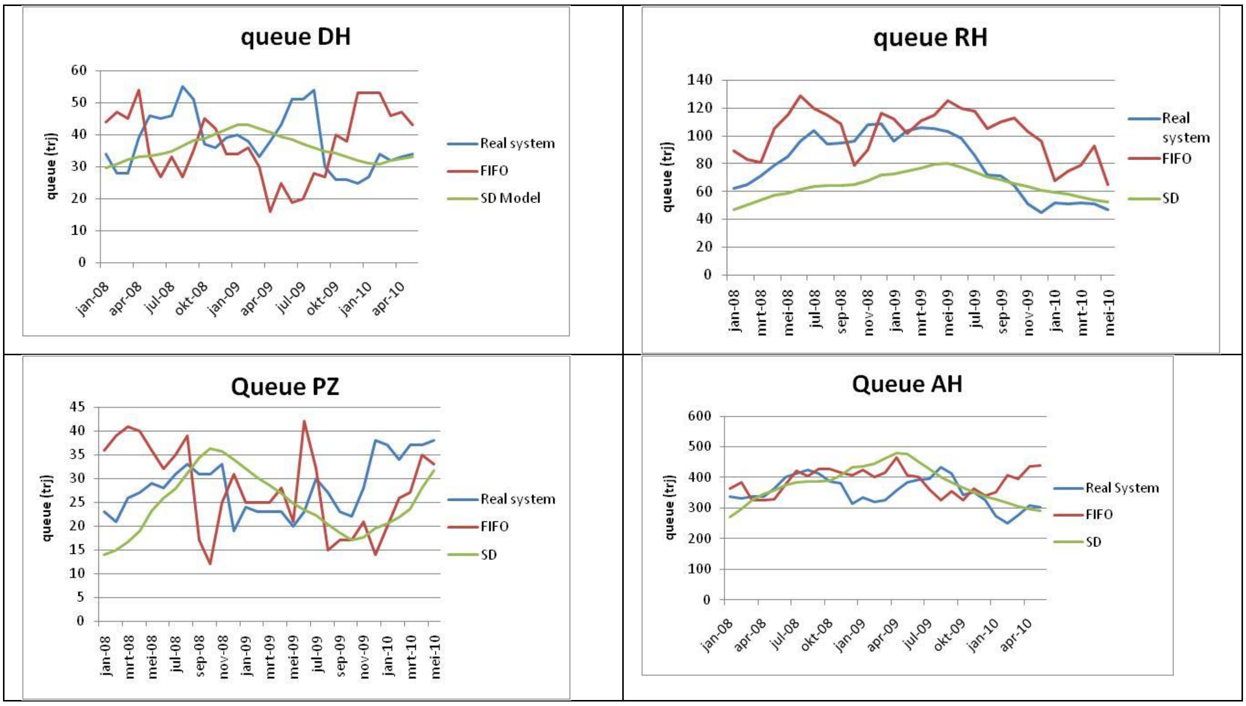


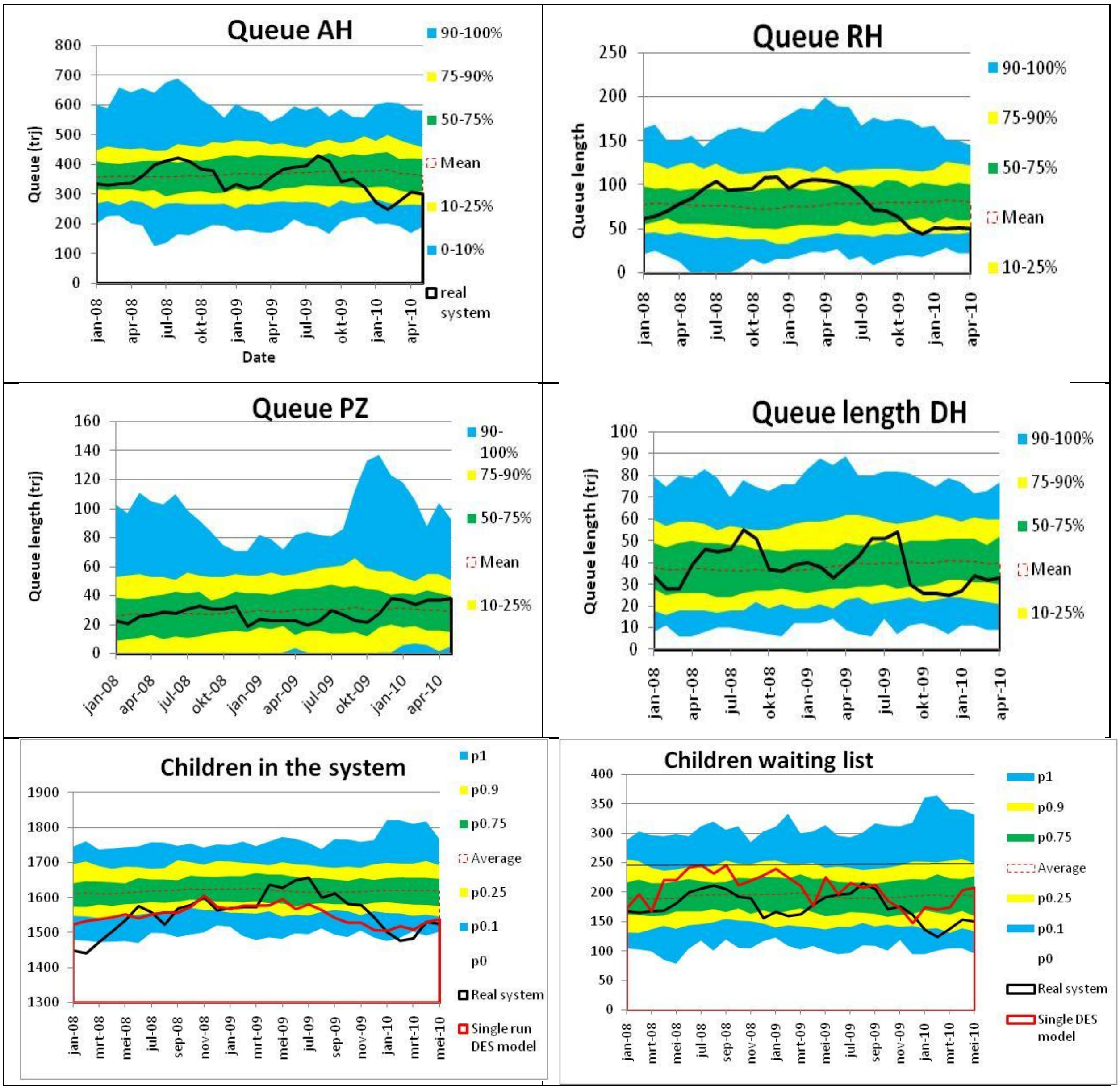
FIGURE 8-3 VALIDATION QUEUE BEHAVIOUR ONE REPLICATOIN

The monthly queue steps created by the DES model look comparable to the real world steps for DH, RH and AH. A combination of high frequency peaks and dips and large low frequency steps can be distinct. The behaviour of the PZ system in the DES models looks less stabile in the model run than in the real world system. The SD models abstracted the queue behaviour as a smooth line without the sharp peaks and sudden direction changes observed in the real world queues. The variability and behaviour observed in real world system is better abstracted in the DES model than in the SD model. The difference is models is likely to be created by the heterogeneity and individual variability better abstracted in the DES model. Its recommended to the problem owner, INITI8, to validated the DES model by performing a Turing test with domain experts.

8.7.2 Waiting list spread 100 replications

The variability abstracted in the DES model is visually validated by comparing the spread of 100 replications runs to the historical waiting list data. This experiment graphically validates if the real world observed queue behaviour is likely to be a possible single replication run of the simulation model. The experiment is performed with a FIFO queue mechanism and exists of 100 replications with a warm-up time of 10 years.

For each care type, the conclusion can be drawn that the real observed records lie in the output space of the simulation model. It is important to notice that average waiting list output of the simulation model is partly a result of calibration of the withdrawal curves and there for does not increase the validity of the system. However the variability of the system cannot be calibrated, there for the credibility of the simulation is increased by the fact that observed data falls insight the possible output space of the model. Furthermore, the simulation outputs proof that the observed behaviour in the real system is possibly created by variability in a stationary system. This is one of the made assumptions necessary to initialize the DES model.



The simulation model abstract the average number of children larger than observed in the real world system. Most of the real system outputs fall in the output space of the DES model. The DES abstraction of one single run looks more stable than the real system. The waiting abstraction is in middle of the DES output interval and looks on the face like a realistic abstraction.

8.8 Empirical assumption tests

The goal of this step of the validation process is to test the assumptions made during the initial stages of the model development quantitatively. A sensitivity analysis is performed to determine if the simulation output changes significantly when the values of assumed mechanisms and parameters change. Analyzed are the queue mechanism, the withdrawal curves and the return probabilities after receiving care.

8.8.1 Sensitivity queue mechanism

The mean steady state of the DES model is compared for three different queue mechanisms in order to analyze the sensitivity of the output parameters to the different queue mechanisms. The analyzed queue mechanisms are FIFO, Priority with 15% crisis arrivals at each care system and SIRO. For each queue mechanism, the outputs of an experiment set up of 100 replications are cross-compared. Each replication consists of a 10-year warm-up time and a 10-year simulation length. The relative difference between the output parameters of the different queue mechanisms are analyzed based on the mean value of these parameters over the experiments. The relative differences for the care systems are presented in Figure 8-4, the mean output values are presented in Appendix E.

		DH			AH			RH			PZ		
	Base Experiment	FIFO Priority	Priority RANDOM	FIFO RANDOM	FIFO Priority	Priority RANDOM	FIFO RANDOM	FIFO Priority	Priority RANDOM	FIFO RANDOM	FIFO Priority	Priority RANDOM	FIFO RANDOM
Withdrawal flow (trj/month)	Mean	0%	0%	0%	1%	-1%	1%	-1%	1%	0%	3%	3%	6%
	Median	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
	st. deviation	13%	-11%	0%	-3%	1%	-2%	-7%	6%	2%	6%	-6%	0%
outflow (trj/month)	Mean	0%	0%	0%	0%	0%	0%	0%	-1%	0%	0%	0%	0%
	Median	0%	0%	0%	0%	1%	1%	0%	0%	0%	0%	0%	0%
	st. deviation	0%	0%	0%	1%	-3%	-2%	2%	-2%	0%	2%	-2%	0%
Waitinglist (trj)	mean	20%	26%	51%	-3%	3%	0%	-13%	-2%	17%	5%	27%	33%
	Median	22%	26%	53%	0%	0%	0%	-13%	-2%	17%	0%	28%	28%
	st. deviation	26%	6%	33%	-10%	34%	21%	-14%	-5%	22%	9%	27%	39%
Waiting time (week)	mean	18%	27%	50%	0%	10%	10%	-12%	-2%	16%	7%	27%	35%
	Median	27%	-24%	-3%	11%	-40%	-33%	-23%	31%	-2%	0%	-30%	-30%
	st. deviation	106%	112%	336%	131%	123%	417%	-43%	-55%	288%	30%	100%	160%

FIGURE 8-4 CARE SYSTEM SENSITIVY TO QUEUE MECHANISMS

Figure 8-4 indicates the sensitivity of the flows though the different queue mechanisms are minimal. The waiting list and waiting time are sensitive to the queue mechanism. A FIFO queue mechanism result in general in the smallest mean waiting list, a Random queue mechanism in the largest. The shape of the waiting list distribution does not seem to change however the variability in waiting lists increases. The mean waiting time is strongly sensitive, especially for DH and PZ. The shape of the waiting time distribution changes, in comparison to FIFO both the priority and random mechanism increase the mean waiting time. The priority mechanism results in larger increase of the median and there for in a right skewed distribution, the random queue mechanisms results in a small median and a left skewed distribution. The resulting distributions for ambulatory care are presented Figure 8-5.

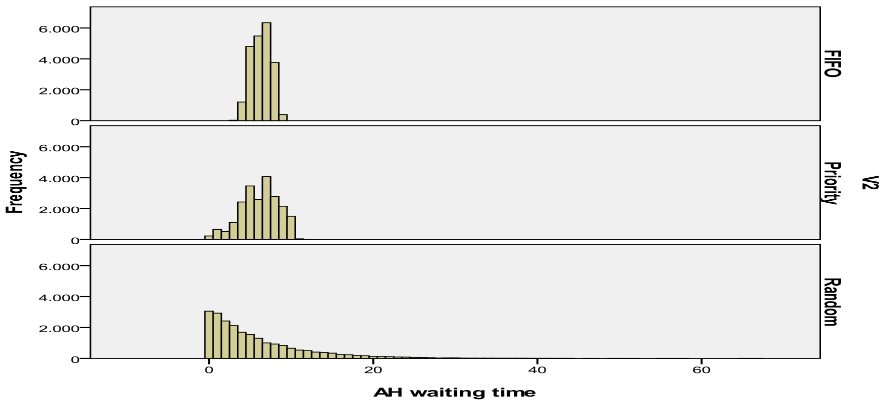


FIGURE 8-5 WAITING TIME DISTRIBUTION AH (WK)

The impact of different queue mechanisms on the different care systems is determined. Based on the large sensitivity of the trajectory waiting list and waiting time an significant impact on the child layer outputs are expected

	Queue mechanisms		
Statistic	FIFo	Priority	Random
Mean	191	106	182
Median	189	106	181
Stdev.	4,1E+06	1,2E+06	4,7E+06

TABLE 8-2 CHILD LAYER QUEUE LENGTH(TRJ)

	Relative queue length:		
	FIFO Priority	Priority Random	FIFO Random
Mean	-45%	72%	-5%
Median	-44%	71%	-4%
stdev	-71%	300%	15%

Table 8-3 Relative Sensitivity children queue length to queue mechanism (%)

Surprisingly, the FIFO system results in the longest average child layer waiting lists. Noticeably is the large decrease in waiting list when applying a priority based queue mechanism. The child waiting time, arguably the most important performance indicator in the sector is analyzed next.

	Waiting time (wk)			Relative difference (%)		
				FIFO	Priority	FIFO
Percentile	FIFO	Priority	Random	Priority	Random	Random
Min	0	0	0	0%	0%	0%
25%	5	2	1	-56%	-46%	-76%
median	7	7	3	3%	-50%	-49%
75%	8	9	8	10%	-8%	1%
Mean	7	6	6	-6%	-3%	-9%
max	**49**	**64**	**234**	**30%**	**267%**	**377%**
<9weeks	88%	79%	78%	-9%	0%	-9%

The mean child waiting is not sensitive the queue mechanism, the individual child waiting time distribution is.

8.8.2 Sensitivity withdrawal curves

The abstraction and calibration of the withdrawal curves into the simulation model is described previously in section 6.6 and in sub-section 7.4.5 A trend line through a set of scattered data points implements the withdrawal curve into the simulation model. The validity of some of these data points is small due to a low frequency of children in the long waiting time intervals. The withdrawal curve is calibrated in between the boundaries of the observed data points, to mitigate this implementation risk. A sensitivity analysis is performed to test the impact of small changes of the withdrawal curve on the system behaviour. For each care type the withdrawal curve is decreased by 10%, the resulting percentages of change of the average withdrawal flows and the queue lengths are presented in Table 8-4. The base case and the experimental run are calibrated with a FIFO queue mechanism.

TABLE 8-4 SENSITIVITY WITHDRAWAL CURVE

Variable	DH	AH	PZ	RH	Child
Withdrawal curve	**-10%**	**-10,0%**	**-10,0%**	**-10,0%**	
Withdrawal flow (trj/month)	-2,6%	-2,8%	-0,3%	-3,0%	
Queue length (trj)/(child)	12,0%	8,6%	7,7%	2,4%	7,5%
Waiting time(wk)	11.2%	9.9%	12.4%	8.2%	9.9%

In conclusion, the withdrawal flows and queue lengths are stable to changes in the withdrawal curve. The change in queue lengths and waiting times are proportional to the change in withdrawal curve. When calibrating the withdrawal curve it is necessary to optimize both the withdrawal flow and the queue length. Basing the analysis purely on the withdrawal curve is likely to lead to significant discrepancy in queue length.

8.8.3 Child return probabilities

Because the distribution of the number of sequencing care sets a child was not determinable with the available data sources an alternative approach was used to specify to model, as elaborated on in section 7.4. The children return behaviour is implemented to the model, with a conditional return probability dependent on the accommodation type of the previous care set. The values of these return probabilities where determined by a calibration experiment. This section evaluates the sensitivity of the simulation model to these return probabilities in order to provide further inside into the conditionality relations and to determine the value of risks embedded in the made assumptions.

Important to note is the difficult interaction of the different care system in relation to these return probabilities. While the return probability is dependent on the accommodation type of previous care set the accommodation type of the returning care set depends on the sequential care sets relations. A change in one of the return probabilities could have impact on each of the care systems.

A set of experiments is performed to increase the insight and understanding into these mechanisms. The model outputs of a base case run are compared to a set of experimentation runs. The experimentation runs are initialized with a 10% increase in comparison to the base case of one of the independent return probability variables. The resulting change in output variables is normalized to the base case outputs for each experimental run. Table 8-5, presents the normalized experiment outputs.

		Independent variable: return probability			
	Dependent variable	**DH+10%**	**PZ+10%**	**RH+10%**	**AH+10%**
DH	Inflow (trj/month)	-0,8%	1,1%	1,1%	**16,0%**
	Queue length (trj)	-1,9%	7,9%	7,9%	**135,5%**
PZ	Inflow (trj/month)	0,4%	0,6%	0,6%	**24,5%**
	Queue length (trj)	7,7%	12,4%	3,7%	**201,5%**
RH	Inflow (trj/month)	0,6%	1,2%	0,2%	**20,7%**
	Queue length (trj)	2,0%	1,7%	1,7%	**132,0%**
AH	Inflow (trj/month)	-0,6%	0,1%	0,1%	**17,7%**
	Queue length (trj)	0,5%	1,9%	1,9%	**131,6%**

TABLE 8-5 SENSITIVITY RETURN PROBABILITIES

Each care system is highly sensitive to the return probability after a care set which exist solely of ambulatory care, due to their high frequency. The sensitivity to the other return probabilities is low. This test provides a first indication that the model structure can be simplified by using the same return probability after every care set.

8.8.4 Conclusion empirical assumption tests

The queue mechanism of a care system has a large impact, not only on the distribution of waiting times, but also on the average waiting time and queue length of the trajectories in that care system. The children waiting list length and the mean waiting time is not sensitive to different queue mechanisms. The distribution of individual waiting times is sensitive to the queue mechanism. It can be concluded that more insight into the queue mechanism is required in order to make quantitative predictions with the DES model.

The care systems are not sensitive to changes in the withdrawal curves, the calibrated withdrawal curve calibrated on the available data is considered accurate enough for the modelling purpose.

The system is sensitive to the withdrawal probability after care sets, which solely exist of ambulatory trajectories due to high frequency of these care sets into the system. The system is not sensitive to the withdrawal probabilities after care sets with accommodation care. Based on this insight, it is likely that system simplification to one return probability independent of the care type will have a low impact on the system accuracy.

8.9 Quantitative validation

The most definitive test of a simulation model's validity is establishing that its output data closely resemble the output data that would be expected from the real world system. If the two sets of data compare with the accuracy required for the indented model purpose then the model is considered "valid". Validated are the process that determines the care set composition, the trajectory and the child layer.

8.9.1 Trajectory and care set composition

This section validates the process that creates a child's care profile when a child arrives. The process is dependent on the abstracted parallel relations in care sets, the sequential relations between care sets and the conditional return probability after a care set. As described in previous chapter the parallel and sequential relations are quantified with the help of observed data over 2009. The return probabilities are quantified by a calibration experiments, which optimize the average monthly trajectory arrivals at the four care systems over 2008. The model view is based on disaggregated individual care sets that assign trajectories to individual children. The validation takes a helicopter view by comparing the resulting aggregates from the model with the aggregates from the real system observed over 2009. The care type division, the distribution of the number of trajectories a care set and the distributions of ambulatory trajectories a care set are cross-compared with real system. The abstraction of the care set composition in the SD model is cross-compared to the DES model and the observed real world data. While the care set composition is an output of the disaggregated DES model, it serves as an input for the aggregated SD model. The composition of care sets in the DES model is not related to the state of the system, therefore no warm-up time is considered. A run length of 10 years assures enough child arrivals to derive a statistical significant result.

Experiment set-up DES model		
Warm-up time	:	0 years
Run length	:	20 years
Replication	:	1

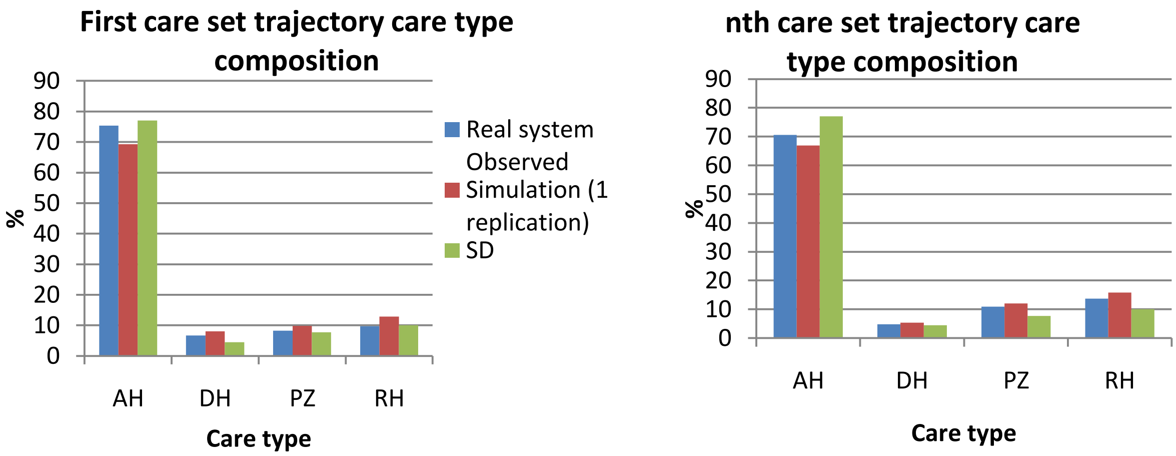


FIGURE 8-6 VALIDATION BAR CHART CARE SET COMPOSITION

The SD model does not make a distinction between the composition of new and return care sets. Chi square tests are performed to check if there is a significant difference between the care set division in the real world and both models. The test statistics are presented in Table 8-6, all statistics are above the 0.05% significance level and therefore not significantly different than the real deviation. The deviation of the SD model scores better for care sets assigned to new arrived children, the DES models scores higher for returning children.

TABLE 8-6 CHI-SQUARE STATISTICS CARE SET COMPOSITION

	Chi square statistic	
Arrival type	DES	SD
New	0,41	0,75
return	0,89	0,35

The number of care set is abstracted in the SD model by a constant of 3.04 trajectories a care set. This constant is remarkably higher than the average of the real world and DES distribution. This can be explained by the abstraction of a care set in the SD model. Care set arrivals in the SD model are based on the children flows. Overlapping care set arrivals do not involve child flows, the children are already in the system before and after care set arrival. As a result overlapping care sets cannot be abstracted in the SD model. Each care set arrival creates a larger amount of trajectories to keep the total amount of trajectories consistent with the real system. The constant is calculated by dividing the total amount of trajectories a month by the total children inflow. The bar chart that presents the distribution of the number trajectories in first arrival care sets is presented in
Figure 1-1.

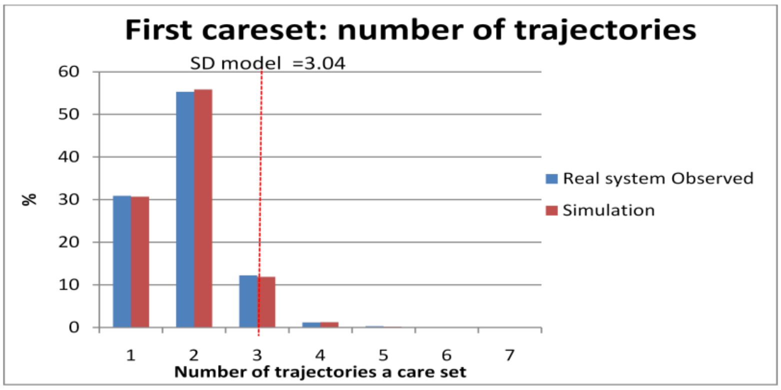


FIGURE 8-7 VALIDATION BAR CHART NUMBER OF TRAJECTORIES A CARE SET

The bar charts, which present a comparison of the distribution of the number of trajectories a care set for returning children and the distribution of the number of ambulatory trajectories a care set for both arrival categories, are presented in appendix E.2. A chi-square is performed to test if the simulation output differs significantly from the real system, the test statistics are presented in Table 8-7

TABLE 8-7 CHI-SQUARE TEST STATISTICS NUMBER OF TRAJECTORIES A CARE SET

Distribution number of a care set	Care set category	Chi square statistic Real system-DES model
trajectories	new	0,991
	return	0,989
AH trajectories	new	0,999
	return	0,991

Conclusion

The care set composition in a DES model results in a division care types, a distribution of the number of trajectories a care set and distribution of the number of ambulatory trajectories a care set. The differences between these distributions, in the DES model and in the case study, do not differ significantly. The care set composition algorithms and relations are accurate enough for the intended modelling purpose.

8.9.2 Limitation quantitative stock and flow validation

Section 8.4 described the available data sources for model calibration and validation. The conclusion was drawn that based on 29 monthly records, taking into account the expected randomness and expected auto correlation, the variance of the real world system can be expected to be larger than the observed sample variance in the data set. That creates increased uncertainty into the validation process and especially entwines a risk for the mean queue length, because it also used to calibrate the model. This section attempts to create a better understanding of the vulnerability of the mean queue value of the data sample of 29 records created by inherent system uncertainty and auto correlation of the sample records.

Experimental settings
Experiments with the simulation model are performed to increase the understanding into the risk of using a data sample of 29 monthly data records to calculate the mean queue values, under the assumptions that the simulation model is a creditable representation of the real world system. A simulation experiment of 100 replications, with a 10 year warm-up time and a run length of 29 months is performed. The model is configured with a FIFO queue mechanism. The risks for the mean queue values over a data sample of 29 records, of the care systems, are analyzed because those are used both to calibrate and validate the model.

Output analysis
For each care system, the mean queue values of the replications are visualized in a box plot in order to provide insight into the expected spread of a 29 month data sample.

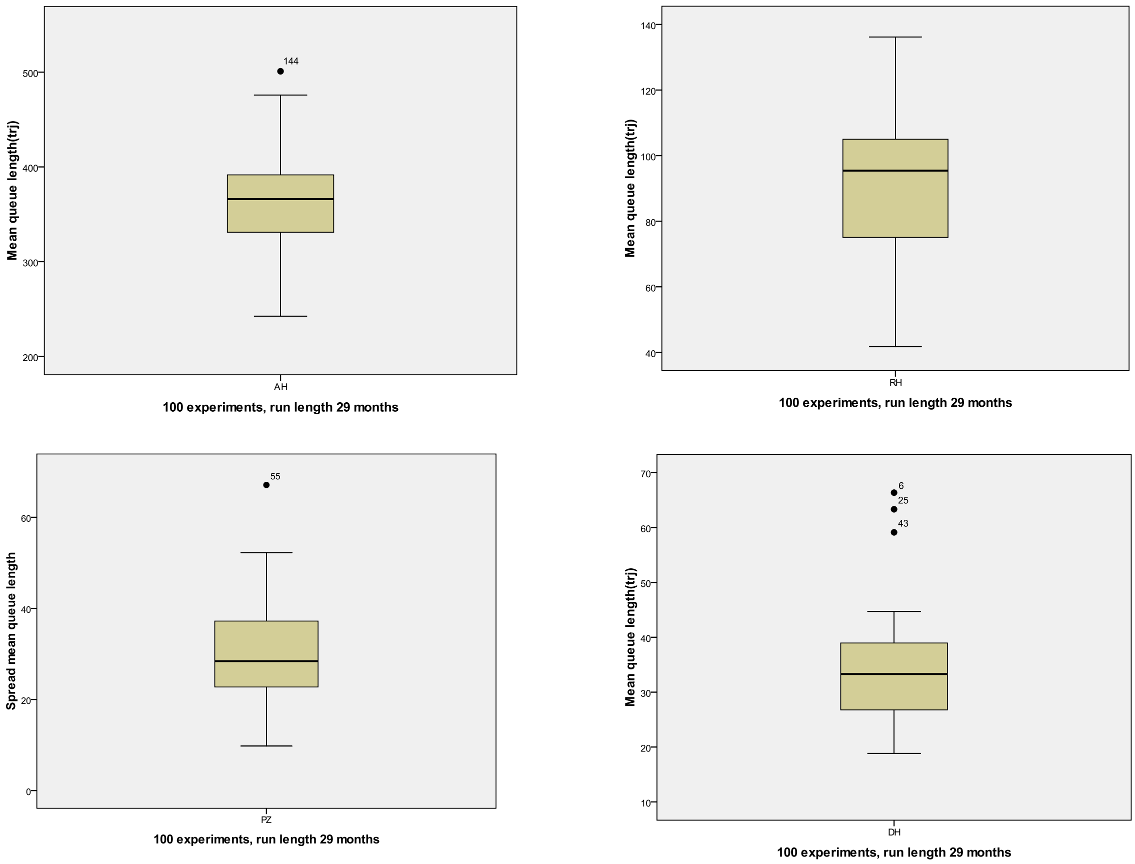


FIGURE 8-8 BOXPLOT MEAN QUEUE LENGTHS (DATA SAMPLE OF 29 MONTHS)

The inter quartile range is large for every care type, on the basis of this knowledge it can be concluded that the data set of 29 months is too small to provide an accurate quantitative validation of the care systems. Furthermore, calibrating the system to the observed mean in the data entwines a large risk of wrongly perceiving system validity, while the predictive validity of the model is in reality not proven. It should be noticed that this wrongly perceived system knowledge is a risk for both DES modelling for as the currently used SD model.

8.9.3 Care system quantitative comparison

Based on the small real world data sample and the risk of determining a mean value theses data samples statistical procedures are not applicable. Therefore, a heuristic approach is chosen that compares box plots and histograms of the output of the real system and the simulation model.

DES model set-up
For each queue mechanism, the output of an experiment of 100 replications, with a run-length of 10 years and a warm-up time of 10 years are compared.

SD model set-up
A model run of the deterministic SD model is compared the real world data. The SD model is started at the observed historical values and ran until it reaches its steady state condition.

The box plots and histogram are presented Appendix E. The power to reject the simulation outputs of this method is low. It is concluded that the DES model is not able to produce the variability and the extreme values observed in the ambulatory treated outflow, as concluded from the box plot presented in Figure 8-9. Furthermore, the extreme values observed in the DH treatment outflow, which are arguably the result of seasonal behaviour, are not accounted for in the DES model either. For the other stocks and flows no clear difference between the simulation and real system output can be distinct. For current research no disaggregated waiting time data is available, the author argues that a validation with this disaggregated waiting time data would provided additional insight in the best suitable queue mechanism.

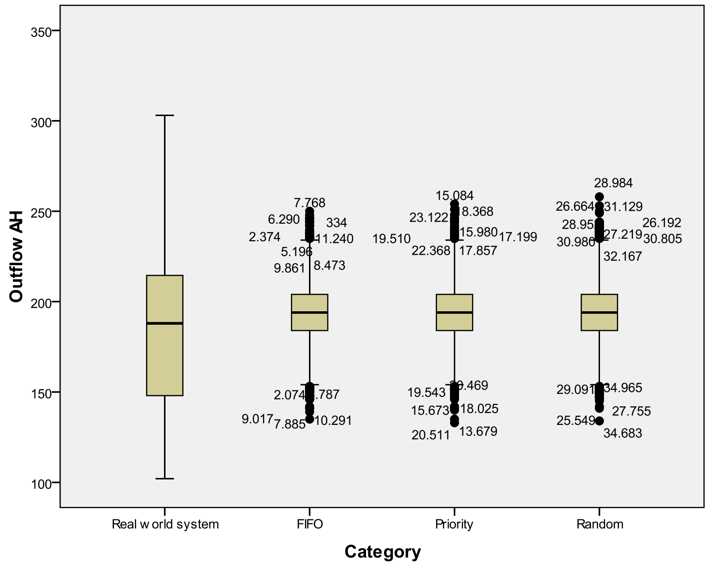


FIGURE 8-9 BOXPLOT VALIDATION AMBULATORY TREATED OUTFLOW

An overview of the mean, median and stand deviation statistics of the real world, the DES model with the three distinct queue mechanism and the SD model are presented in appendix E.3. Based on the data limitations introduced in previous section the main statistics of the data sample cannot be used. Consequently directly comparing the real world statistics with the simulation outputs is there for meaningless. For the same reason it is impossible to validate the SD model based on these statistics.

8.9.4 Children layer validation

This section validates the DES model children stocks and flow to the children stock and flow information in the case study data sources. It should noticed that INITI8 current information systems does not measure the individual child waiting list and waiting time. An overview of the available statistics from the available and the mean statistics of the DES model outputs are presented in Table 8-8. Appendix E.8 presents the box plot of the distinct variable. There is no significant difference between the exogenous children inflow in the real system and in the simulation model. The child layer dynamics are driven by the trajectory dynamics, the author argues that to increase the credibility of the child layer it is important that first the trajectory waiting times are proven valid. Current section provides insight into the gap between the real world and the DES performance indicators without attempting to provide a proof of validity.

		DES model Queue mechanism		
	data	FIFO	Priority	Random
New children inflow (child/month)	69,38	69,45		
Active children (child)	1555,07	1617,52	1617,42	1632,36
Return inflow children (child/month)	25,21	37,99	37,23	36,21
System outflow (child)	92,1	107,41	106,36	105,69

TABLE 8-8 CHILD LAYER MEAN STATISTICS OVERVIEW

The DES model generates the number of children significantly higher than observed in the real world system. The relative differences between both means values are small, around 4%. Based on the box plot and the difference in mean it can be concluded that the performance indicator cannot be used for quantitative prediction, it however does provide quantitative insight into the system relations. Furthermore, the sensitivity to the different queue mechanisms is small.

The return inflow in the system and the system outflow are abstracted significantly higher than in the real system. The observed difference in flow size is likely to be influenced by definition. Children in the youth care sector are only registered flown out of the system if the did not receive care for more than six months, in the simulation model however they become inactive at the moment they do not have any active trajectories in the care systems.

8.10 Conclusion verification and validation

During the different phase of the modelling cycles various verification experiments and techniques have been performed to check if the model been coded and transferred from the conceptual phase into the specification as intended. Furthermore, the validity of the inputs into the model have are checked.

The first phase of the validation increased the model creditability by a face validation. A comparison of the real world queue behaviour, the queue behaviour of a single DES model run and the queue behaviour of a single run of the SD model increased the creditability of the DES model, the monthly queue steps are better abstracted in the DES than in the SD model[13]. A comparison of the observed real world queue behaviour and the output space of the DES model over 100 replications runs provides trust in the creditability of both the DES model and into the intrinsic assumption of the DES model that the observed real world system behaviour is the result of steady state variability.

[13] DES model configured with a FIFO queue mechanism, arguments are valid for all care systems.

The second phase of the validation quantitatively tests the assumptions made during the development of the DES model. A sensitivity analysis is performed to get a better understanding of the risk embedded in the made assumptions, the following assumptions where analyzed: the queue mechanism, the withdrawal curve and the return probability.

> *Queue mechanism:* Not only the distribution of waiting times is sensitive to the queue mechanism, the queue length and average waiting time are also sensitive. In conclusion, the DES model cannot provide insight into the queue length or expected mean waiting time without rising insight into the queue mechanism used in the real system.
>
> *Withdrawal curve:* The sensitivity of the withdrawal flow to the withdrawal curve is small; the change in queue length is in proportion to change input. Given the accuracy of the withdrawal curve data and the small sensitivity of the care systems to the withdrawal curve indicated that the risk embedded in the withdrawal curve assumptions is low. When manually calibrating the system to the withdrawal curve it is required to base the calibration not solely on the withdrawal flow to queue length should also be taken into account.
>
> *Return probability.* The return probability after a care set is modelled dependent on the accommodation care type of that care set. It can be concluded that the outputs of each care system are insensitive to the return probability after a care set with one or more RH, PZ or DH trajectories, the system is very sensitive to the return probability after care sets with ambulatory care arguably due to the high frequency of those care sets. The insensitivity to the other return probabilities provides a first indication that it might be justified to simply the model to a non-care set dependent uniform return probability.

The third phase of validation quantitatively compares the model output data and the output of the real system. The validity and limitations of the available data sources are analyzed after which the care set composition process, the care system sub-model and the child layer dynamics are validated.

> *Validation care set composition.* The distribution of the distinct care types over the trajectories and the number of trajectories a care type are compared for both the DES and the SD model. No significant differce between the real world care type distribution and the DES and SD model are found. The SD model does not abstracts the difference in composition between new and returning care sets, however the aggregate of both does not significantly differ from the new and returning care set composition. No significant difference was found between the numbers of trajectories a care set abstracted in the DES model, for both new and returning care sets. The SD model does not allow to abstract different number of trajectories a care set due to perfect mixing, every care set is abstracted with the same number of trajectories.
>
> *Data limitations stocks and flow validation.* The expected auto correlation in sequencing observations biases the standard deviation of the small data set as estimator of the population standard deviation. As a consequence, the confidence interval of the mean is expected to be much larger than calculated from the sample statistic. The simulation model is used to create insight into the expected risk of calibrating and validating the model on the bias of estimators of a small data source. A simulation experiment, with the DES model configured with a FIFO queue mechanism, of 100 replications with a run-length of 29 months was performed. The large spread of mean queue values of replications indicates that calibration and validation the mean queue length of data with a 29 month span imposes large risks in the youth care sector.
>
> *Care system quantitative validation.* Due to the possible bias in the mean indicator of the small data sample, the quantitative validation cannot based on these statistics and the SD model cannot be validated to the real world output. A heuristic approach of comparing the box plots and histograms of the real world and The DES simulation outputs is applied. The heuristic validation approach has a low power to reject the simulation outputs. The validity of the AH and DH treatment outflow can be rejected. The DES model does not resemble the variability observed in the real system; arguably the variability in the real system can be the

result of seasonal effects. The validity of the other model variables cannot be rejected based on the currently available data.

Children layer. The relations of the children layer are dependent on the validity of the trajectory waiting times in the care system. In order to validate the relations of this process the inputs, the trajectory waiting times, require to be valid. The number of active children in the system is significantly higher than in the real world, however the relative difference between the outputs of the real world and the simulation model are small (4%). The performance indicator can there for be used a qualitative indicator. The children outflow and return flow are abstracted significantly higher in the DES model; the possible influence of "definitions" is likely to have a large influence on this error.

Chapter 9

Cross-comparison: Sensitivity to scenario's and policy measures

Previous chapter cross validated, where possible, the SD and DES model in the base case situation. This chapter presents a cross-comparison of the sensitivity of both models to a scenario in which the children inflow increases and to a number of policy measures, which increase the capacity places of the distinct care types.

9.1 Scenario increase children demand

The sensitivity of both models to scenario in which a 10% increase in the number of new children arrivals at the care provider is analyzed. For the DES model, the percentage of change between the steady state mean of the base experiment and the steady state mean of an experiment with a 10% increase of daily children arrivals are calculated for the FIFO, priority and SIRO queue mechanism. For the SD model the percentage of change between the initial steady state and the resulting steady are compared.

The impact of a scenario of 10% increase in the number of children arrivals is experienced at the care provider evaluated for both the DES and SD model. For the DES model, the percentage of change of a between a base case experiments and an experiment with a 10% increase of daily children arrivals is compared. The percentage change is evaluated for the FIFO, priority and SIRO queue mechanism, to evaluate the impact of different queue mechanisms on the demand sensitivity. For the SD model the percentage of change is calculated by the initial steady state and resulting steady state situation after a 10% increase in child arrivals. For both models the transient behaviour to arrive to this new steady states are not taken into account.

An overview of the mean output values for both the base case and scenario experiments is presented in appendix F.1, Table 9-1 presents an overview of the resulting relative changes in the care system performance indicators.

		SD	FIFO	Priority	Random
Inflow (trj/month)	**AH**	11%	10%	10%	10%
Withdrawal (trj/month)		51%	66%	67%	65%
Waiting list (trj)		28%	68%	80%	83%
Waiting time(wk)		15%	52%	65%	66%
Inflow (trj/month)	**DH**	11%	11%	10%	10%
Withdrawal (trj/month)		55%	45%	42%	39%
Waiting list (trj)		35%	70%	79%	70%
Waiting time(wk)		22%	53%	63%	55%
Inflow (trj/month)	**PZ**	11%	10%	11%	10%
Withdrawal (trj/month)		137%	79%	79%	78%
Waiting list (trj)		66%	73%	77%	89%
Waiting time(wk)		50%	58%	58%	72%
Inflow (trj/month)	**RH**	11%	10%	10%	11%
Withdrawal (trj/month)		42%	30%	37%	34%
Waiting list (trj)		27%	49%	66%	61%
Waiting time(wk)		17%	39%	49%	48%

TABLE 9-1 SENSITIVITY CARE SYSTEM SCENARIO 10% CHILD DEMAND INCREASE

The relative changes in the trajectory inflow of each care system are in proportion to the relative increase in children arrivals for both the SD model and DES model. A difference is observed in the relative change of withdrawals flows for the SD and DES model. The increase of these flows measured in terms of trajectories is small; the large relative changes are a result of the small initial withdrawal flows. It appears that the waiting list length in the DES model is more sensitive for changes in the new children inflow than the waiting list length in the SD model. Furthermore, the queue configuration has an impact on the waiting list sensitivity to changes in the children inflow. The average waiting time in the SD model is less sensitive to changes in the children inflow than the waiting time indicator in the DES model.

Table 9-2 presents the output from the DES model configured with the priority queue mechanism, for the base case and the experiment run for a 10% increase in children inflow. Three performance indicators are considered, the number of children on the waiting list, the mean waiting time in weeks, and the percentage of children that wait less than 9 weeks. These three performance indicators are all sensitive to changes in the exogenous inflow of new children.

	Child waiting list	Mean waiting time	Percentage< 9 week
Base	179.8	6.2	0.8
Experiment	324.1	10.1	0.3
Percentage	80%	62%	-59%

TABLE 9-2 SENSITIVITY CHILD LAYER TO 10% ICNREASE NEW CHILDREN INFLOW

9.2 Sensitivity capacity changes

The sensitivity of the care provider system to a 10% increase of capacity for the different care system is analyzed for both the SD and DES model. The outputs of both models are visualized in Table 9-3. The first column presents the care system of the capacity change, the second column the output variables. For both models the steady state mean of the base case, the mean of the experimental run and the relative difference between both are presented.

		SD model			DES model: priority		
		base	Capacity+10%	%	base	Capacity+10%	%
AH	withdrawal	44,65	25,36	-43%	34,88	16,38	-53%
	waitinglist	351	262,3	-25%	353,31	227,75	-36%
	waitingtime	6,69	5,03	-25%	6,67	4,33	-35%
	outflow	179,92	197,91	10%	194,03	213,35	10%
DH	withdrawal	2,64	1,55	-41%	3,07	2,13	-31%
	waitinglist	33,52	24,24	-28%	39,82	22,64	-43%
	waitingtime	11,13	8,11	-27%	13,22	7,38	-44%
	outlfow	10,27	11,27	10%	9,99	11,04	10%
PZ	withdrawal	1,75	0	-100%	3,12	1,32	-58%
	waitinglist	25,4	0,74	-97%	26,81	12,48	-53%
	waitingtime	4,88	0,14	-97%	4,82	2,24	-54%
	outlfow	20,55	22,13	8%	21,17	23,00	9%
RH	withdrawal	6,8	4,34	-36%	9,41	7,18	-24%
	waitinglist	60,52	46,82	-23%	94,17	58,09	-38%
	waitingtime	8,87	6,91	-22%	12,72	7,83	-38%
	outlfow	22,46	24,7	10%	22,64	25,12	11%

TABLE 9-3 SENSITIVITY CARE SYSTEM TO 10% CAPACITY INCREASE

No general conclusion can be drawn about the sensitivity of the withdrawal flow. For the PZ care system the withdrawal and the average waiting list become close to zero in the +10% capacity scenario. For the other care systems, the sensitivity of the DES model is larger than the sensitivity of the SD model. The differences in outflows are comparable for both models.

	Child layer performance indicator	Base	Capacity+10%	%
AH	Waiting list (trj)	191.03	131.95	-30.92%
	Mean waiting time (wk)	6.74	4.79	-28.87%
	Percent waiting<9 weeks (%)	79.30%	92.90%	13.60%
DH	Waiting list (trj)	191.03	182.26	-4.59%
	Mean waiting time (wk)	6.74	6.52	-3.27%
	Percent waiting<9 weeks (%)	79.30%	89.90%	10.60%
PZ	Waiting list (trj)	191.03	182.26	-3.01%
	Mean waiting time (wk)	6.74	6.52	-3.88%
	Percent waiting<9 weeks (%)	79.30%	89.90%	10.60%
RH	Waiting list (trj)	191.03	131.95	-30.92%
	Mean waiting time (wk)	6.74	4.79	-28.87%
	Percent waiting<9 weeks (%)	79.30%	92.90%	13.60%

TABLE 9-4 SENSITIVITY CHILDREN LAYER TO 10% CAPACITY INCREASE

Table 9-4, presents the sensitivity of the model, configured with the priority based queue mechanism. The children waiting list and waiting time are sensitive to capacity changes in to the ambulatory and residential care system, the system is not sensitive to changes in day care and foster care system. The larger number of children can explain these findings in the ambulatory and residential care system. It however surprising that the percentage of children that waits less than nine weeks is equally for capacity changes in all care systems. In order to use the model get insight in the most effective strategy it is important to put the capacity not in percentage of change, but as a percentage of costs.

9.3 Conclusion cross comparison

The waiting list and waiting time of the DES model are more sensitive to changes in the inflow of new children than the SD model. This difference in sensitivity is a result of translating the aggregated mechanism of the SD model to disaggregated individual mechanism, which account for stochastic variability for both the withdrawal mechanism and the treatment times. Furthermore, the sensitivity of the DES models differs for the different queue mechanism. In conclusion, individual variability has an impact on the sensitivity of the care provider system, in order to make valid prediction with the DES model further insight into the queue mechanism is required.

In general, the DES model care systems are more sensitive to capacity changes than the care system abstraction in a DES model. No general relation can be found between the sensitivity of the withdrawal flows. The sensitivity of the DES model child layer to capacity changes at the different care providers is analyzed for a priority queue mechanism. The child waiting list and waiting time are sensitive to changes in the care systems with large trajectory flows, the waiting list and waiting time are insensitive to capacity changes of the smaller PZ and RH care systems. Surprisingly, the sensitivity of the percentage of children, which receives care is equally sensitive to capacity changes of the all care systems. In other words, the child waiting list length has not a direct and obvious relation with the percentage of children that wait less than nine weeks before receiving care. The DES simulation model can provide insight this relation.

Part 5: Evaluation

Chapter 10
Evaluation, Recommendation and Reflection

In this final chapter, we return to the main research objective: evaluating the DES modelling methodology in the youth care decision-making process. This research was initiated based on the assumption of both the author and problem owner INITI8 that in the youth care sector, which has a high intolerance to failure for every child, the disaggregated DES methodology better fits the model worldview and modelling objectives than the aggregated SD methodology.

10.1 Evaluation research questions

We answer the main research question, presented in the first chapter in two parts. First by providing, a structured overview of the answers to the research questions found scattered through the thesis. Based on the knowledge embedded in this research question, the main research question is answered in the second part. The main research question was defined as:

"What additional insights can a DES decision support model provide, in addition to currently used SD model, to evaluate the DES modelling methodology in the youth care capacity decision making process?"

10.1.1 A review of the research questions

The set of chronological research questions that together tackle the main research question are answered in this section.

Research question 1: *What are the objectives for a decision support model in the youth care sector (Chapter 2)?*
The Youth Care Act defines the legal entitlement of youth care to children within an acceptable waiting time of maximum nine weeks. The authorities of the provinces and urbanized regions are responsible for a sufficient provision of care capacity and provide the budget for that capacity to the autonomic care providers in their region. The Dutch youth care sector faces long waiting lists and over utilized resources. The government provided additional capacity injections to increase capacity. The policy resulted in an initial decrease of waiting lists, however shortly after the capacity increase unexpected increases in waiting lists and waiting times occurred. The provincial and regional systems did not manage to guarantee the maximum child waiting time of nine weeks.

Management in the youth care sector is complex and in-transparent due to different horizontal and vertical aggregations layers (Leewen, Naborn et al. 2008). The national performance indicators measure the number of children on the waiting lists and the waiting time for each child. A child can receive multiple care services called trajectories. The trajectories can be subdivided in four main care types according to their resource needs; *Ambulatory care (AH), Day care (DH), Residential care (RH)* and *Foster care (PZ).* The care provision processes are subdivided in four independent parallel sub-systems aggregated to these care types, the care systems. (Section 2.4.2)

The objective of decision support modelling in the youth care sector is to create insight into the interrelations between the anticipated child demands, optimal capacity policies for the different care systems and the resulting waiting times for individual children.

Research question 2: *What are the expected benefits of a DES model in addition to currently used SD model (Chapter 3, Chapter 4)?*

The essential difference between the SD and DES methodology is their difference in system aggregation. A SD model abstracts the system as a continuous quantity rather like a fluid no individual entities are distinct. A DES model disaggregates the system to individual entities, each of those entities can posses characteristics that determine their individual flow through the system.

The effectiveness of a decision support system can be expressed in a combination of three factors: *Usefulness, Usability and Usage* (Keen and Sol 2005).The *usefulness* of a decision support model relates to the analytical model, the embedded knowledge and the information resources available in the model or tool. The *usability* of a decision support model expresses the communicative value, stakeholders trust and understanding of the decision support model. The *usage* of a decision model expresses the suitability of the model for the organizational, technical or social context. It refers the time and cost of adapting the model to changing environment and objectives.

In a DES model, individual children and the heterogeneity in their characteristics that determine their path through the system are directly abstracted by individual entities in a DES model. As in the real system, children are assigned a set of trajectories and performance indicators can be calculated for individual child and trajectory in the model. Unlike a DES model, currently used SD model cannot capture the variability in individual characteristics neither can it abstract the coupling between children and trajectories. The SD model can only provide insight into the aggregated system behaviour, individual child or trajectory waiting times cannot be analyzed.

A disaggregated model however requires disaggregated data, for each child the specific characteristics which determine its path through the system, needs to be determined and quantified to accurately calculate the individual performance indicators. The question arises if this disaggregated data is available or even collectable. In terms of *usability*, the disaggregated worldview of a DES model is a clear advantage to derive stakeholder comprehension and trust into the simulation outputs. It involves however a downside, experiments need to be set-up by stochastic distributions which increase the time and cost of initializing an experiment. Furthermore, a DES experiment requires additional time to run because of the increased level of detail and the need to run multiple replications due to the stochastic nature of the models. The *disaggregation level of the* model also influences *the usage* of a decision support model. An aggregated SD model is generally less sensitive to changing environments and objectives than a detailed disaggregated DES model.

A DES model has benefits in comparison to a SD model for the modelling of real world systems that face heterogeneous entities, a large impact of individual variability and a high intolerance to failure for those entities, such as in the field health and youth care. A precondition for those benefits in such a system is the availability or collectability of data to quantify the individual characteristics. Furthermore, the higher level of detail should be worth the required additional investments of time and costs.

Research question 3: *What are the differences between the abstraction of the care provider system in aggregated SD and disaggregated DES concepts (Chapter 4, Chapter 5,Chapter 7)?*

A care provider consists of a set of independent sub-process the care systems. Children are the entities that flow through the care provider system. The care systems describe the flow of trajectories through the care provider system. Trajectories are matched to a care system with the appropriate resource by the care type attribute. Four care types are distinct: Ambulatory care, Day care, Residential care and Foster care. Each care system has its own number of capacity places. This main structure is comparable between both the SD and DES model.

The coupling between children and trajectories is made by assigning the children care sets. A care set holds an arrival time and a set of trajectories of one or multiple care types. Each trajectory distinguishes three state transitions: trajectory registration, start care and end care. A child can have *parallel, overlapping* and *sequential trajectories.* (Section 5.2). The SD model assumes perfect mixing of children and care sets in the care provider systems and of trajectories in a care system. Only parallel and sequential trajectories are abstracted in the SD model, in order to compensate for the not abstracted overlapping trajectories, the number of parallel trajectories in each care set is increased.

A DES model can capture heterogeneity of children and care sets by abstracting conditionality and dependency relations. In order to simplify the data study and the abstraction of those relations, the assumption is made that a child's trajectories that are registered in the same calendar month belong to the same arrival care set. The DES model abstracts these trajectories as arriving at the same day.

The care systems are essentially queuing systems. Unlike the SD model, the DES models distinguish individual trajectories in those queues. A queue mechanism, which determines the order of the trajectories in the queue, needs to be defined for each queue system. In the real world system children can withdraw trajectories for a variety of reasons. In the SD model the withdrawal percentage is abstracted dependent on the mean waiting time in the care system. In the DES model the withdrawal probability for each trajectory is dependent on its individual waiting time.

In the SD model the trajectory treatment times, in each care system, are assumed to be exponential distributed, the model is initialized with the mean value observed in the real system. In the DES model for each trajectory an individual treatment time is drawn from a stochastic distribution. The SD model cannot calculate different children states. In the DES model the children states are steered by the states of their trajectories. The number of children on the waiting list and their waiting time can be calculated.

Research question 4: *What are the heterogeneity and conditionality relations of influence in the care provider system (Chapter 6)?*

In order to abstract the heterogeneity in the care provider system the important system objects and relation need to be distinct. The impact of both children's first care sets and additional care sets on the total inflow of trajectories of each care system is significant, in size and variability. The care set composition of first and additional care sets significantly differs, both in number of trajectories and in the care types of assigned trajectories. A purposeful DES model requires abstracting both children's first and additional care sets, each with different composition algorithms (Section 6.2).

There are significant conditionality relations between the care types of trajectories in a common care set for both children's first care sets and additional care sets. The three accommodation care types DH, PZ and RH are mutual exclusive in a common care set. A significant parallel conditionality relation exists between the accommodation care type of a care set and the occurrence of ambulatory care in that care set. The accommodation type of children's sequencing care sets are related to the accommodation type of the child's previous care set (section 6.3). Furthermore, the time between a child's sequencing care sets is related to the accommodation type of the previous care set (Section 6.4). The time span of the available data was too small to provide accurate and reliable insight into distribution of the number of care set assigned a child and the relations that influence this distribution (Section 6.5). A heuristic graphical approach proved that a longer trajectory waiting increases the probability of trajectory withdrawal (Section 6.6).

Research question 5: *Can we abstract and quantify the care provider system in a DES simulation model (Chapter 7)?*

The discrete conceptualization, presented in chapter 5, used class diagrams, state charts and process flows to make the body of knowledge transparent. AnyLogic simulation software is chosen because it is based on a native java environment, which provides a full object-oriented structure, and it enables to mix process oriented flowcharts and dynamic state chart elements in a visual development environment.

A first step of quantifying the inputs was to analyze if the input variables in the data set were stationary over time. Based on the time span of the available data and the observed behavioural patterns in the data set, the assumptions can be made that the distribution of all input variables were stationary over the time span of the data set (Section 6.7).

The discrete model quantification with the available dataset imposes a set of challenges. The time span of the data set is too small to derive the distribution of the number of sequencing care sets a child, the relation between trajectory waiting times and withdrawal probabilities is scattered and the queue mechanism is unknown. An alternative model structure based on a binominal return probability after each care set and a quantification method based on calibration solved the first challenge (Section 7.4.3). A calibration difficulty was found, the interrelation between the withdrawal curves and the queue mechanisms make the average waiting time dependent on the queue mechanism in the system. Accurate calibration of the withdrawal curve requires a better insight into the applied queue mechanism at the care providers (Section 7.4.4). The real world queue mechanism cannot be defined form the available data sources. In order to create more insight into the impact and stability of conclusions for different queue mechanisms experiments are cross-compared for a FIFO, Priority based and SIRO queue mechanisms (Section 7.4.6).

Research question 6: *Do the DES and SD model represent and correctly reproduce the behaviour of the real world system (Chapter 8, Chapter 9)?*

Unlike the stochastic configuration of the SD model, the DES model abstract a comparable variability in monthly waiting lists changes as observed in the output of the real world system. Furthermore, the observed real world outputs lie in the boundaries of the DES model output space, which provides a proof that the observed waiting list dynamics can be produced by variability in a stationary system and increases the credibility of the DES model (Section 8.7).

A limitation was found with respect to the available data for model validation and calibration. To assure that the calibrated model is a valid model of the system and not only representative for the particular set of input data, an independent data set is required for model calibration and validation. The available data set is, given the observed variability, however too small to subdivide it in two accurate independent data sets for calibration and validation. Consequentially more confidence in the uniqueness of predictions was obtained by assessing the sensitivity of the system prediction to variation in model and calibration assumptions (Section 8.4).

Further research into the applied queue mechanism is indispensable to predict future waiting lists and waiting times. Not only is the distribution of trajectory waiting times sensitive to the applied queue mechanism the average waiting time is also influenced. The sensitivity of the system to the withdrawal curve was found to be in proportion to the input percentage of chance of the withdrawal curve. The system is insensitive for changes in the probability of receiving an additional care set, after a care set with accommodation trajectories (RH, PZ, DH). The system is highly sensitive to the probability of receiving a sequential care set after a care set with solely ambulatory care. Which indicates that it might be possible to simplify the current DES model by abstracting the probability for a sequencing care set independent from the composition of previous care. (Section 0)

Due to the infinite nature of the youth care system, the large process times of multiple months until multiple years, the large variability and the auto-correlation of monthly data points, a large time span of validation data is required to determine accurate estimators of system statistics. The available data set of 29 months is too small for a quantitative validation; it imposes a large risk to validate the model based on biased data estimators (Section 8.9.2). The credibility of the DES outputs are increased by comparing box plots and histogram of the real system and model outputs. The calculated trajectory stocks are creditable (Section 8.9.3), the children stocks and flows are abstracted significantly higher than observed in the real system (Section 8.9.4).

The DES model is, for every queue mechanism, significantly more sensitive to scenario and policy changes than currently used SD model. Arguable, these conflicting insights are a result of a better abstraction of the care provider system and the variability in that system by the DES model (Chapter 9).

10.1.2 Review of the main research question

This section evaluates the main research question:

"What additional insights can a DES decision support model provide, in addition to currently used SD model, to evaluate the DES modelling methodology in the youth care capacity decision making process?"

This section answers the main research question and makes the overlapping knowledge created during the research transparent. From the sixth research question, it is concluded that the DES model cannot provide accurate quantitative predictions without a better insight into the queue mechanism. The DES model can be used to create qualitative insight into the care provider system, controlled for the stability of the conclusions for different queue mechanisms, to derive a funded conclusion for the real world system. In this research the DES model provided additional insight into the system behaviour. A base case experiment with the DES model showed that the dynamics in the real world outputs can be produced by the observed variability in a stationary system. Furthermore, cross comparison of the DES and SD model provided a first glance of conflicting insights in system sensitivity between the disaggregated and aggregated system abstraction.

The following additional system insights can be created by further experimentation with the developed DES model:

Robustness of the stationary system behaviour. While the queue mechanism is unknown, the robustness of the system with different queue mechanisms can be analyzed. Furthermore, the spread in outputs of the stationary DES model makes the dynamic complexity of decision making in the youth care sector transparent and thereby provides insight in the extreme difficulties the authorities face in the youth care sector.

Queue mechanisms. Experimentation with the DES model makes the expected effects of alternative queue mechanisms transparent. For instance, the impact of implementing a multi layer policy that evaluates priorities based on children waiting times instead of trajectory waiting times can be evaluated.

Robustness of future scenario's. In a sector with such a high uncertainty to failure as the youth care sector it can be defended to base policy measures on expected worst case scenario's rather than management on averages. A DES model can provide insight into the expected spread and possible worst case scenarios.

Multi-layer impact capacity changes. The impact of possible capacity changes make on a care system are difficult to oversee. The impact on the child layer and especially on the number of children which exceed the nine weeks waiting time performance indicators are impossible to oversee for a human mind. The DES model can provide insight into the effect of different capacity policies, controlled for the stability of the policies for different queue mechanisms.

Data validation. A creditable DES model can provide insight into the possible bias of data sample estimators, by evaluating the variability of these estimators for a set of replication runs, controlled for different queue mechanisms.

10.2 Barriers for simulation in health and youth care

As aforementioned, recent studies suggest that the way modelling and methods are often used in industry and defence are often to failure in health care (Chanal and Eldabi 2010). Patients are not typical customer, mainly because each has an individual urgency and they are responsive and increasingly keen to exercise meaning full and informed choice. The main difficulty of simulation youth care found in thesis is the quantification and specification of human behaviour in the youth care system. The interactions of the queue and withdrawal behaviour in the care provider system where found to be difficult to interpret, quantify, calibrate and validate.

The challenge of simulation in the youth care sector faces arguably even larger difficulties than experienced in most health care systems. The challenges are created by the non-finite system characteristics; the long treatment times and the extreme variability in those treatment times create extreme drawbacks for the understanding of observed system behaviour and the requirements for specification and validation data sources. A large time span of historical data is required to derive unbiased sample estimators for the real system. The challenge of collecting data over such a large time span is that reality keeps changing; the distributions of no real world system are stationary over times. The long treatment times and large variability make it difficult to determine if the characteristics of the system behaviour are the result of transient or steady state behaviour.

10.3 Recommendations

This research provides a proof of concept of DES modelling in the youth care sector. The additional insights a DES model can provide are evaluated and additional system knowledge is created. Recommendations are made to the problem owner INITI8 with regard to further research necessary to implement the DES care provider system successfully in the youth care decision-making process.

Queue mechanism and priority categories. This research showed that the queue mechanism and priority order applied in the youth care sector has a large impact on both the individual waiting times and the mean waiting time. It is recommended to INITI8 to increase the insight in the priority categories applied in the youth care sector and into the subjective decision making process behind the queue decisions. If objective priority categories are distinct, it is recommended to disaggregate the data collection to these priority categories. Interviewing the care provider employees responsible for the queue management is recommended to create further insight into the subjective child selection process

Validation with domain experts. The author recognizes that a simulation model should not be an abstraction developed by an analyst working in isolation. Involving domain experts in the modelling process helps to determine the level of model detail and can provide insight into what components of the proposed model are likely to have the greatest impact on the model behaviour. Furthermore, expert involvement increases model validity, credibility and the likelihood of implementation. Sadly, the involvement of the problem owner and domain experts in the modelling process of this research is not considered satisfaction able, partly due to the long research delay as elaborated on in the reflection. It is recommended to problem owner to fully utilize the domain knowledge in an additional model validation with additional involvement of domain experts.

Cross comparison SD model. This research provides a first glance of conflicting insights created by the SD and DES model. After further research increased insights towards the applied queue mechanism and priority categories, and if the credibility of the DES model is increased by domain experts, a cross comparison is recommended to evaluate the validity of the SD model. It is recommended to evaluate both the steady state and the transient behaviour of the DES and SD model.

Care set assumption. The impact of the care set assumption, which assumes that a child's trajectories arriving in the same calendar month belong to the same care set and there for arrive at the same moment in the DES model can be tested. For example by comparing the outputs with a model initialized with the assumption trajectories arriving in the same week belong to a common care set.

10.4 Reflection

Simulation projects can consume much more time than typically presumed, in fact it has been observed that many simulation projects take at least twice as long as originally estimated (Benneyan 1994). That certainly holds true for this research, initiated as a four month EPA graduation project the total span of this project turned out to more than 1.5 year. In this section the author reflects on the causes of this delay and the lesson he learned throughout the long process.

"There are some serious misunderstandings concerning the nature of simulation and its ease of employment. The truth of the matter is that there's no such thing as "simple simulation" (Keller, Harrel et al. 1991)

Looking backwards, the author did not realize the full complexity entwined with simulation modelling. While the author, with a mechanical engineering background, had previous experience with process oriented flow chart modelling in ARENA, the author was inexperienced in modelling with other conceptual views and the concept of object orientation. The process of learning these methodologies while applying them on the complex youth care system was a time consuming challenge. Furthermore, the unavailability of the Any Logic software made it difficult to transform the extensive simulation literature into practical understanding of the subject.

The complexity of the data study, which involved capturing the returning children flows and the parallel, overlapping and sequential trajectories of those children, formed a large barrier in the preceding of this research. This barrier was overcome after one year of struggling thanks to the insights Alexander Verbraeck provided. The required AnyLogic software license became available at the start of November 2010. From that moment all the pieces of available literature, conceptual methodologies and the data study came together and the process of model building was like a walk in the park.

"Building a model may be the easiest part of the process; addressing the technical concerns of simulation, designing a valid simulation experiment, and conducting a rigorous analysis of the results remain sophisticated endeavours" (Benneyan 1994).

A number of interesting challenges occurred during the model validation. The author learned that simulation in a real world context imposes larger challenges than in an educational context. The availability of a large amount of data does not necessarily make it possible to quantify all parameters. The consequence of losing the critical pad at the start of the research resulted in the withdrawal of the problem owner's involvement and trust before the first model was build. The verification and validation was therefore a process of the modeller in isolation. Furthermore, the access to domain experts and additional data in the validation and verification process was hampered.

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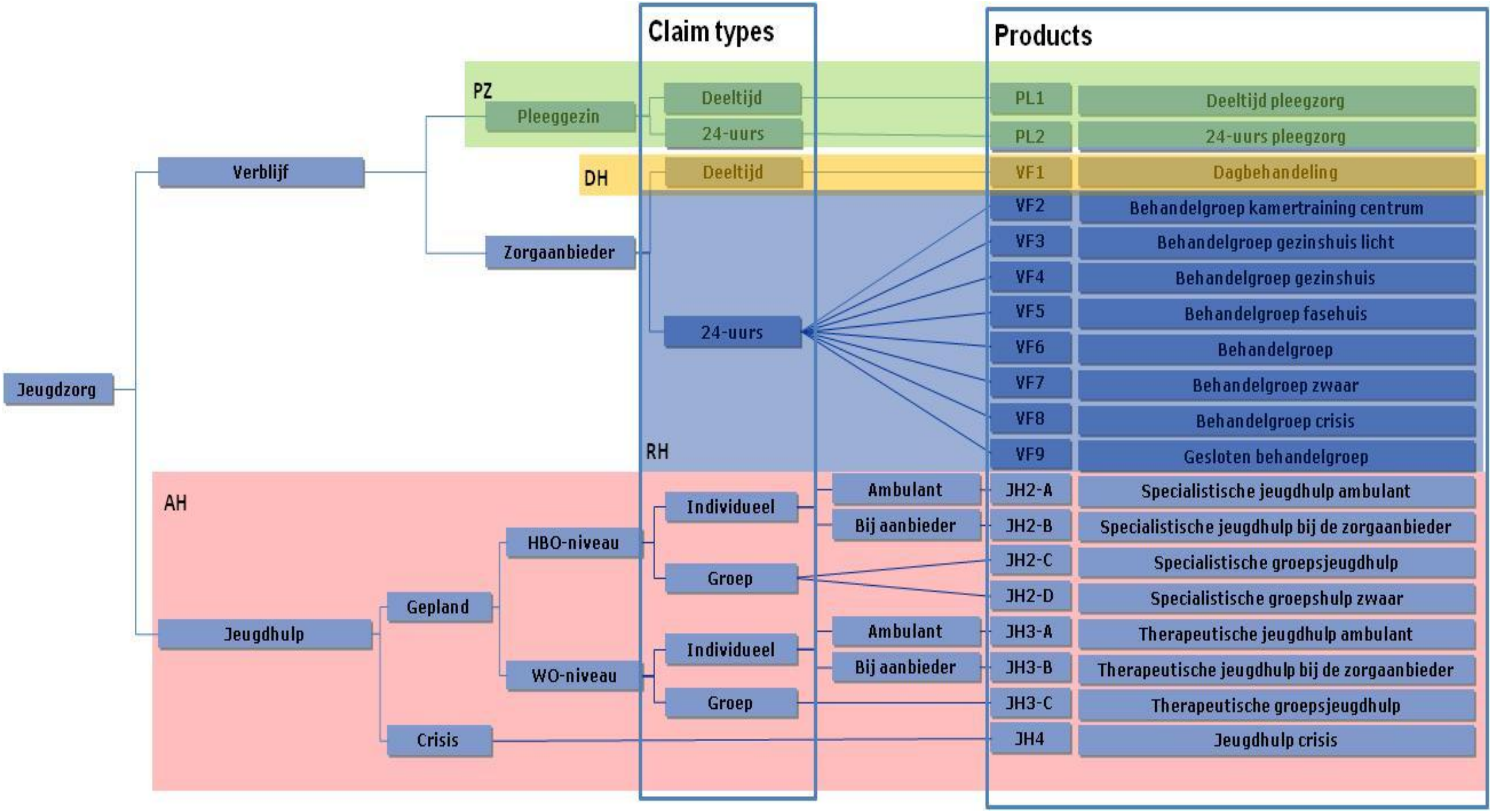
Appendix

Appendix A
Taxonomy of youth care service



Appendix B
System dynamics Model(confidential)

Confidential Appendix

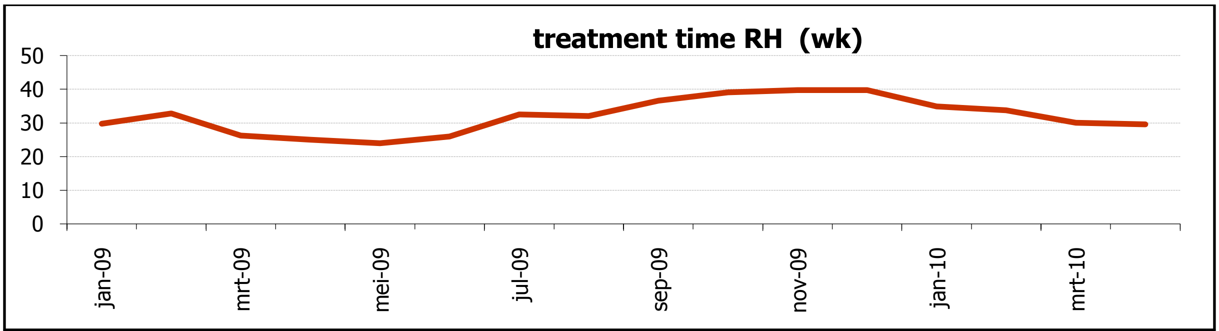
Appendix C
Data study : Variance Heterogeneity & conditionality

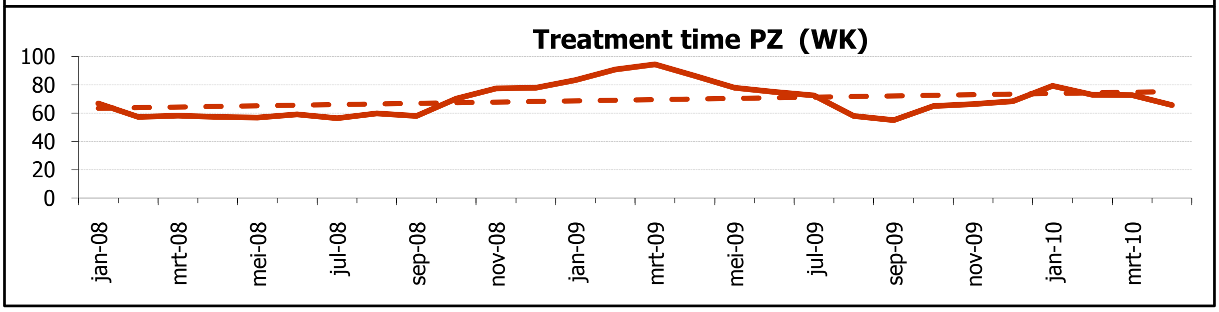
C.1 Care provider treatment times

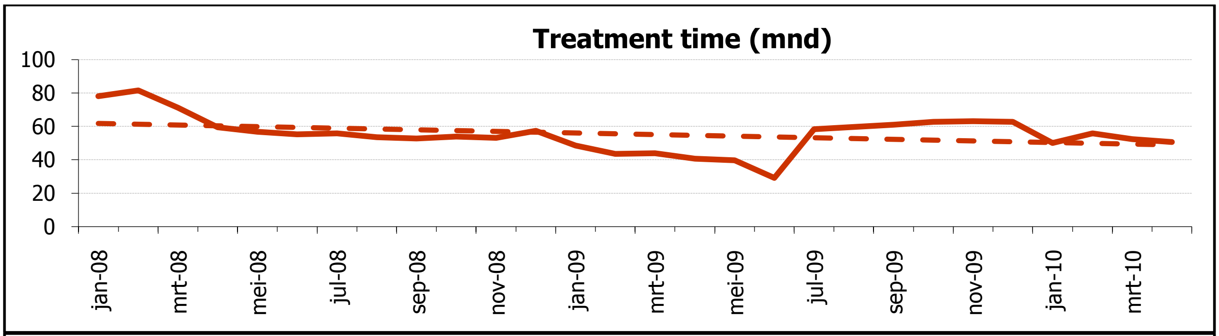
Observed treatment time in months over 2008 and 2009, categorized to their care type.

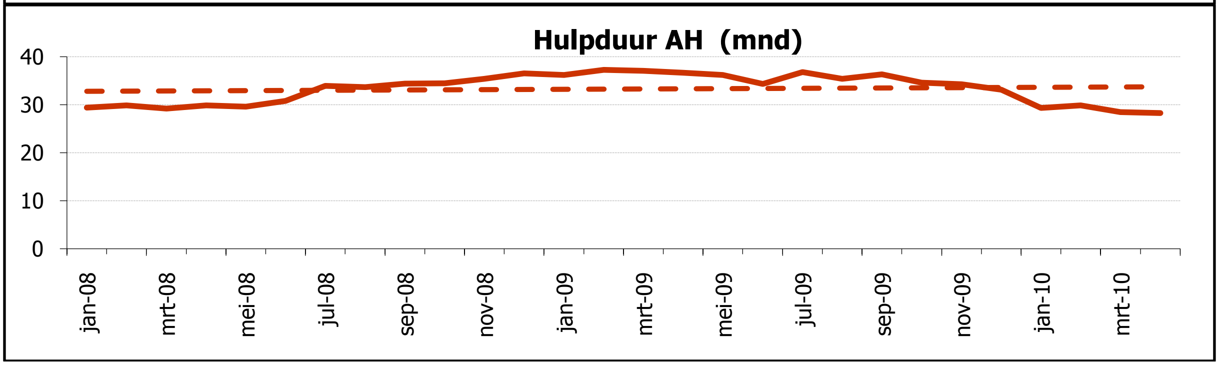
Treatment time in months

Statistics		AH	DH	PZ	RH
n		4445	232	428	615
Mean		7,7533	12,5125	16,3118	7,6284
95% Confidence Interval for Mean	Lower Bound	7,4995	11,393	13,7285	6,7378
	Upper Bound	8,0072	13,632	18,8951	8,519
5% Trimmed Mean		6,6378	11,9796	11,8692	6,072
Median		4,7333	11,1167	5,2667	2,4
Variance		74,525	74,895	739,32	126,484
Std. Deviation		8,6328	8,65421	27,19044	11,24651
Minimum		0,03	0,03	0,1	0,03
Maximum		81,33	41,1	165,3	72,97
Range		81,3	41,07	165,2	72,93
Interquartile Range		8,17	12,23	14,6	10,6
Skewness		2,442	0,801	2,944	2,252
Kurtosis		8,462	0,271	9,672	5,976

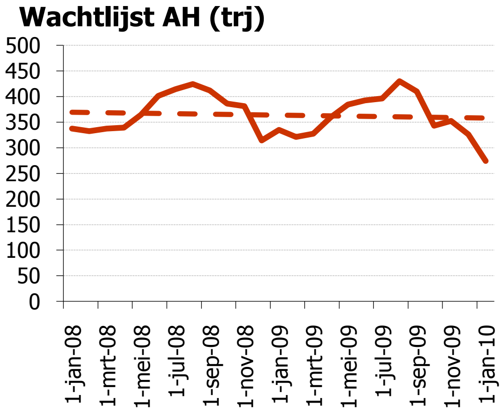


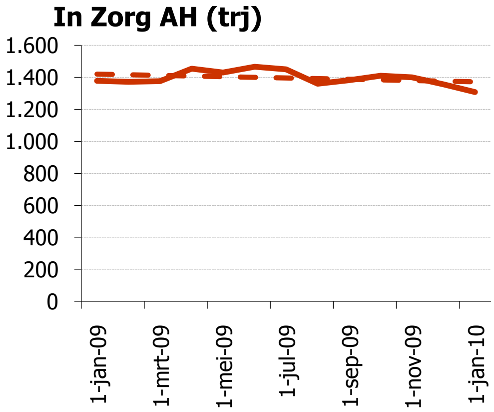


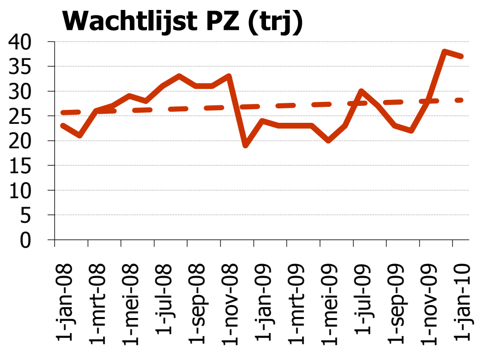


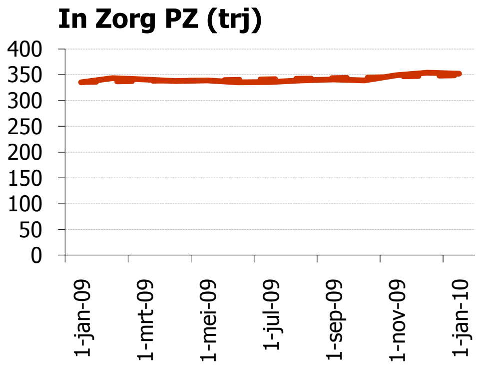


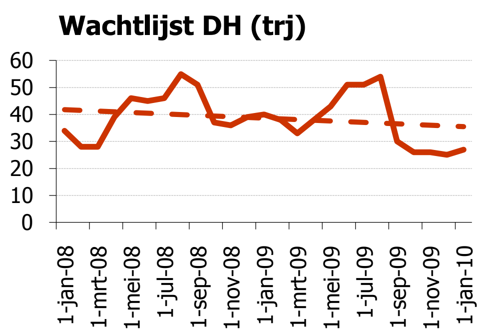
C.2 Behavioural graphs trajectory waiting lists and incare

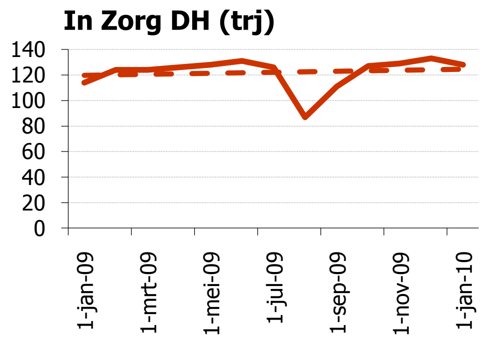


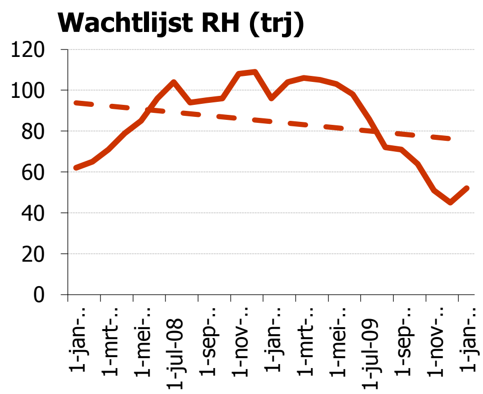


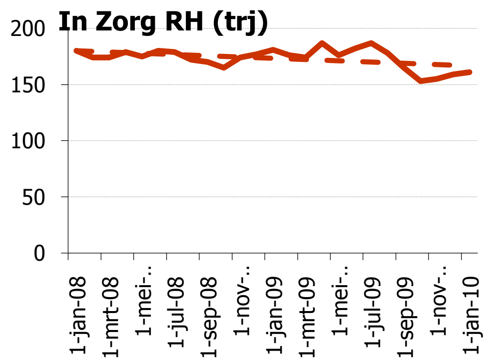












C.3 Differences in number of trajectories per care set for new and returning children.

TEST FOR EQUAL VARIANCES

F-test: for equal variances

	Variable 1	*Variable 2*
Average	1,846385542	1,20902256
Variance	0,483916571	0,22565217
Sample Size	996	1330
degrees of freedom	995	1329
F	2,144524372	
P(F<=f) one tailed	1,18718E-38	
Critical area One tailed	1,102040322	

T-TEST DIFFERENCE IN TRAJECTORIES A CARE SET

T-test: two samples with unequal variances

	Variable 1	*Variable 2*
Average	1,846385542	1,20902256
Variance	0,483916571	0,22565217
Sample size	996	1330
Difference in average	0	
Degrees of freedom	1660	
T- statistics	24,89389046	
P(T<=t) one tailed	8,3801E-117	
Critic area T-test: one tailed	1,645772076	
P(T<=t) two tailed	1,676E-116	
Critical are T-test: two tailed	1,961394039	

C.4 Chi square tests parallel relations

Cross tabulation and chi-square test parallel relations in care sets.

	counted	PH			expected	PH		
		yes	no	total	0	yes	no	total
	yes	4	113	117	yes	11,74699	105,253	117
RH	No	96	783	879	No	88,25301	790,747	879
	total	100	896	996	total	100	896	996

square P(X^2>=x^2) 0,011188152 < α=0,05

	counted	D			expected			
		yes	no	total	0	yes	no	total
	yes	4	113	117	yes	9,51506	107,4849	117
RH	No	77	802	879	No	71,48494	807,5151	879
	total	81	915	996	total	81	915	996

square P(X^2>=x^2) 0,047074167 < α=0,05

	counted	Pz			expected			
		yes	no	total	0	yes	no	total
	yes	0	81	81	yes	8,13253	72,86747	81
DH	No	100	815	915	No	91,86747	823,1325	915
	total	100	896	996	total	100	896	996

square P(X^2>=x^2) 0,001707151 < α=0,05

	counted	DH			expected			
		yes	no	total	0	yes	no	total
	yes	68	842	910	yes	74,00602	835,994	910
AH	No	13	73	86	No	6,993976	79,00602	86
	total	81	915	996	total	81	915	996

Chi square P(X^2>=x^2) 0,013180072 < α=0,05

	counted	PZ			expected			
		yes	no	total	0	yes	no	total
	yes	48	862	910	yes	91,36546	818,6345	910
AH	No	52	34	86	No	8,634538	77,36546	86
	total	100	896	996	total	100	896	996

Chi square P(X^2>=x^2) 1,40723E-59 < α=0,05

	counted	RH			expected			
		yes	no	total	0	yes	no	total
	yes	96	814	910	yes	106,8976	803,1024	910
A	No	21	65	86	No	10,10241	75,89759	86
	total	117	879	996	total	117	879	996

Chi square P(X^2>=x^2) 0,000134412 < α=0,05

APPENDIX C.4-1 CHI SQUARE TEST FIRST ARRIVAL

	counted	Pz			expected	PZ		
		yes	no	total	0	yes	no	total
RH	yes	5	190	195	yes	22,87218	172,1278	195
	No	151	984	1135	No	133,1278	1001,872	1135
	total	156	1174	1330	total	156	1174	1330

Chi square P(X^2>=x^2) 1,66461E-05 < α=0,05

	counted	D			expected			
		yes	no	total	0	yes	no	total
	yes	1	194	195	yes	9,969925	185,0301	195
R	No	67	1068	1135	No	58,03008	1076,97	1135
	total	68	1262	1330	total	68	1262	1330

Chi square P(X^2>=x^2) 0,001594319 < α=0,05

	counted	P			expected			
		yes	no	total	0	yes	no	total
	yes	2	68	68	yes	7,97594	60,02406	68
D	No	154	1106	1262	No	148,0241	1113,976	1262
	total	156	1174	1330	total	156	1174	1330

Chi square P(X^2>=x^2) 0,015704631 < α=0,05

	counted	D			expected			
		yes	no	total	0	yes	no	total
	yes	20	985	1005	yes	51,38346	953,6165	1005
A	No	48	277	325	No	16,61654	308,3835	325
	total	68	1262	1330	total	68	1262	1330

Chi square P(X^2>=x^2) 9,70467E-20 < α=0,05

	counted	P			expected			
		yes	no	total	0	yes	no	total
	yes	21	984	1005	yes	117,8797	887,1203	1005
	No	135	190	325	No	38,1203	286,8797	325
A	total	156	1174	1330	total	156	1174	1330

Chi square P(X^2>=x^2) 2,89602E-82 < α=0,05

	counted	R			expected			
		yes	no	total	0	yes	no	total
	yes	47	958	1005	yes	88,40977	916,5902	1005
	No	70	255	325	No	28,59023	296,4098	325
A	total	117	1213	1330	total	117	1213	1330

Chi square P(X^2>=x^2) 1,06935E-20 < α=0,05

APPENDIX C.4-2 CHI SQUARE TEST RETURNING CHILDREN

C.5 Layered sequential contingency table main care type

The cross tabulation presents the relations between the occurrence of youth care in the previous care set and the accommodation care type of the sequencing care set, controlled for the previously found influence of the accommodation care type in the previous care set.

APPENDIX C.5-1 CROSSTABULATION SEQUENTIAL RELATIONS ACCOMMODATION TYPE

N_youth assistence * N_accommodation * N+1_accommodation Crosstabulation

N_Accomodation service				N+1_accommodation service None	DH	PZ	RH	Total
None	N_ Youth Assistance	yes	Count	841	62	56	126	1085
			Expected Count	841,0	62,0	56,0	126,0	1085,0
			% within N0_supportcat	77,5%	5,7%	5,2%	11,6%	100,0%
	Total		Count	841	62	56	126	1085
			Expected Count	841,0	62,0	56,0	126,0	1085,0
			% within N0_supportcat	77,5%	5,7%	5,2%	11,6%	100,0%
DH	N_ Youth Assistance	no	Count	44	6	3	6	59
			Expected Count	49,4	3,6	2,0	4,0	59,0
			% within N0_supportcat	74,6%	10,2%	5,1%	10,2%	100,0%
		yes	Count	105	5	3	6	119
			Expected Count	99,6	7,4	4,0	8,0	119,0
			% within N0_supportcat	88,2%	4,2%	2,5%	5,0%	100,0%
	Total		Count	149	11	6	12	178
			Expected Count	149,0	11,0	6,0	12,0	178,0
			% within N0_supportcat	83,7%	6,2%	3,4%	6,7%	100,0%
PZ	N_ Youth Assistance	no	Count	48	4	85	26	163
			Expected Count	41,6	5,4	85,2	30,9	163,0
			% within N0_supportcat	29,4%	2,5%	52,1%	16,0%	100,0%
		yes	Count	14	4	42	20	80
			Expected Count	20,4	2,6	41,8	15,1	80,0
			% within N0_supportcat	17,5%	5,0%	52,5%	25,0%	100,0%
	Total		Count	62	8	127	46	243
			Expected Count	62,0	8,0	127,0	46,0	243,0
			% within N0_supportcat	25,5%	3,3%	52,3%	18,9%	100,0%
RH	N_ Youth Assistance	no	Count	81	5	14	74	174
			Expected Count	94,7	7,4	14,4	57,5	174,0
			% within N0_supportcat	46,6%	2,9%	8,0%	42,5%	100,0%
		yes	Count	110	10	15	42	177
			Expected Count	96,3	7,6	14,6	58,5	177,0
			% within N0_supportcat	62,1%	5,6%	8,5%	23,7%	100,0%
	Total		Count	191	15	29	116	351

C.6 Sequential and parallel relations return youth assistance

Case Processing Summary

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
Youth assistence N * youth assistence N+1 * Accommodation service N+1.	1857	100,0%	0	,0%	1857	100,0%

APPENDIX C.6-1 CROSSTABULATION SEQUENTIAL AND PARRALEL RELATIONS YOUTH ASSISTANCE

Youth assistance N * youth assistance N+1 * Accommodation service N+1. Crosstabulation

Accommodation service N+1.				youth assistance N+1 NO	youth assistance N+1 yes	Total
DH	Youth assistance N	NO	Count	75	31	106
			Expected Count	77,7	28,3	106,0
			% within Youth assistance N	70,8%	29,2%	100,0%
			% within youth assistance N+1	34,1%	38,8%	35,3%
		yes	Count	145	49	194
			Expected Count	142,3	51,7	194,0
			% within Youth assistance N	74,7%	25,3%	100,0%
			% within youth assistance N+1	65,9%	61,3%	64,7%
	Total		Count	220	80	300
			Expected Count	220,0	80,0	300,0
			% within Youth assistance N	73,3%	26,7%	100,0%
			% within youth assistance N+1	100,0%	100,0%	100,0%
NO	Youth assistance N	NO	Count		173	173
			Expected Count		173,0	173,0
			% within Youth assistance N		100,0%	100,0%
			% within youth assistance N+1		13,9%	13,9%
		yes	Count		1070	1070
			Expected Count		1070,0	1070,0
			% within Youth assistance N		100,0%	100,0%
			% within youth assistance N+1		86,1%	86,1%
	Total		Count		1243	1243
			Expected Count		1243,0	1243,0
			% within Youth assistance N		100,0%	100,0%
			% within youth assistance N+1		100,0%	100,0%
PZ	Youth assistance N	NO	Count	97	5	102

			Expected Count	89,8	12,2	102,0
			% within Youth assistance N	95,1%	4,9%	100,0%
			% within youth assistance N+1	50,5%	19,2%	46,8%
		yes	Count	95	21	116
			Expected Count	102,2	13,8	116,0
			% within Youth assistance N	81,9%	18,1%	100,0%
			% within youth assistance N+1	49,5%	80,8%	53,2%
	Total		Count	192	26	218
			Expected Count	192,0	26,0	218,0
			% within Youth assistance N	88,1%	11,9%	100,0%
			% within youth assistance N+1	100,0%	100,0%	100,0%
RH	Youth assistance N	NO	Count	10	5	15
			Expected Count	10,2	4,8	15,0
			% within Youth assistance N	66,7%	33,3%	100,0%
			% within youth assistance N+1	15,4%	16,1%	15,6%
		yes	Count	55	26	81
			Expected Count	54,8	26,2	81,0
			% within Youth assistance N	67,9%	32,1%	100,0%
			% within youth assistance N+1	84,6%	83,9%	84,4%
	Total		Count	65	31	96
			Expected Count	65,0	31,0	96,0
			% within Youth assistance N	67,7%	32,3%	100,0%
			% within youth assistance N+1	100,0%	100,0%	100,0%

APPENDIX C.6-2 PEARSON CHI-SQURE TEST

Chi-Square Tests

Accommodation service N+1.		Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
DH	Pearson Chi-Square	,557[a]	1	,455		
	Continuity Correction[b]	,372	1	,542		
	Likelihood Ratio	,553	1	,457		
	Fisher's Exact Test				,496	,270
	N of Valid Cases	300				
None	Pearson Chi-Square	.[c]				
	N of Valid Cases	1243				
PZ	Pearson Chi-Square	9,005[d]	1	,003		
	Continuity Correction[b]	7,792	1	,005		
	Likelihood Ratio	9,708	1	,002		
	Fisher's Exact Test				,003	,002
	N of Valid Cases	218				
RH	Pearson Chi-Square	,009[e]	1	,925		
	Continuity Correction[b]	,000	1	1,000		
	Likelihood Ratio	,009	1	,925		
	Fisher's Exact Test				1,000	,572
	N of Valid Cases	96				

a. 0 cells (,0%) have expected count less than 5. The minimum expected count is 28,27.

b. Computed only for a 2x2 table

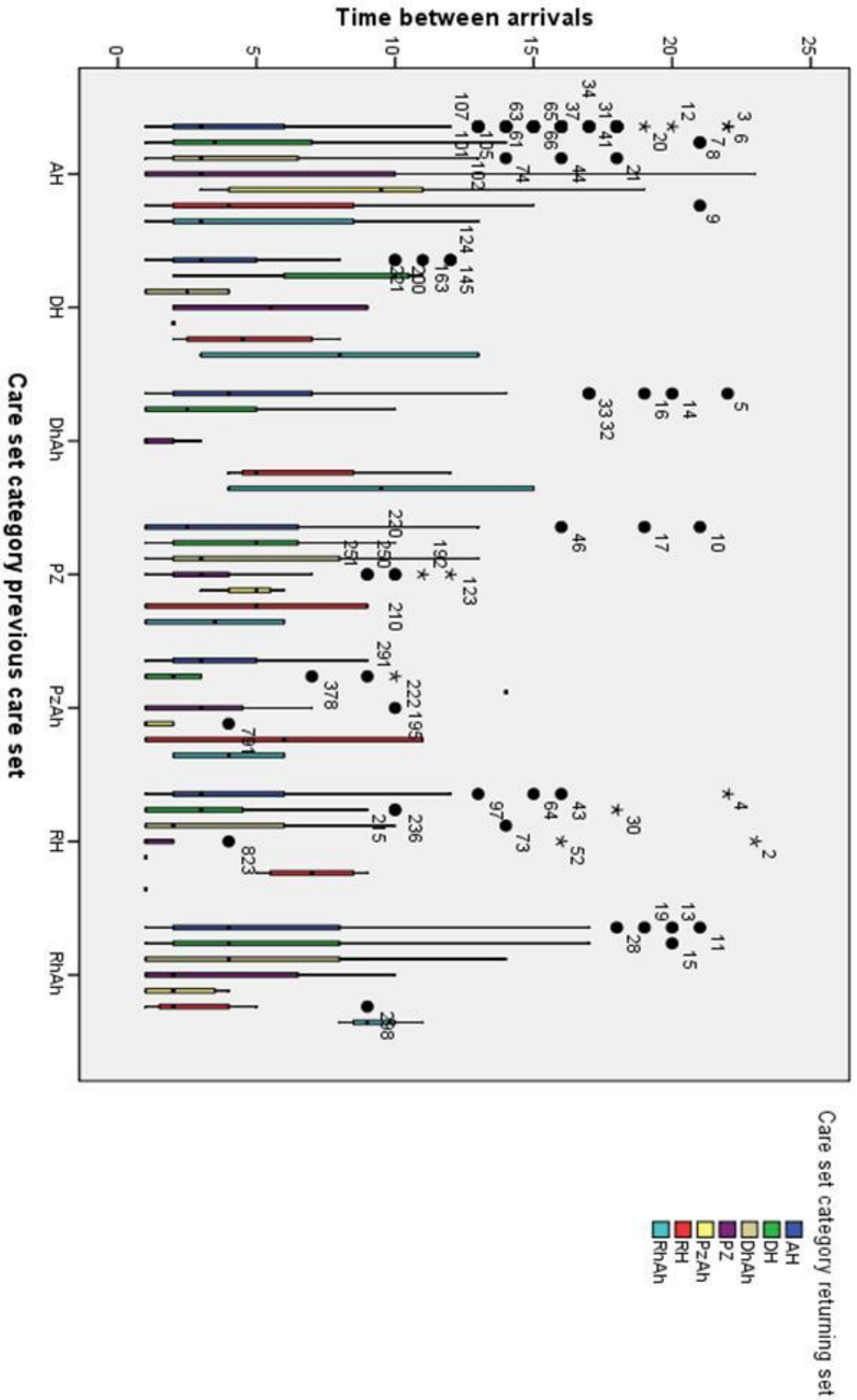
c. No statistics are computed because youth assistence N+1 is a constant.

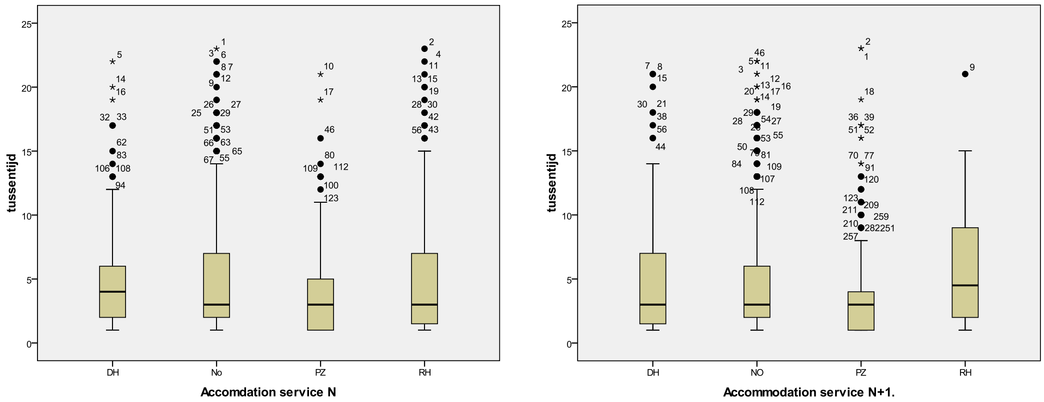
d. 0 cells (,0%) have expected count less than 5. The minimum expected count is 12,17.

e. 1 cells (25,0%) have expected count less than 5. The minimum expected count is 4,84.

C.7 Dependency relations return time

APPENDIX C.7-1 BOXPLOT RETURN TIME IN MONTHS DIFFERENT CATEGORIES





APPENDIX C.7-2 BOXPLOT RETURN TIME CATEGORIZED TO PREVIOUS AND RETURN ACCOMMODATION CARE TYPE

C.7.1 Relation 1 : The influence of accommodation care type in care set N on the time between arrivals

Descriptive Statistics

	N	Mean	Std. Deviation	Minimum	Maximum
Time between arrivalsets	1857	4,66	4,132	1	23
residence0cat	1857	,9246	1,21091	,00	3,00

APPENDIX C.7-3 DESCRIPTIVE STATISTICS CATEGORIES RELATION 1

Test of Homogeneity of Variances

Time between arrival sets

Levene Statistic	df1	df2	Sig.
7,830	3	1853	,000

APPENDIX C.7-4 HOMOGENEITY OF VARIANCES TEST

Ranks

	residence0cat	N	Mean Rank
Time between arrivalsets	,00	1085	941,98
	1,00	178	994,36
	2,00	243	838,89
	3,00	351	918,11
	Total	1857	

Test Statistics[a,b]

	Time between arrivalsets
Chi-Square	10,516
df	3
Asymp. Sig.	,015

a. Kruskal Wallis Test

b. Grouping Variable: residence0cat

APPENDIX C.7-5 KRUSKAL-WALLIS TEST RETURN TIME RELATION 1

Multiple Comparisons

Time between arrivalsets

Tamhane

(I) residence0cat	(J) residence0cat	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
None	DH	-,281	,341	,958	-1,19	,62
	PZ	,914*	,248	,002	,26	1,57
	RH	-,048	,268	1,000	-,76	,66
DH	None	,281	,341	,958	-,62	1,19
	PZ	1,195*	,382	,011	,18	2,21
	RH	,233	,395	,992	-,81	1,28
PZ	None	-,914*	,248	,002	-1,57	-,26
	DH	-1,195*	,382	,011	-2,21	-,18
	RH	-,962*	,319	,016	-1,80	-,12
RH	None	,048	,268	1,000	-,66	,76
	DH	-,233	,395	,992	-1,28	,81
	PZ	,962*	,319	,016	,12	1,80

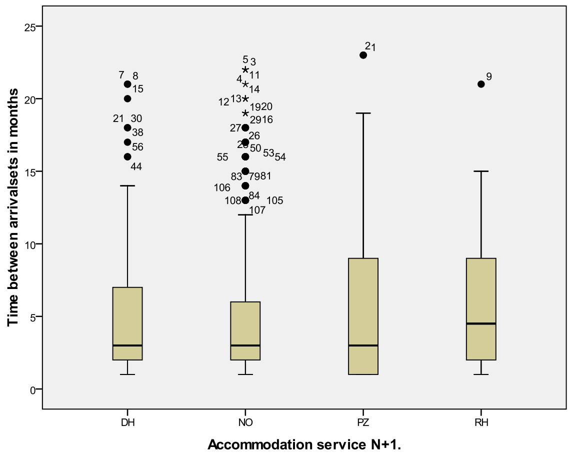
*. The mean difference is significant at the 0.05 level.

APPENDIX C.7-6 TAMHANA POST HOC TES

C.7.2 Relation 2: Influence of the accommodation type of the returning care set on the time between care set arrivals

H_1 : There is a relation between the accommodation type of the return care set and the time between care set arrivals.
H_0 : There is no relation between the accommodation type of the return care set and the time between care set arrivals.

Group1: first care set accommodation type no PZ



CATEGORIZED TO THE ACCOMODATION TYPE OF THE RETURN CARE SET ARRIVAL

Descriptives

Time between arrivalsets

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean Lower Bound	95% Confidence Interval for Mean Upper Bound	Minimum	Maximum
None	1181	4,67	4,086	,119	4,44	4,91	1	22
DH	254	4,76	4,231	,265	4,24	5,28	1	21
PZ	91	5,29	5,590	,586	4,12	6,45	1	23
RH	88	5,77	4,338	,462	4,85	6,69	1	21
Total	1614	4,78	4,226	,105	4,58	4,99	1	23

APPENDIX C.7-7 DESCRIPTIVE CATOGRIES RELATION 2 GROUP 1 NO PZ

Test of Homogeneity of Variances

Time between arrivalsets

Levene Statistic	df1	df2	Sig.
8,168	3	1610	,000

Ranks

	Acommodation n+1	N	Mean Rank
Time between arrivalsets	None	1181	803,93
	DH	254	797,45
	PZ	91	760,70
	RH	88	932,81
	Total	1614	

**APPE
NDIX C.7-8 HOMOGENEITY OF VARIANCES GROUP 1 NO PZ**

Test Statistics[a,b]

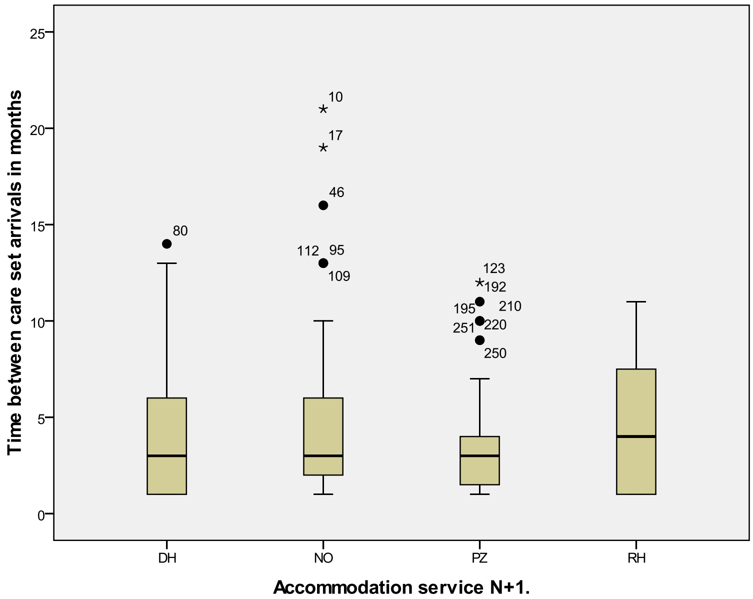
	Time between arrivalsets
Chi-Square	7,626
df	3
Asymp. Sig.	,054

a. Kruskal Wallis Test

b. Grouping Variable: Acommodation n+1

APPENDIX C.7-9 KRUSKALL WALLIS TEST GROUP 1 NO PZ

Group2: first care accommodation type PZ



Descriptives

Time between arrivalsets

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
None	62	4,60	4,543	,577	3,44	5,75	1	21
DH	46	4,15	3,445	,508	3,13	5,18	1	14
PZ	127	3,28	2,363	,210	2,87	3,70	1	12
RH	8	4,63	3,962	1,401	1,31	7,94	1	11
Total	243	3,83	3,334	,214	3,41	4,25	1	21

APPENDIX C.7-10 DESCRIPTIVE GROUP 2

Test of Homogeneity of Variances

Time between arrivalsets

Levene Statistic	df1	df2	Sig.
10,157	3	239	,000

APPENDIX C.7-11 HOMOGENEITY OF VARIANCES GROUP 2

Ranks

	Acommodation type return careset	N	Mean Rank
Time between arrivalsets	,00	62	127,93
	1,00	46	125,80
	2,00	127	117,35
	3,00	8	128,00
	Total	243	

Test Statistics[a,b]

	Time between arrivalsets
Chi-Square	1,231
df	3
Asymp. Sig.	,746

a. Kruskal Wallis Test

b. Grouping Variable: Acommodation type return care set

APPENDIX C.7-12 KRUSKAL WALLIS TEST GROUP 2

C.7.3 Relation 3: Relation 3 : Influence of youth assistance in the N care set on the time between care set arrivals

Group 1: Return time after care set with accommodation type not PZ
Group2 return time after care set with accommodation type PZ

The following hypothesis is separately tested for the two groups:
H_1 : There is a relation between the occurrence of youth assistance in the first care set and the time until a sequencing care set arrival.
H_0 : There is no relation between the occurrence of youth assistance in the first care set and the time until a sequencing care set arrival.

APPENDIX C.7-13 RELATION 3 :DESCRIPTIVE STATISTICS GROUP 1

Group Statistics

	Youth assistance first care set	N	Mean	Std. Deviation	Std. Error Mean
Time between arrival Sets in months	NO	396	4,23	3,771	,190
	yes	1461	4,77	4,218	,110

APPENDIX C.7-14 RELATION 3: DESCRIPTIVE STATISTICS GROUP 2

Group Statistics

	Youth assistance first care type	N	Mean	Std. Deviation	Std. Error Mean
Time between arrival sets in months	NO	163	4,08	3,552	,278
	yes	80	3,31	2,791	,312

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Time between arrivalsets	Equal variances assumed	3,253	,071	-1,750	1612	,080	-,523	,299	-1,110	,063
	Equal variances not assumed			-1,859	331,960	,064	-,523	,281	-1,077	,030

APPENDIX C.7-15 RELATION 3: T-TEST GROUP 2

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Time between arrivalsets	Equal variances assumed	2,648	,105	1,692	241	,092	,767	,453	-,126	1,660
	Equal variances not assumed			1,835	194,592	,068	,767	,418	-,057	1,592

C.7.4 Relation 4: Influence of youth assistance in the returning care set on the return time.

APPENDIX C.7-16 RELATION 4: GROUP STATISTICS GROUP 1

Group Statistics

	youth assistence N+1	N	Mean	Std. Deviation	Std. Error Mean
Time between arrivalsets	NO	314	5,06	4,668	,263
	yes	1300	4,72	4,111	,114

APPENDIX C.7-17 RELATION 4: T-TEST GROUP 1

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Time between arrivalsets	Equal variances assumed	8,674	,003	1,299	1612	,194	,345	,266	-,176	,866
	Equal variances not assumed			1,202	437,585	,230	,345	,287	-,219	,909

APPENDIX C.7-18 RELATION 4: GROUP STATISTICS GROUP2

Group Statistics

	youth assistence N+1	N	Mean	Std. Deviation	Std. Error Mean
Time between arrivalsets	NO	163	3,52	2,626	,206
	yes	80	4,46	4,395	,491

APPENDIX C.7-19 RELATION 4: T-TEST GROUP 2

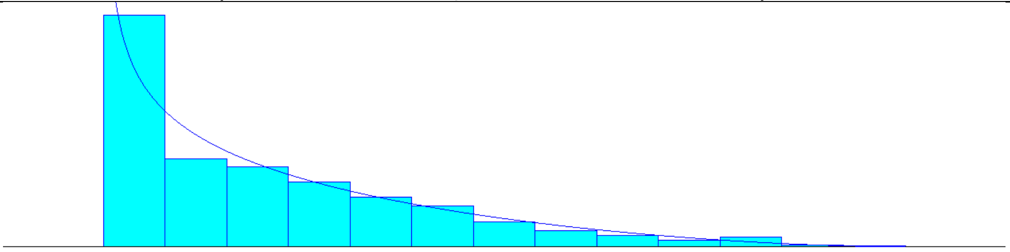
Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Time between arrivalsets	Equal variances assumed	17,623	,000	-2,095	241	,037	-,947	,452	-1,838	-,057
	Equal variances not assumed			-1,778	107,491	,078	-,947	,533	-2,003	,109

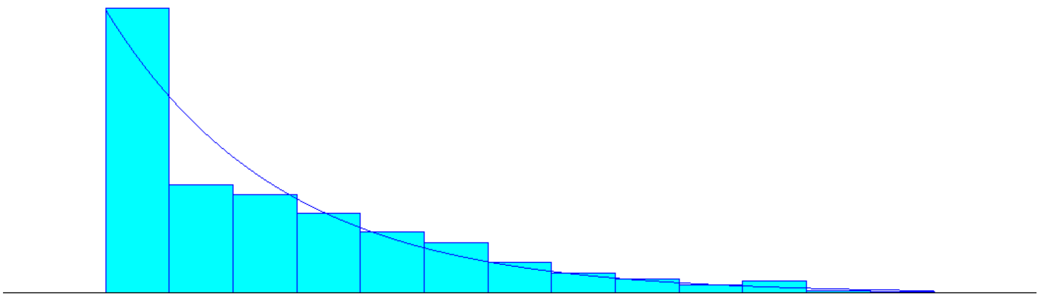
Appendix D
Input Data & Distributions

D.1 Amount of daily children arrivals: over 2008 and 2009

The daily amount of children arrivals is an important driver of the system behaviour and perceived to be the most important scenario variable. The fit between the empirical data over 2008 and 2009 and a multitude of theoretical distributions is analyzed with the Arena Input Analyzer. An exponential distribution is favourable, because the distribution is easy to adapt to different scenarios based on expected average value. The Arena Input Analyzer indicates that the bounded beta distribution is the best fit, both measured in square error and by the chi-square statistic. The chi-square test indicates that the beta distribution is not significantly different from the observed values until a maximum significance level of 0.0952. Unlike the beta distribution, the exponential distribution is significantly different taking into the account the significance level of 0.05%. Therefore, the base case model is initialized with the beta distribution. For both the beta and the exponential distribution, the relevant statistics are presented tables below.



Distribution Summary	Histogram Summary
Distribution: Beta Expression: -0.5 + 13 * BETA(0.701, 2.64)	Histogram Range = -0.5 to 12.5 Number of Intervals = 13
Square Error: 0.002565 Chi Square Test Number of intervals = 10 Degrees of freedom = 7 Test Statistic = 12.2 Corresponding p-value = 0.0952	Data Summary Number of Data Points = 744 Min Data Value = 0 Max Data Value = 12 Sample Mean = 2.23 Sample Std Dev = 2.54



Distribution Summary	Histogram Summary
Distribution: Exponential Expression: -0.5 + EXPO(2.73) Square Error: 0.009959	Histogram Range = -0.5 to 12.5 Number of Intervals = 13
Chi Square Test Number of intervals = 10 Degrees of freedom = 8 Test Statistic = 38.5 Corresponding p-value < 0.005	Data Summary Number of Data Points = 744 Min Data Value = 0 Max Data Value = 12 Sample Mean = 2.23 Sample Std Dev = 2.54

D.2 Optimization: Number of care sets a child

As concluded in section 6.5, the available data sources do not allow an accurate determination of the number of care sets assigned to children and the conditionality relations, which influence this factor. An optimization experiment is performed, which optimizes the minimum error of the experienced average trajectory demand at the different care providers, as a function of the parameters of the chosen distribution.

D.2.1 Implicated optimization and model structure assumptions

The optimization experiment optimizes the process which transforms the child demand behaviour into the trajectory demand at the different care systems.. Based on the analysis of observed demand behaviour, the optimization experiment assumes that the average children and trajectory demand is constant. The observed behaviour is assumed to arise from system variability, not due to changes in arrival patterns or care set relation.

Assumption dependency relation
The dependency relations found in chapter 6, indicate a clear dependency of all factors on the accommodation care type of a care set. The assumption is made that the chance of return after a care set is dependent on the accommodation of this care set.

Structure and distribution choice
First, a choice has to be made concerning the model structure and as a result of this structure the distribution to optimize. In general, two possible alternative model structures are explored:

1. A model structure in which a distribution is drawn to directly determine a child's number of care sets
2. A model structure in which after every care set drawing a binominal distribution is drawn to decide whether the child returns.

The first model structure does not allow modelling dependency relations between the composition of each care set and the chance of return after this care set. Only the dependency between the composition of the first care set and the amount of returns can be incorporated. The second structure on the other allows modelling the dependency between the composition of each care set and the return chance after this care set. Furthermore, the data limitations introduced in section 6.5 make it impossible to determine the shape and boundaries of the distribution, which needs to be embedded in the first structure. The binominal distribution on the other hand, only has one input parameter the probability.

Another practical, but convincing, argument to choose the second structure, is that optimizing the distributions in the first structure will require an optimization with at least 2 variables for each depend distribution. Taking the assumed dependency relation with the four accommodation type into account, an optimization of four distributions results in a minimal of 8 independent optimization variables. The Any Logic University License supports optimization with a maximum of 5 variables. Each binominal distribution requires one input parameter, which results in a optimization with 4 variables. Based on those considerations the second structure is implemented in the simulation model.

D.2.2 Objective function

The goal of the optimization experiment is to find the probability parameter inputs of the binominal distribution that results in a minimum of a function called the objective function. The objective function is a mathematical expression, which describes a relationship of the optimization parameters or the results of an operation that use the optimization parameters as inputs. The objective of the optimization experiment is to find the return probabilities, which results in a simulated trajectory which is equal to the in the real world observed trajectory arrival pattern.

The objective function is based on the student T-test for unequal variances, which compares the dataset of simulated monthly averages with the monthly averages observed in the real world for each care type. The following sub-function is determined for each care type.

Objective sub-function 1: $$T_{careType} = \frac{\mathrm{abs}(\overline{x_S} - \overline{x_O})}{\mathrm{s_D}}$$

The introduced sub-function calculates the student T-test statistics between the averages of monthly-observed trajectory arrivals in the simulation model and in the real world system. The standard deviation of both groups is unknown and assumed unequal. Therefore, the standard deviation of the differences is estimated with the following equation:

Standard deviation of the difference: $$S_D = \sqrt{\frac{{S_1}^2}{n_1} + \frac{{S_1}^2}{n_2}}$$

The objective is to minimize the objective sub-function for all care types. Furthermore, the total deviation needs to be divided equally over all care system, to assure the best system wide performance. Therefore, the following main objective function is minimalized during the optimization experiment:

Main objective function: $$Objective_{min} = \max(\, T_{ah}; T_{dh}\,; T_{rh}\,; T_{pz})$$

D.2.3 Experiment set-up

Run length: 400 months.
Iterations: 10.
Replications: 500

The optimization parameters are the probability of returns after a main care set of each care type. The variation range of the four parameters in chosen between 0.3 and 0.85.

D.2.4 Results

The optimization experiment indication that the optimal parameter values are:

APPENDIX D.2-1 INPUT PARAMETERS RETURN PROBABILITY

Accommodation type	**Return probability**
DH	0,436
PZ	0,772
RH	0,786
None (AH)	0,637

D.3 Input sheet care set relations

Care profile Input Sheet

Accommodation Care | **Youth Assistance**

First CareSet

FirstCareSetAccommodationCareTypeDistribution

AccommodationDependencyDimension

	DH	PZ	RH	NONE
frq.	81	100	130	698

FirstCareSetAccommodationAmountDistribution

AccomodationAmountDimension / *AccommodationDependencyDimension*

	DH	PZ	RH
one	79	98	105
two	2	2	9
three	0	0	2
four	0	0	1

firstCareSetYouthAssistanceDistribution

AmountDimension / *AccommodationDependencyDimension*

	DH	PZ	RH	NONE
zero	13	52	21	0
one	27	39	81	224
two	40	9	14	420
three	1	0	0	51
four	0	0	1	7

Return Care Set

nthAccommodationAmountDistribuiton

AccommodationDependencyDimension / *AccommodationDependencyDimension*

	DH	PZ	RH	None
DH	11	8	15	62
PZ	56	127	29	56
RH	12	46	116	126
None	149	62	191	841

nthCareSetYouthAssistanceDistribution

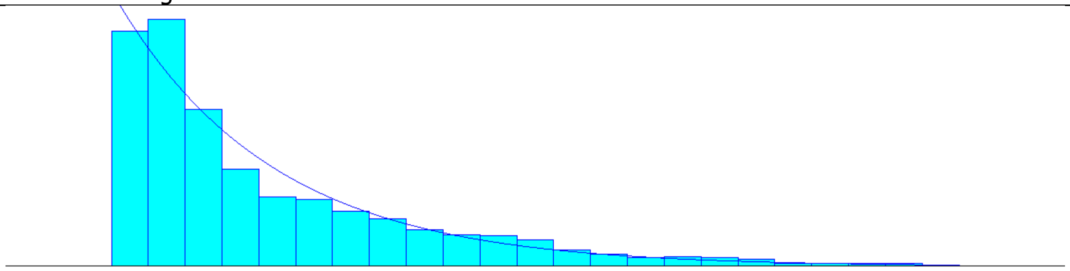
AmountDimension / *AccommodationDependencyDimension*

	DH	PZ	RH	None
zero	65	192	220	0
one	24	19	69	1065
two	6	6	11	162
three	1	1	0	13
four	0	0	0	3

D.4 Time between care set returns

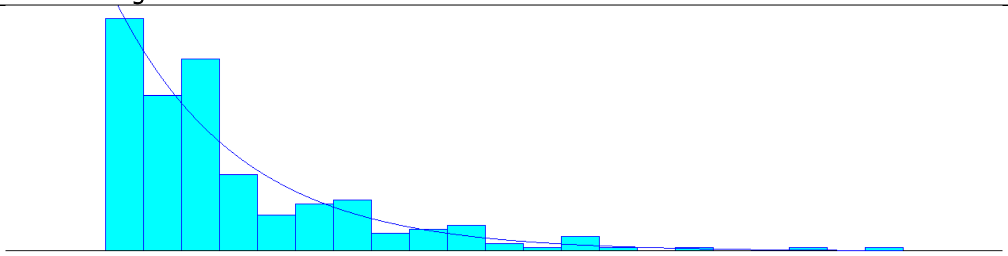
The time between care set returns faces the next data limitation. Each trajectory, which arrives in a common month, is perceived to belong to the same common care set. An analysis of the time between care set returns requires the grouping of trajectories to care sets, the arrival day of each trajectory is aggregated to the common care set arrival month. The time between those care sets can therefore, only be determined in months. In the simulation model the exact day of arrival needs to determined. The only found variable, with a significant influence on the return time, found in section 6.4 is the accommodation type of the previous care set. Furthermore, a post hoc test proved that the only significant difference is found between PZ and all accommodation care types. In conclusion, two separate distributions are necessary to model the returns after PZ and the other care sets. This section will first analyse the observed time between care set return distributions in months, followed by an explanation how these months are recalculated to days in the simulation model

The histogram of the return times observed in months, after a care set with accommodation type RH, DH or None is presented below. The square error indicates that the mean difference between the fitted exponential distribution and the observed return time are small. The chi-square indicates that there is a (large) significance difference between the fitted exponential function and the observed values. On the basis of this chi-square test, the return time after care sets with RH, DH, or no accommodation care type is implemented in the simulation model with an empirical distribution. The relevant descriptives are presented in the following table.



Distribution Summary		Histogram Summary	
Distribution:	Exponential	Histogram Range	= 0.5 to 23.5
Expression:	0.5 + EXPO(4.27)	Number of Intervals	= 23
Square Error:	0.003193		
Chi Square Test		**Data Summary**	
Number of intervals	= 18	Number of Data Points	= 1640
Degrees of freedom	= 16	Min Data Value	= 1
Test Statistic	= 52.6	Max Data Value	= 23
Corresponding p-value	< 0.005	Sample Mean	= 4.77
		Sample Std Dev	= 4.21

Histogram of the return time distribution in months after care sets with accommodation type PZ. The square error between the observed measures and the exponential function fitted is low. The chi-square test indicates that there is a significant error, taking into account significance level of 0.005. Based on the relatively low amount number of data points in relation to the intervals, the decision is made the implemented the exponential distribution in simulation model. The relevant descriptives are presented in the following table.



Distribution Summary		*Histogram Summary*	
Distribution:	Exponential	Histogram Range	= 0.5 to 21.5
Expression:	0.5 + EXPO(3.3)	Number of Intervals	= 21
Square Error:	0.008007		

Chi Square Test		*Data Summary*	
Number of intervals	= 9	Number of Data Points	= 247
Degrees of freedom	= 7	Min Data Value	= 1
Test Statistic	= 17.5	Max Data Value	= 21
Corresponding p-value	= 0.016	Sample Mean	= 3.8
		Sample Std Dev	= 3.32

From months between arrivals to days between arrivals.
Understanding the source of discard, which is the implemented definition of a care set, no alternative data sources can provide additional insight in the exact arrival day. To overcome this knowledge limitation, the simulation model uses the following procedure to recalculate the months between arrivals to the exact arrival day:

1) Draw the time between care set arrivals to determine the in between time in months.
2) Use the calendar function to determine the number days until the end of current month
3) Use the calendar function to determine the number of days of the entire months until next care set arrivals.
4) Use the calendar function to determine the amount of day the drawn proportion of the final months resembles.
5) Calculate the days between care set arrivals by summing the days determined at step 2, 3, 4.

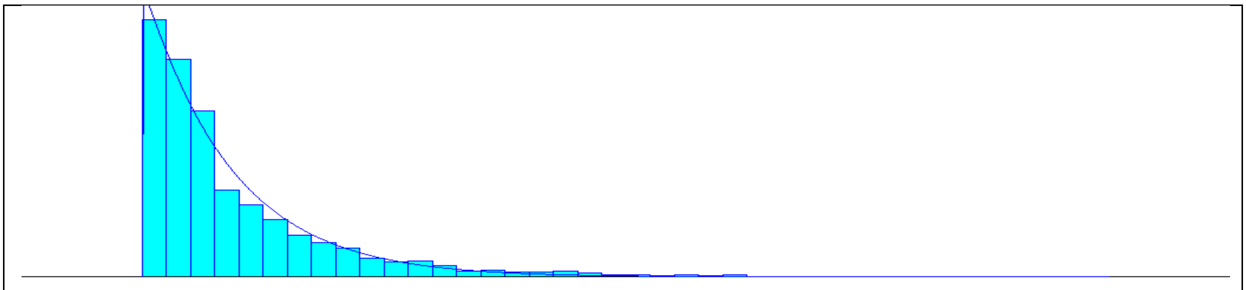
D.5 Treatment time distributions

The observed treatment times over 2008 and 2009, aggregated to their care types are analyzed in this section.

Ambulatory care

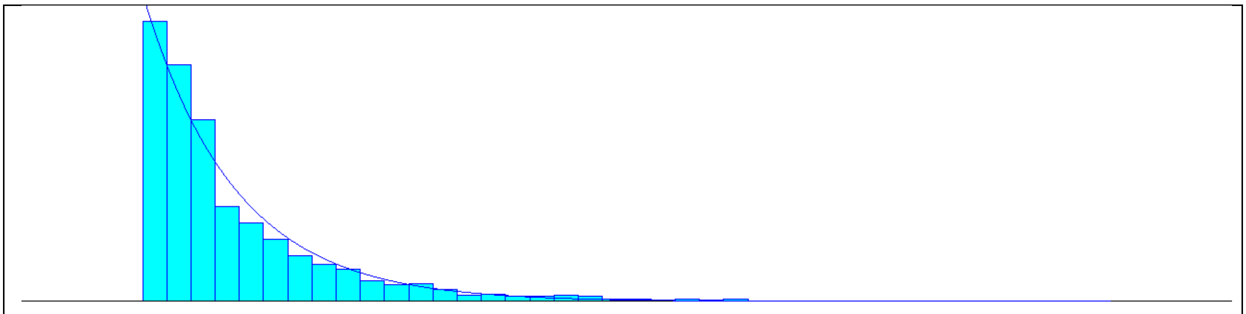
An analysis with the Arena Input Analyzer indicated that a weibull distribution was the best finding distribution followed by an exponential distribution. While the square error of both function where acceptable, the chi-square static shows that there is significant different between both distributions and the empirical data. Based on the significant differing theoretical distributions and the large data set, the empirical distribution is chosen as the best abstraction of the ambulatory treatment time distribution in the model.

The validation face showed that there was a significant between the outflow ambulatory trajectories in the real system and in the simulation, when using the empirical distribution. The outflow of trajectories was significantly lower than the observed outflow in the real system. The insight that the treatment is the only parameters of influence on the trajectory outflow, in the situation that the queue size is constantly higher than zero, provides an opportunity for a simple calibration experiment with the theoretical distributions. The objective of the calibration experiment is to minimize the difference between the monthly average outflow observed the simulation model and in the real system. The calibration experiments with the empirical distribution, the exponential distribution and the Weibull distribution indicated that the Weibull distribution resulted in a minimum objective function. A chi-square test found no significant difference between the outflow of treated trajectories, with the Weibull treatment time distribution. Based on these conclusion the Weibull treatment distribution is implemented in the simulation model.



Distribution Summary		*Histogram Summary*	
Distribution:	Weibull	Histogram Range	= 0.999 to 996
Expression:	0.999 + WEIB(219, 1.01)	Number of Intervals	= 40
Square Error:	0.001542		

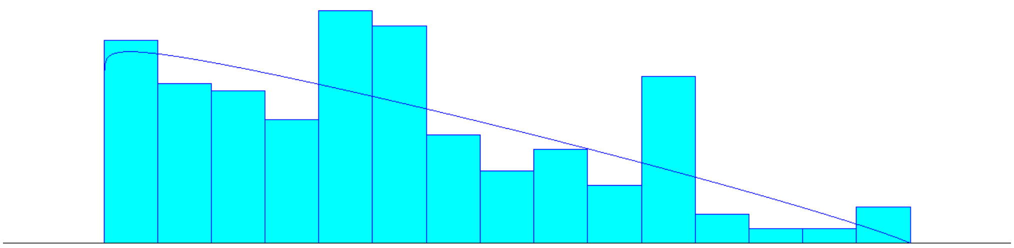
Chi Square Test	*Data* Summary
Number of intervals = 19	Number of Data Points = 4445
Degrees of freedom = 16	Min Data Value = 1
Test Statistic = 188	Max Data Value = 2.44e+003
Corresponding p-value < 0.005	Sample Mean = 233
	Sample Std Dev = 259



Distribution Summary	*Histogram Summary*
Distribution: Exponential	Histogram Range = 0.999 to 996
Expression: 0.999 + EXPO(232)	Number of Intervals = 40
Square Error: 0.002031	
Chi Square Test	*Data* Summary
Number of intervals = 21	Number of Data Points = 4445
Degrees of freedom = 19	Min Data Value = 1
Test Statistic = 154	Max Data Value = 2.44e+003
Corresponding p-value < 0.005	Sample Mean = 233
	Sample Std Dev = 259

Treatment Time DH

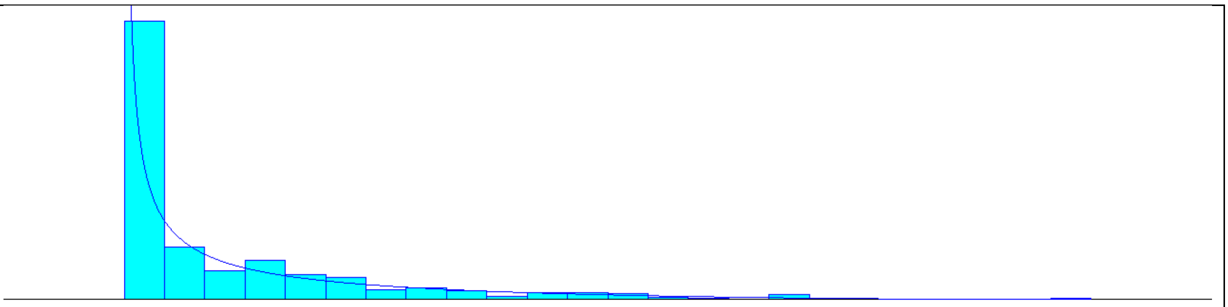
The shape of the observed day care treatment times distribution presents a clear indication that the observed distribution is not the result of one theoretical distribution. This hypothesis is tested by the Arena Input Analyzer, this analysis showed that the best fitting distribution is a beta distribution. The square error and the chi-square test statistic indicate that the beta distribution is significantly different than the distribution of the observed values. There for an empirical distribution is implemented in the simulation model. The relevant descriptive are presented in the following table.



Distribution Summary	*Histogram Summary*
Distribution: Beta	Histogram Range = 0.999 to 996
Expression: 0.999 + 995 * BETA(1.03, 1.9)	Number of Intervals = 15
Square Error: 0.010484	
Chi Square Test	*Data Summary*
Degrees of freedom = 9	Number of Data Points = 232
Test Statistic = 41.1	Min Data Value = 1
Corresponding p-value < 0.005	Max Data Value = 996
	Sample Mean = 351
	Sample Std Dev = 240

Treatment time RH

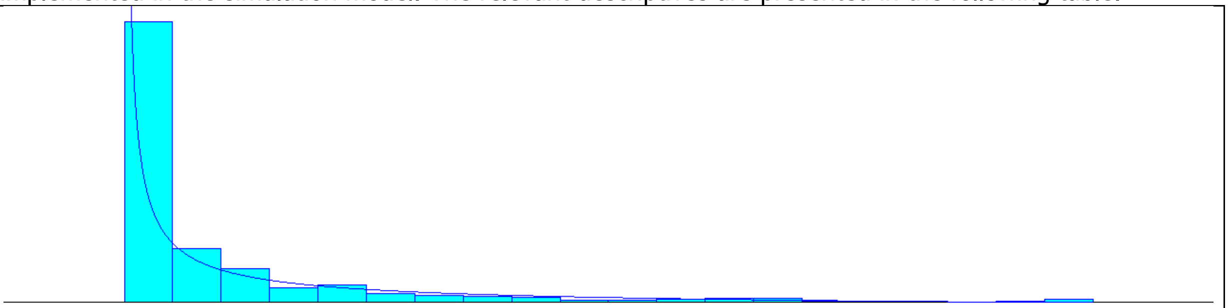
The shape of the residential treatment time is long tailed. The Arena Input Analyzer indicated that the best fitting distribution is a Beta distribution. The square error is acceptably low; the chi-square test indicates that the distribution is equal at a significance level of 0.0266. This indicates that the beta distribution is significantly different at the chosen significance level of 0.05. However, it becomes clear that the empirical values are not smoothed out yet, which could be a results of the relative view data points in combination with the long tail of the distribution. Based on this observations the decision has been made to implemented the beta distribution in the simulation model. The relevant descriptive are presented in the following table.



Distribution: Beta Expression: 0.999 + 2.19e+003 * BETA(0.304, 2.62) Square Error: 0.001366	*Histogram Summary* Histogram Range = 0.999 to 2.19e+03 Number of Intervals = 24
Chi Square Test Number of intervals = 12 Degrees of freedom = 9 Test Statistic = 18.9 Corresponding p-value = 0.0266	*Data Summary* Number of Data Points = 615 Min Data Value = 1 Max Data Value = 2.19e+003 Sample Mean = 229 Sample Std Dev = 337

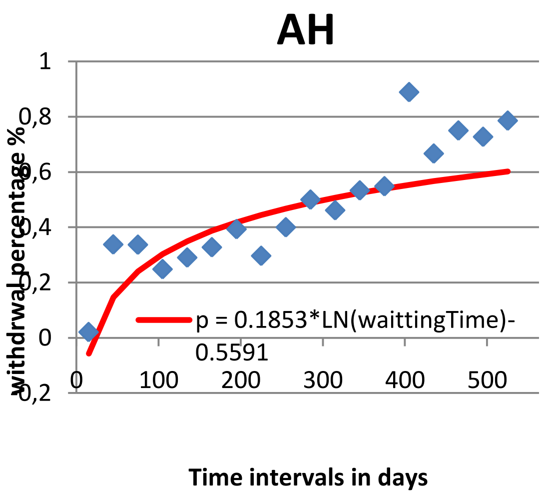
Treatment time PZ

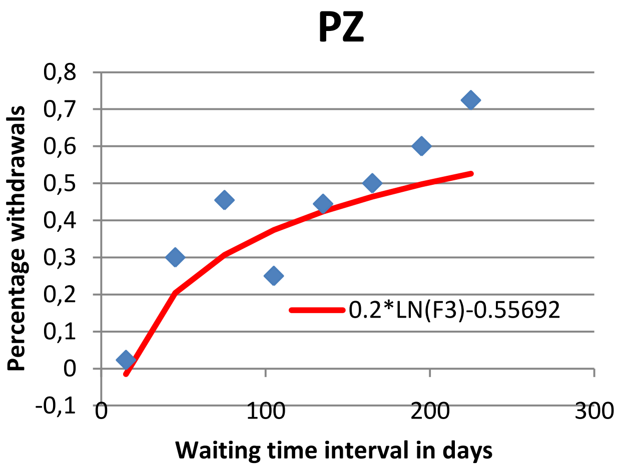
The Arena Input Analyzer indicates that the best fit based on the square error is an beta distribution. The square error is acceptably low, the chi square test indicates that there is no significant different between the fitted data distribution and the observed values. Based on those considerations, the beta distribution is implemented in the simulation model. The relevant descriptives are presented in the following table.

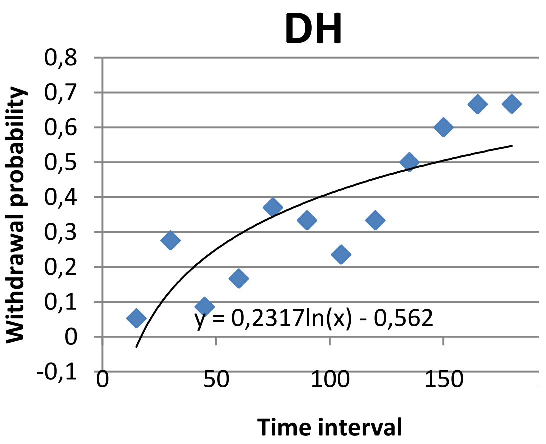


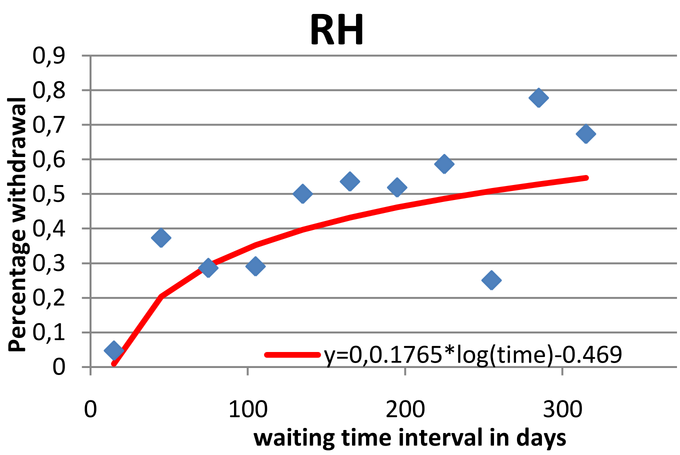
Distribution: Beta Expression: 3 + 4.96e+003 * BETA(0.222, 2.04) Square Error: 0.001535	Histogram Summary Histogram Range = 3 to 4.96e+003 Number of Intervals = 20
Chi Square Test Number of intervals = 9 Degrees of freedom = 6 Test Statistic = 9.41 Corresponding p-value = 0.166	*Data Summary* Number of Data Points = 428 Min Data Value = 3 Max Data Value = 4.96e+003 Sample Mean = 489 Sample Std Dev = 816

D.6 Withdrawal probability graphs


AH
withdrwal percentage %
Time intervals in days
p = 0.1853*LN(waittingTime)-0.5591


PZ
Percentage withdrawals
Waiting time interval in days
0.2*LN(F3)-0.55692


DH
Withdrawal probability
Time interval
y = 0,2317ln(x) - 0,562


RH
Percentage withdrawal
waiting time interval in days
y=0,0.1765*log(time)-0.469

D.7 Care capacity

The care capacity of the SD and DES model are based on the number of children, which can be treated parallel at the same moment of time. The quantification of this capacity is abstracted from the observed amount of children in care over the year 2008 and2009. The graphs of the waiting list and children in care dynamics are presented in Appedix The method to abstract the system capacity from the amount children in care is only valid when the constraining factor is the care capacity and not the care demand. The waiting list observed for each care type indicates that indeed over last years the capacity was the constraining factor for the amount children in care. Based on the rather constant amount children in care for each care type, the decision has been made to quantify the base case model with a constant capacity. The constant capacity chosen is the average observed amount children over 2008 and 2009.

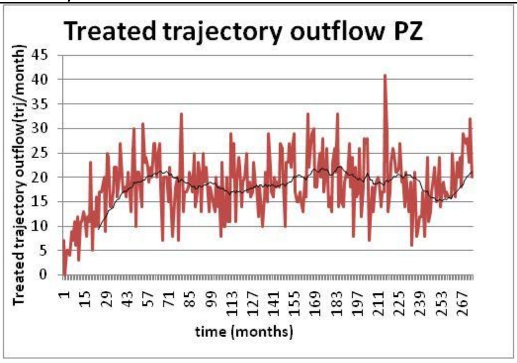
APPENDIX D.7-1 CAPACITY INPUT PARAMETERS

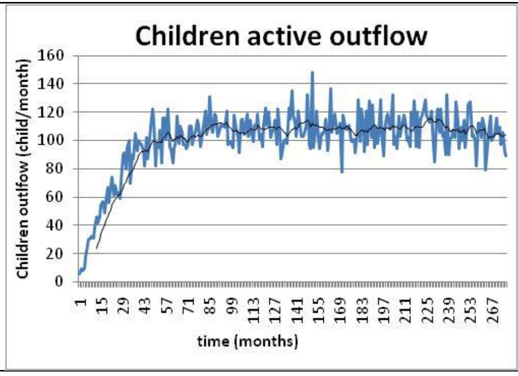
Care type	Capacity (trj)
AH	1395
DH	124
RH	340
PZ	173

Appendix E
Treatment, Verification& Validation

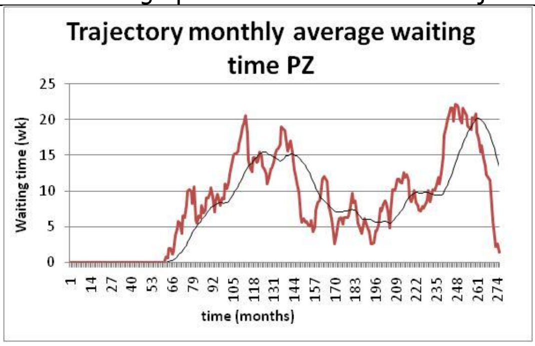
E.1 Start-up time

Start-up time graphs, considered subsystems are the care provider performance from a child layer and the PZ care system. Analyzed performance indicators are the observed average waiting, before care capacity is available, a month for children and foster care trajectories.

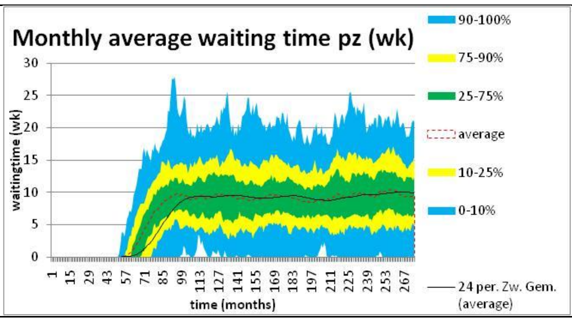


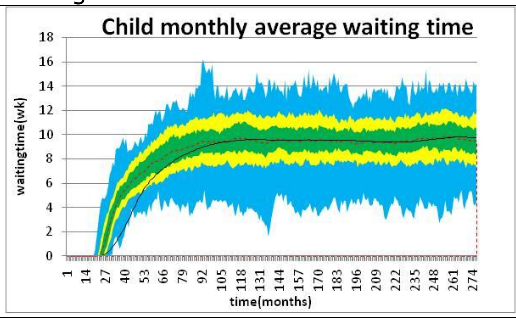


The outflow graphs for both foster care trajectories and children stabilise after 80 months.



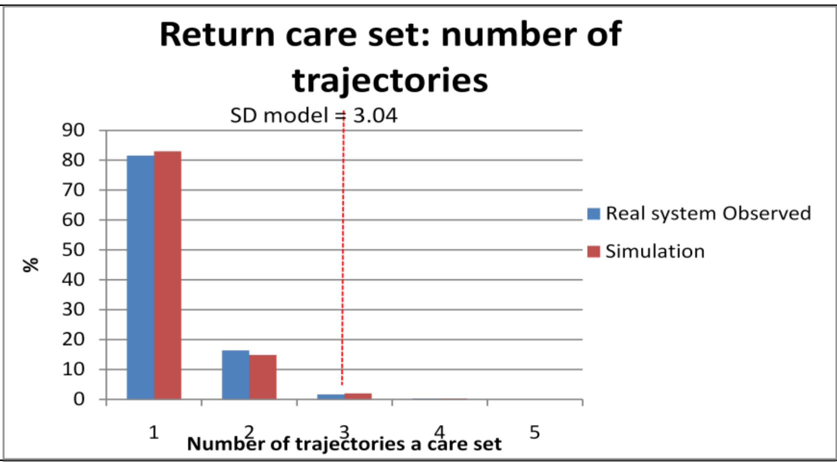
No clear stabilisation moment is observed for the average waiting time a month.

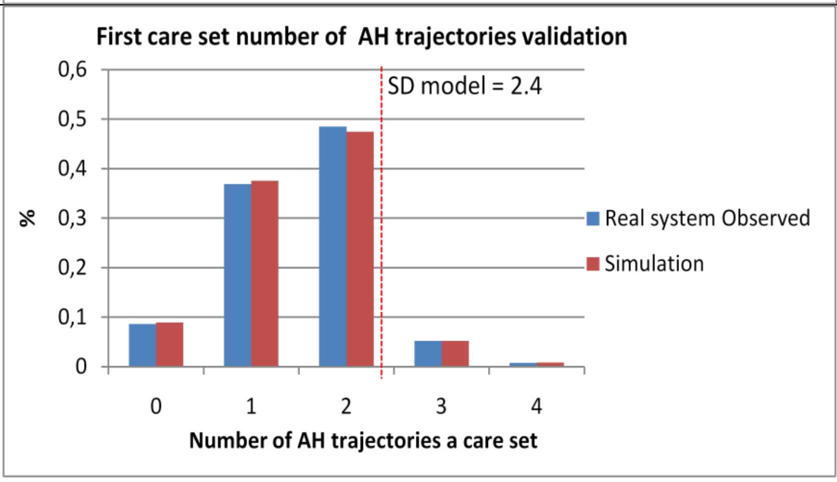


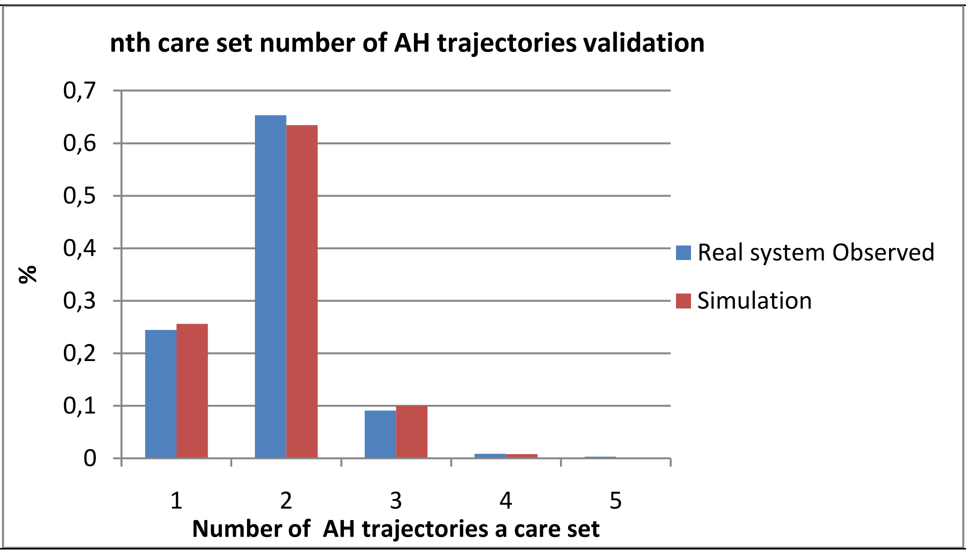


Sensitivity overview of 100 runs, both graphs stabilise after circa 100 months visualized by the weighted average over two years. To stay consistent, in observed simulation and real world months, a start up times of 108 months (9 years) is considered.

E.2 Care set composition validation







E.3 Overview cross-comparison statistics care system

AH		DES Queue mechanism: Data	First in first out	Priorities	Random	SD	Unit
Inflow	mean	220,7	225,6	225,7	225,7	228,11	trj/month
	Median	217	224	224	224		
	st. Deviation	42,5	26,4	26,2	26,3		
Withdrawal flow	mean	31,1	35,3	35,8	35,6	47,49	trj/month
	Median	30	35	35	35		
	st. deviation	10,2	11,9	11,6	11,7		
Outflow treated	mean	187,6	194	194	193,7	197,4	trj/month
	Median	188	194	194	196,5		
	st. deviation	46,2	14,9	15	14,6		
Waiting list	mean	354,8	358,7	350,3	361,2	363	Trj
	Median	348,5	357	357,5	357		
	st. deviation	47,5	84,7	76,5	102,8		
Mean waiting time	mean	7,7	6,8	6,8	7,8	6,8	Week
Appendix E.5							

DH		DES Queue mechanism: Data	First in first out	Priorities	Random	SD	Unit
Inflow	mean	12,8	13,1	13,1	13,1	13,09	trj/month
	Median	13	13	13	13		
	st. deviation	4,9	3,8	3,7	3,8		
Withdrawal flow	mean	2,5	3,1	3,1	3,1	2,49	trj/month
	Median	2	3	3	3		
	st. deviation	1,8	2,4	2,7	2,4		
Outflow treated	mean	9,7	10	10	10	11	trj/month
	Median	7	10	10	10		
	st. deviation	11,6	3	3	3		
WaitingList	mean	37,9	33,5	40,2	50,5	32,54	trj/month
	Median	37	32	39	49		
	st. deviation	10,3	14,1	17,8	18,8		
Mean Waiting time	mean	14,78	11,2	13,2	16,8	10,65	Week
Appendix E.4							

DES Queue mechanism

PZ		Data	First in first out	Priorities	Random	SD	Unit
Inflow	Mean	22,6	24,4	24,5	24,5	22,6	trj/month
	Median	21,5	24	24	24		
	st. deviation	6,3	5,1	5,1	5,2		
Withdrawal flow	Mean	2,4	3,1	3,2	3,3	1,75	trj/month
	Median	2	2	2	2		
	st. deviation	2,7	3,3	3,5	3,3		
Outflow treated	Mean	18,6	21,3	21,3	21,3	18,66	trj/month
	Median	18,5	21	21	21		
	st. deviation	6	5,8	5,9	5,8		
Waiting list	Mean	27,9	26	27,3	34,7	25,53	Trj
	Median	27,5	25	25	32		
	st. deviation	5,7	18,5	20,2	25,7		
Mean Waiting time	Mean	5,5	4,6	4,9	6,2	4,84	Week

Appendix E.7

DES Queue mechanism

RH		Data	First in first out	Priorities	Random	SD	Unit
Inflow	mean	32,5	32,2	32,3	32,3	29,67	trj/month
	Median	33	32	32	32		
	st. deviation	9,1	6,3	6,3	6,3		
Withdrawal flow	mean	7,5	9,4	9,5	9,4	7,47	trj/month
	Median	7	9	9	9		
	st. deviation	3,6	5,1	5,5	5,2		
Outflow treated	mean	26,1	22,8	22,7	22,9	24	trj/month
	Median	25	22	22	22		
	st. deviation	7,1	6,2	6,1	6,2		
Waiting list	mean	81,1	84,2	96,4	98,7	64,23	Trj
	Median	85,5	82	94	96		
	st. deviation	21,5	31,3	36,2	38,3		
Mean Waiting time	mean	11,1	11,4	13	13,2	9,28	Week

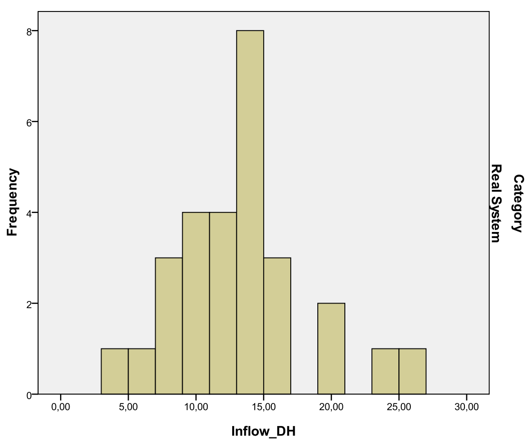
Appendix E.6

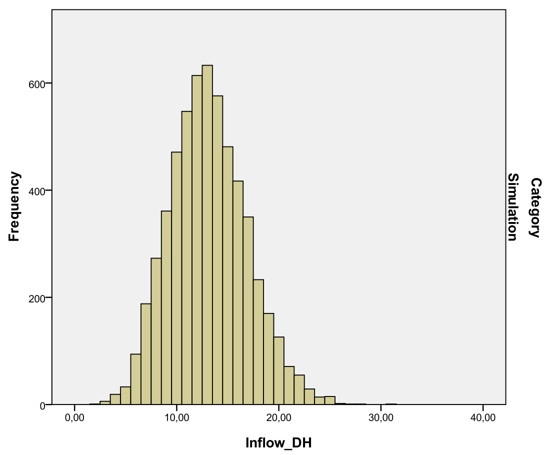
E.4 DH validation

E.4.1 Overview real data statistics

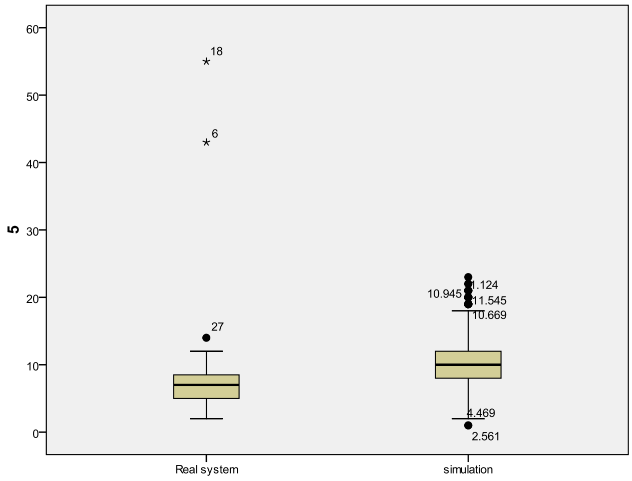
		Inflow(trj/mnth)	Outflow(trj/mnth)	Withdrawal (trj/mnth)	Waitinglist(trj)
Mean		12,74	9,52	2,50	37,90
95% Confidence Interval for Mean	Lower Bound	10,77	4,87	1,81	34,49
	Upper Bound	14,71	14,17	3,19	41,30
5% Trimmed Mean		12,52	7,57	2,42	37,66
Median		13,00	7,00	2,00	37,00
Variance		24,738	138,336	3,148	80,025
Std. Deviation		4,974	11,762	1,774	8,946
Minimum		4	2	0	25
Maximum		26	55	7	55
Range		22	53	7	30
Interquartile Range		6	3	3	15
Skewness		,787	3,305	,578	,409
Kurtosis		1,120	10,671	-,093	-,855

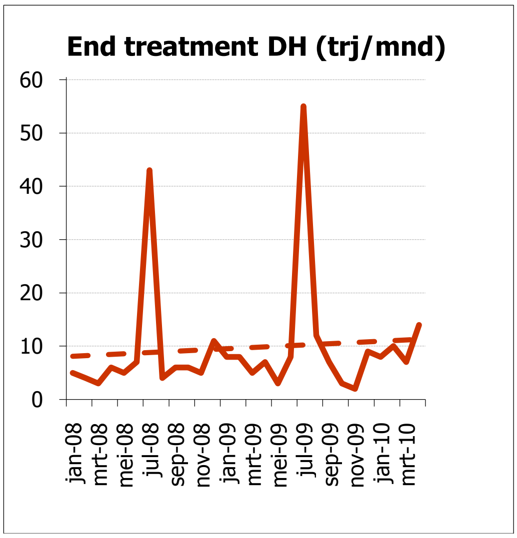
E.4.2 DH inflow validation



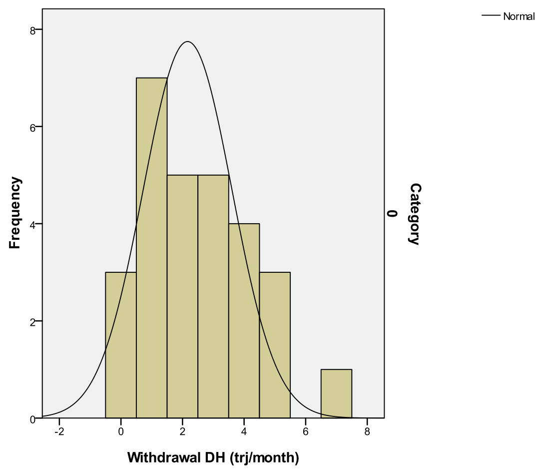


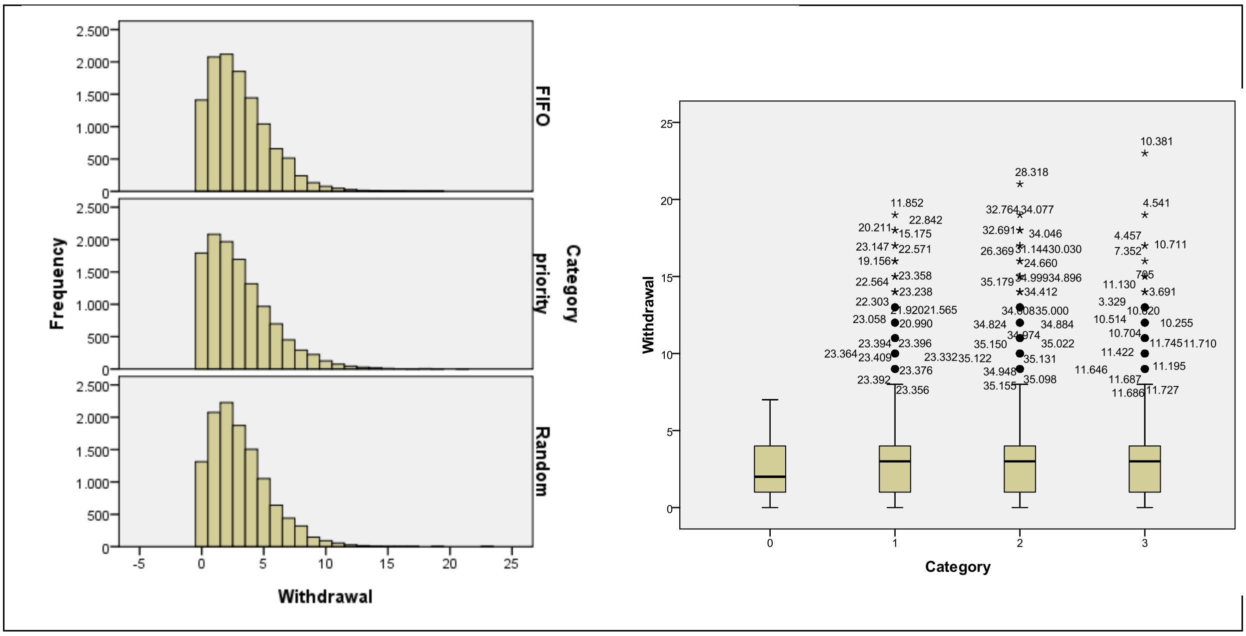
E.4.3 DH outflow treatment



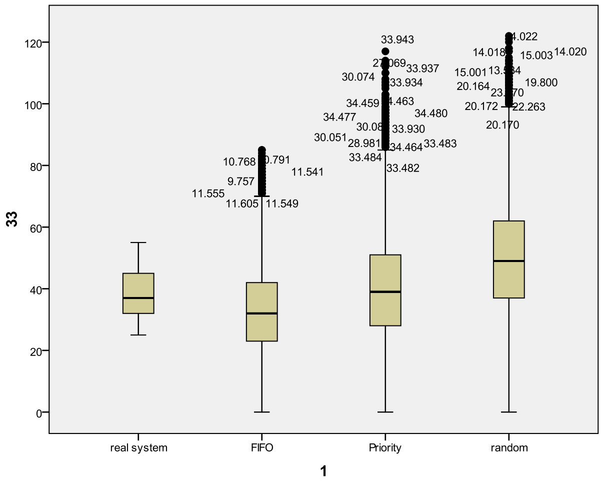


E.4.4 DH withdrawals





E.4.5 DH waiting list

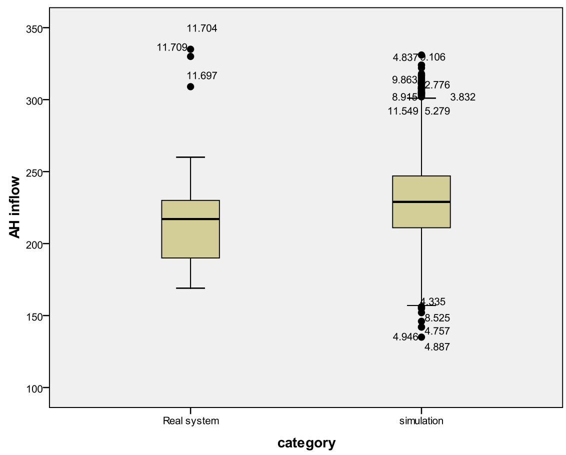


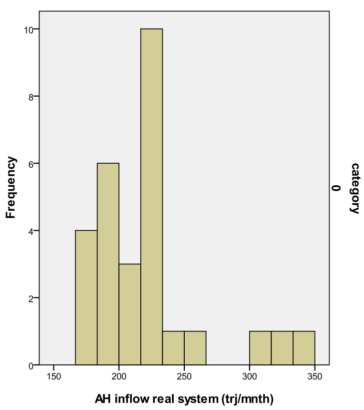
E.5 AH validation

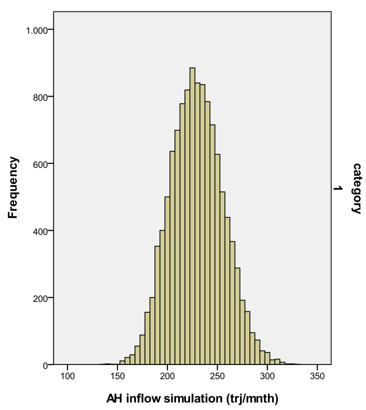
E.5.1 Overview real data statistics

		Inflow(trj/mnth)	Outflow(trj/mnth)	Withdrawal (trj/mnth)	Waitinglist(trj)
Mean		220,71	187,64	31,11	352,97
95% Confidence Interval for Mean	Lower Bound	204,23	169,72	27,14	334,84
	Upper Bound	237,20	205,56	35,07	371,09
5% Trimmed Mean		217,21	186,17	30,06	354,04
Median		217,00	188,00	30,00	344,00
Variance		1807,101	2135,275	104,618	2271,034
Std. Deviation		42,510	46,209	10,228	47,655
Minimum		169	102	17	250
Maximum		335	303	69	432
Range		166	201	52	182
Interquartile Range		42	70	11	72
Skewness		1,568	,515	1,976	-,197
Kurtosis		2,278	-,011	6,117	-,626

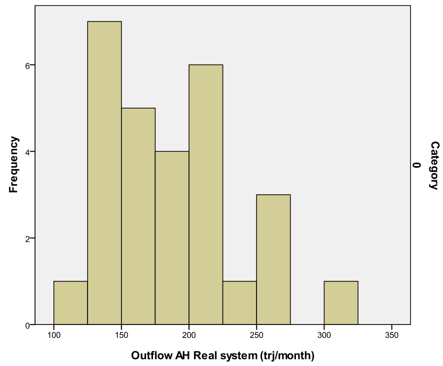
E.5.2 AH inflow validation

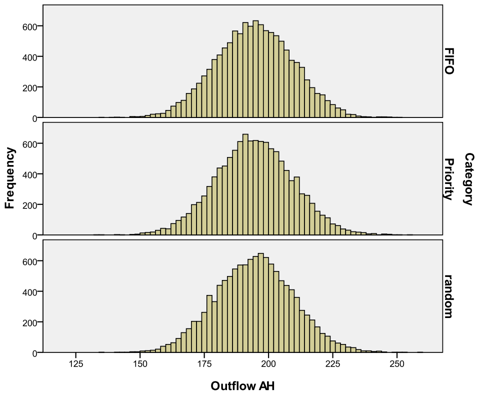




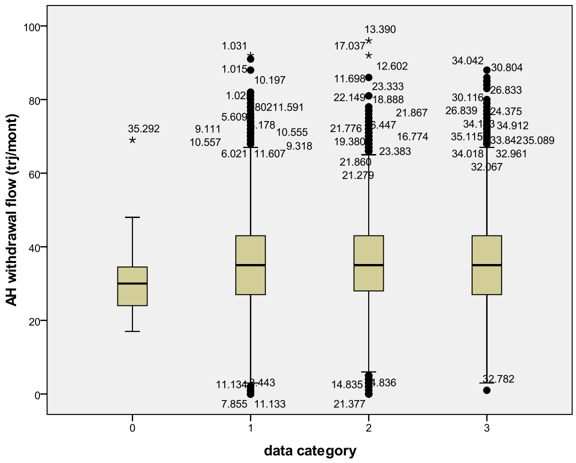


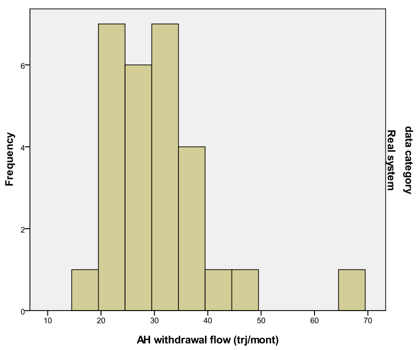
E.5.3 AH treatment outflow validation

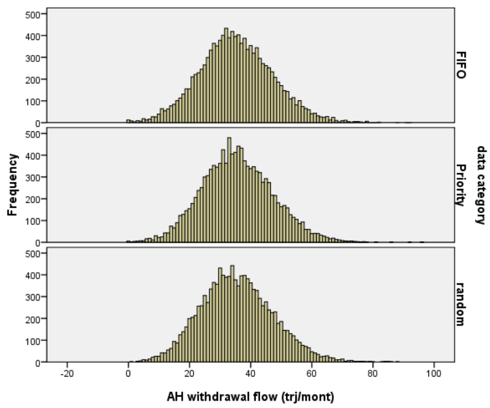




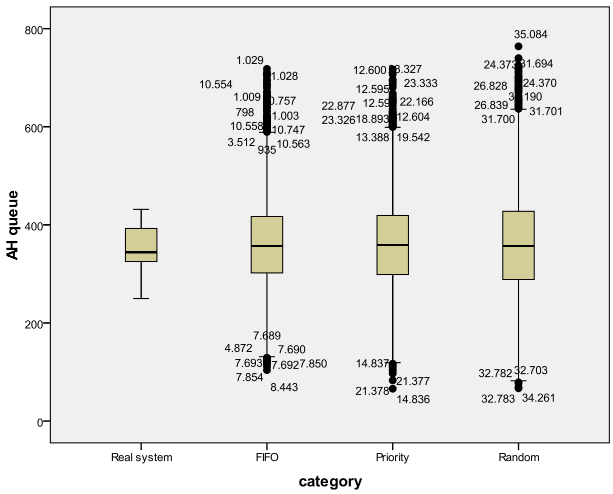
E.5.4 AH withdrawal

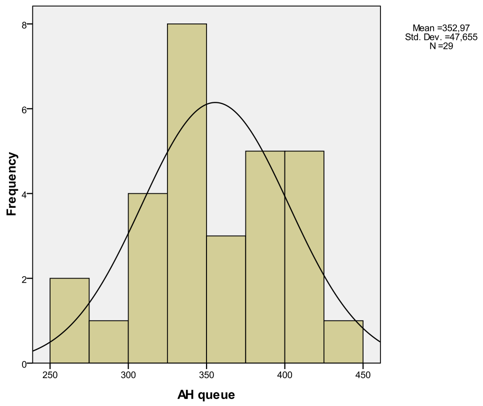


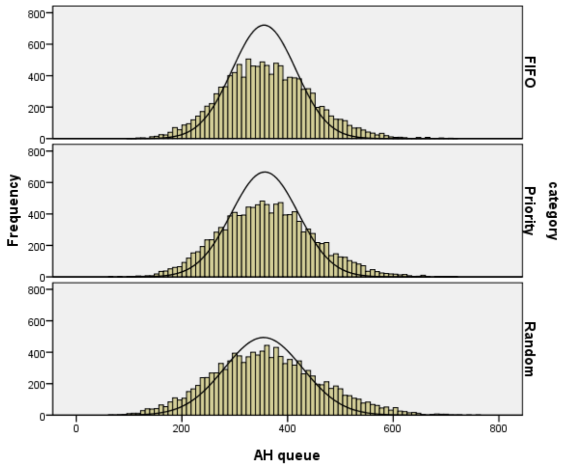




E.5.5 AH waiting list


AH queue
category
Real system
FIFO
Priority
Random
0
200
400
600
800


Mean =352,97
Std. Dev. =47,655
N =29
Frequency
AH queue

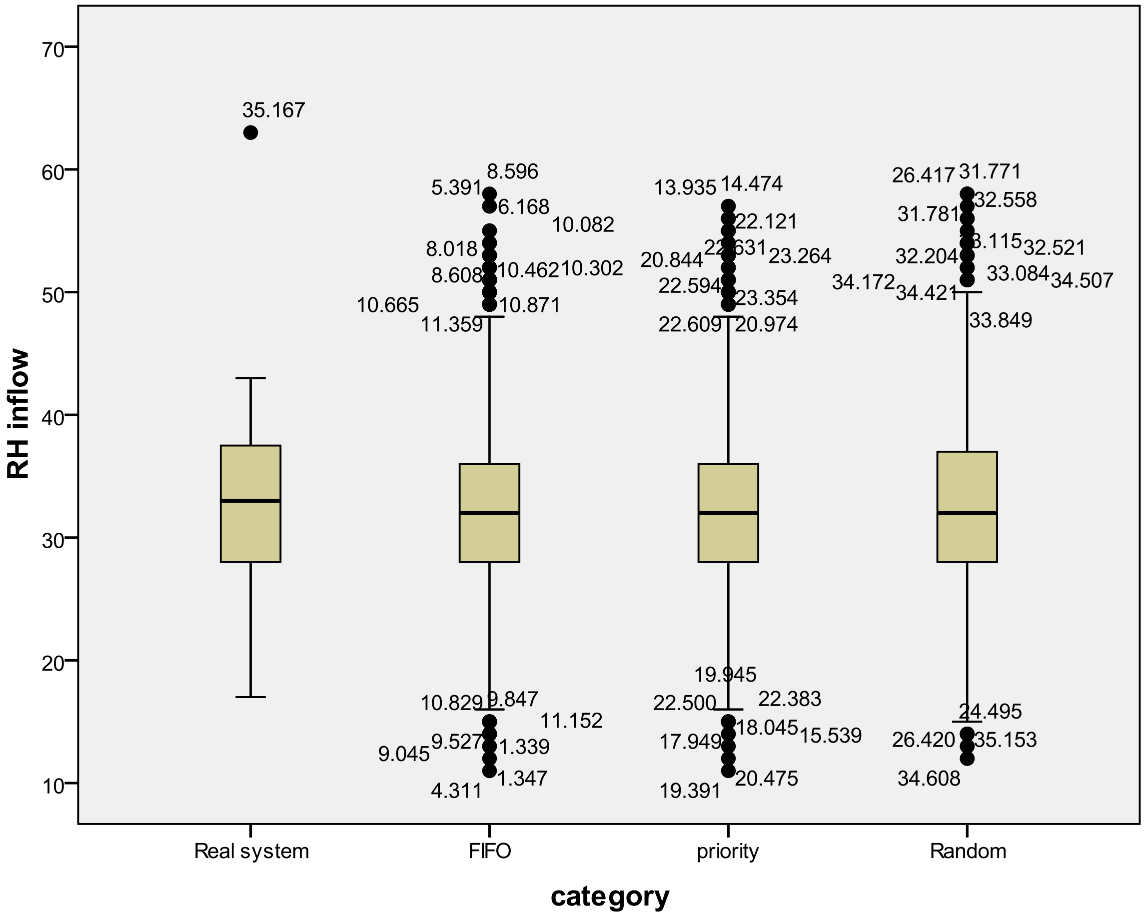

FIFO
Priority
Random
category
Frequency
AH queue

E.6 RH validation

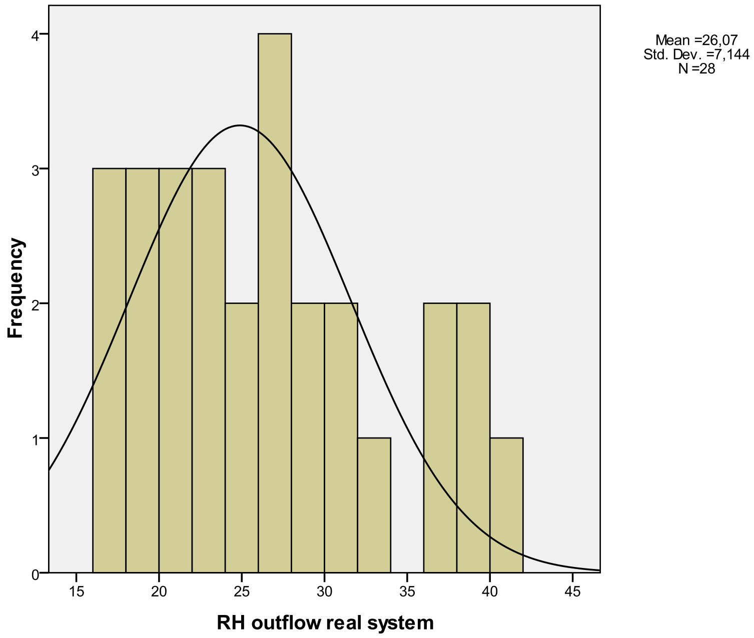
E.6.1 Overview Real data statistics

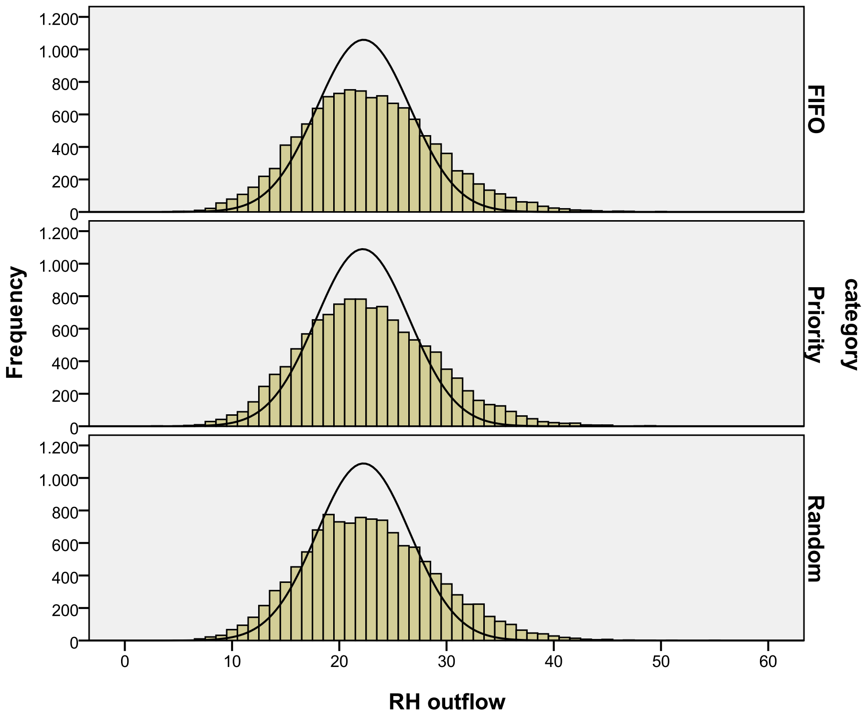
		Inflow(trj/mnth)	Outflow(trj/mnth)	Withdrawal (trj/mnth)	Waitinglist(trj)
Mean		32,54	26,07	7,54	79,93
95% Confidence Interval for Mean	Lower Bound	29,02	23,30	6,14	71,54
	Upper Bound	36,05	28,84	8,93	88,32
5% Trimmed Mean		31,99	25,79	7,39	80,24
Median		33,00	25,00	7,00	85,00
Variance		82,110	51,032	12,925	486,352
Std. Deviation		9,061	7,144	3,595	22,053
Minimum		17	17	3	45
Maximum		63	41	15	109
Range		46	24	12	64
Interquartile Range		10	11	5	44
Skewness		1,118	,566	,687	-,230
Kurtosis		3,637	-,685	-,474	-1,523

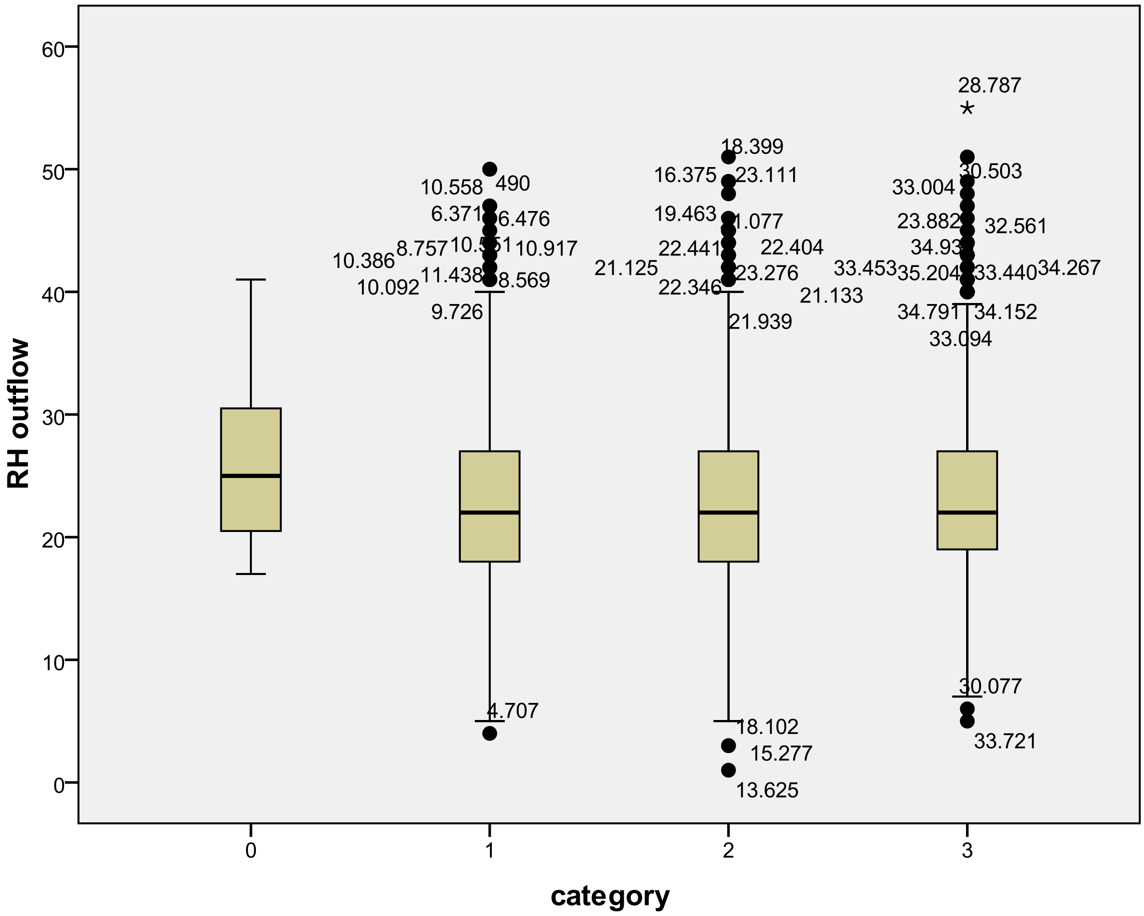
E.6.2 RH inflow



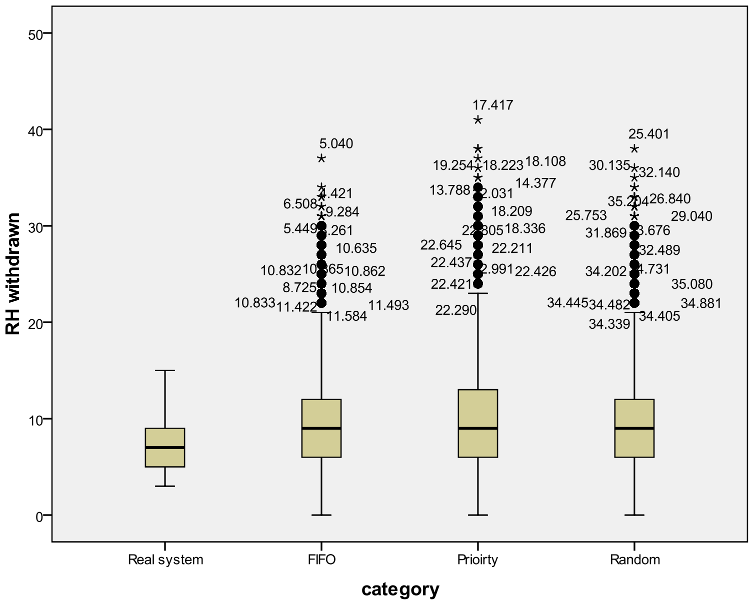
E.6.3 RH treatment outflow

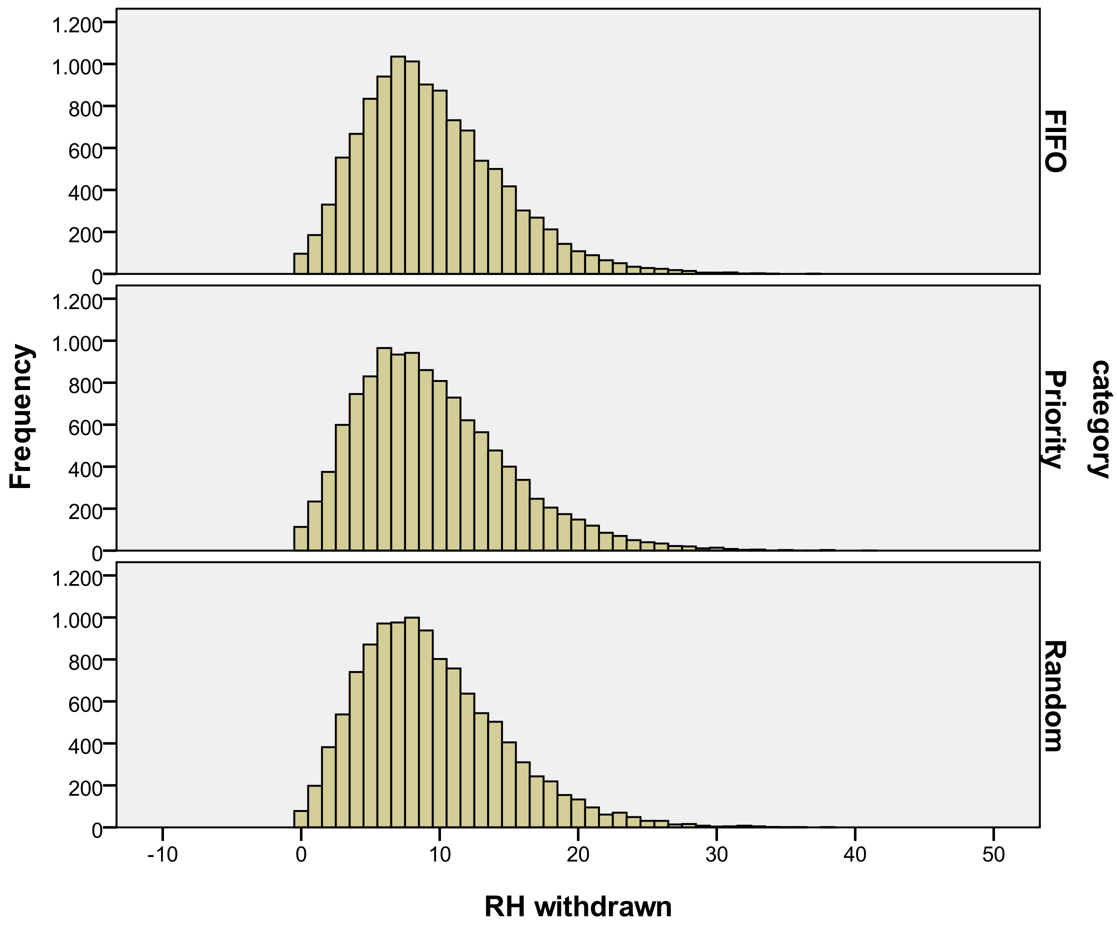




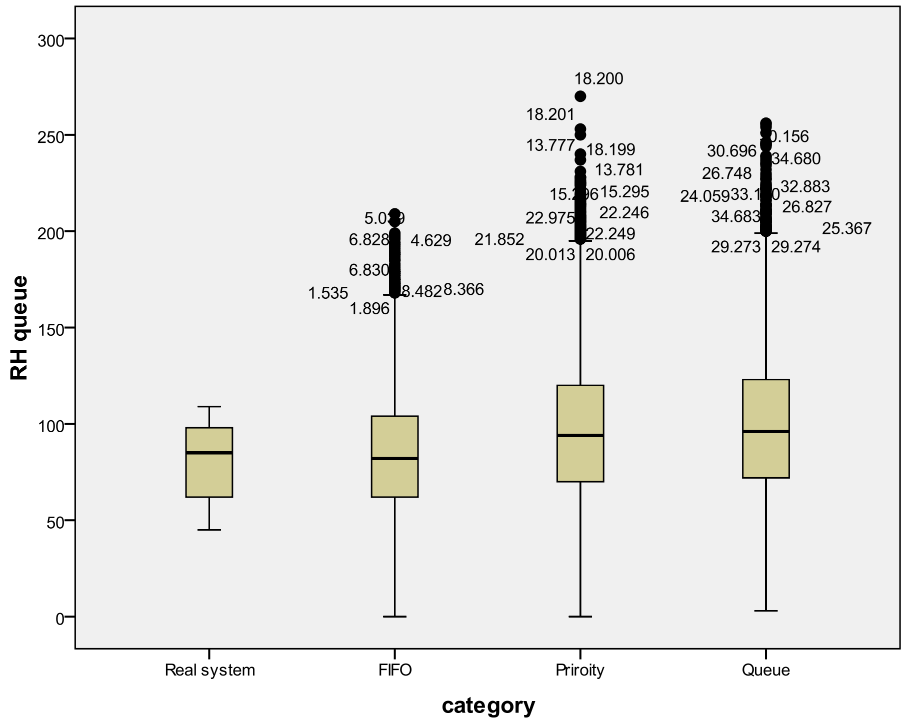


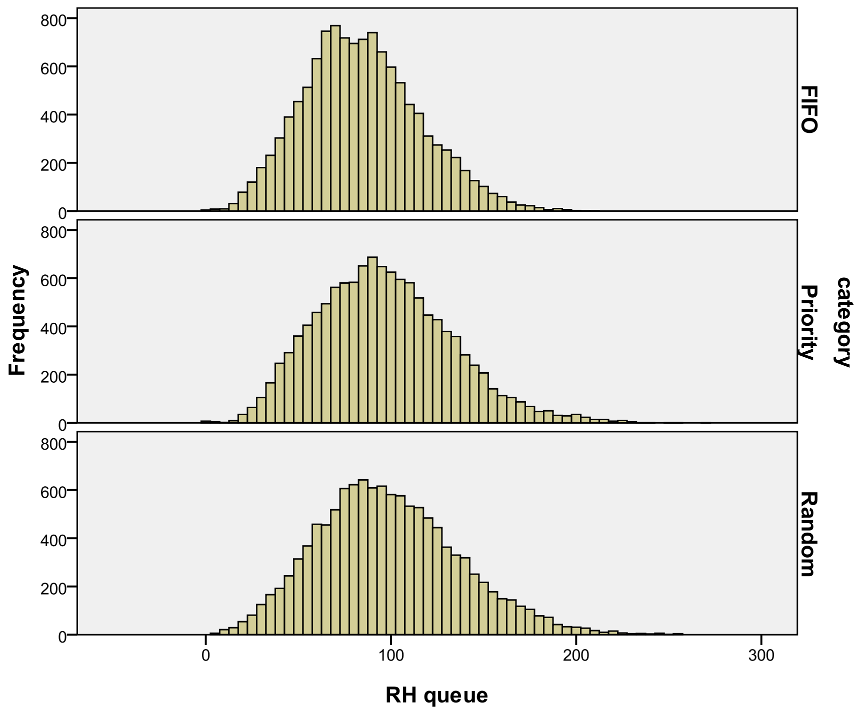
E.6.4 RH withdrawal





E.6.5 RH waiting list

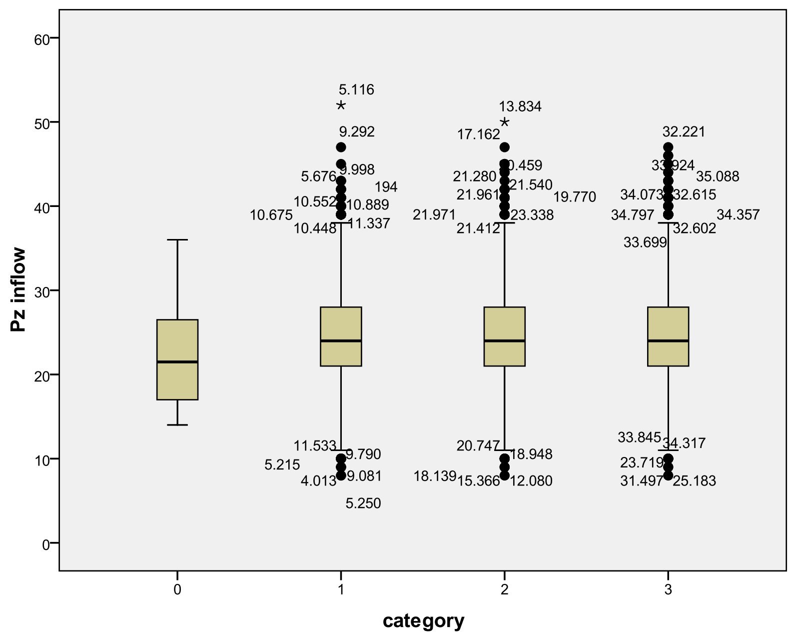


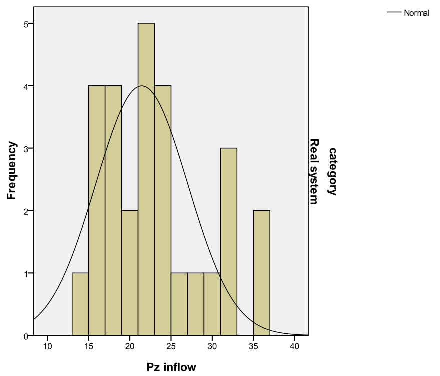


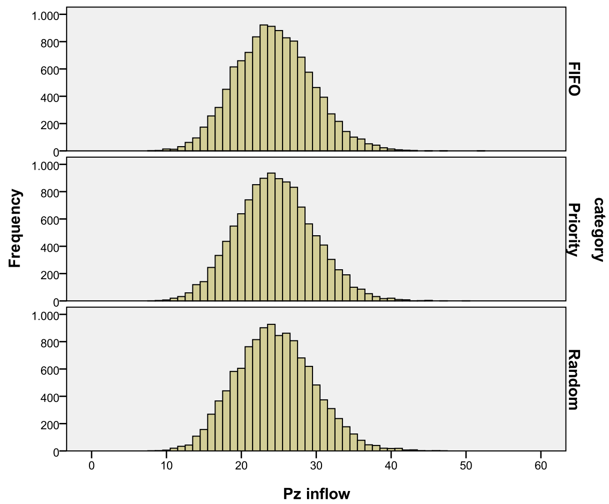
E.7 PZ validation

E.7.1 PZ inflow

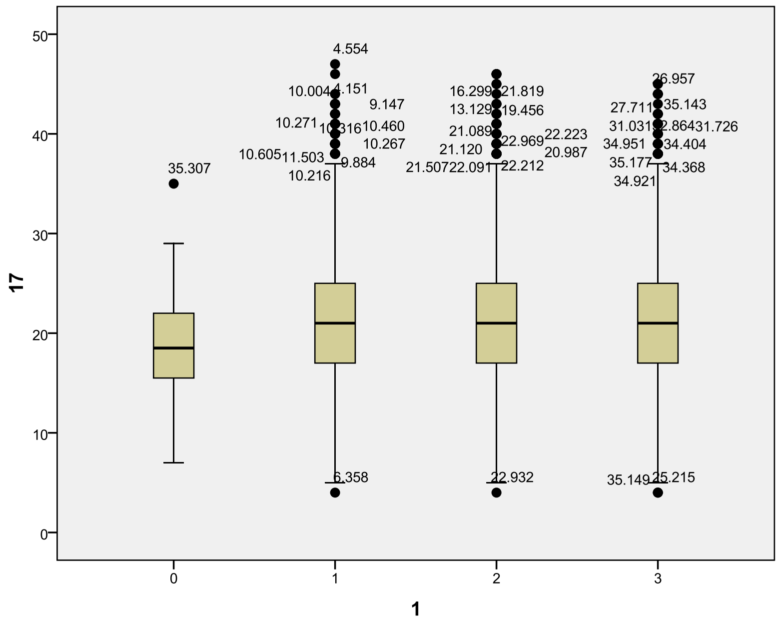
PZ inflow



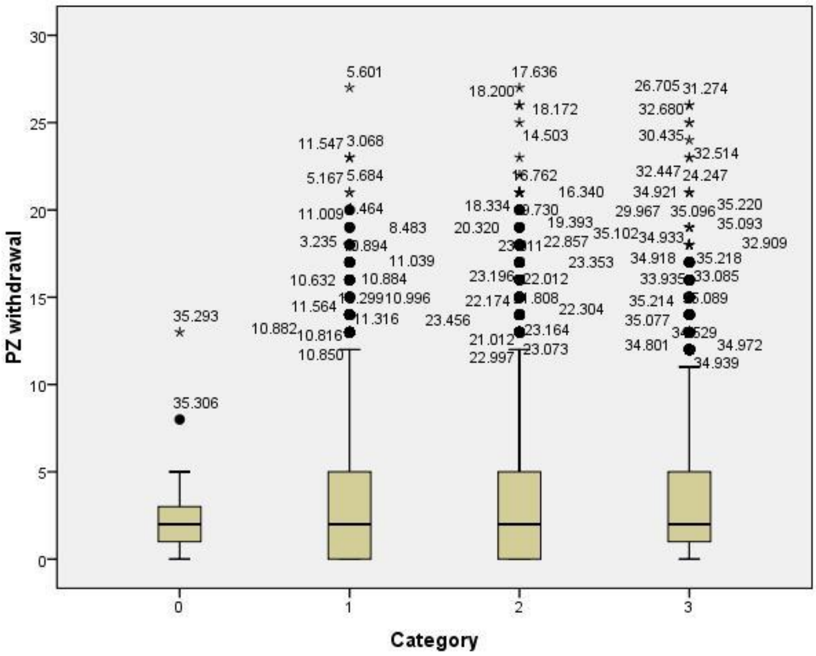


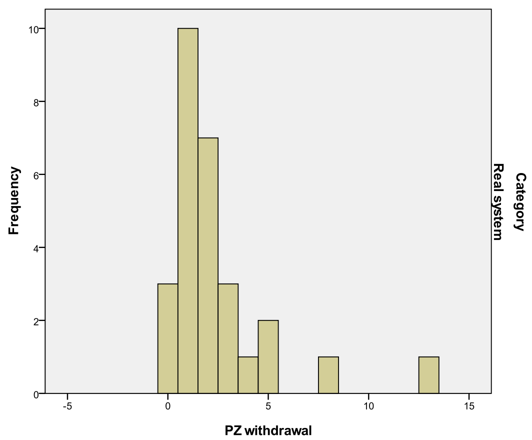


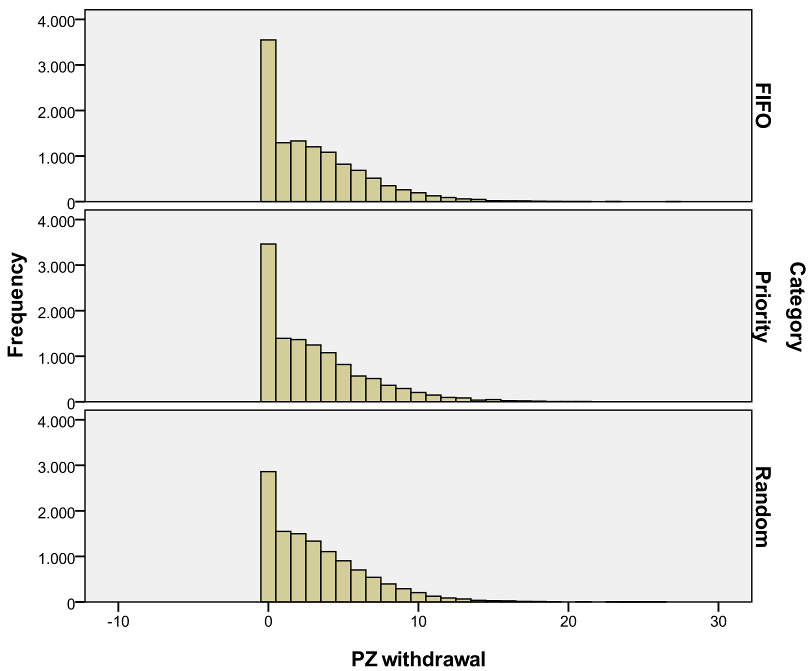
E.7.2 PZ outflow



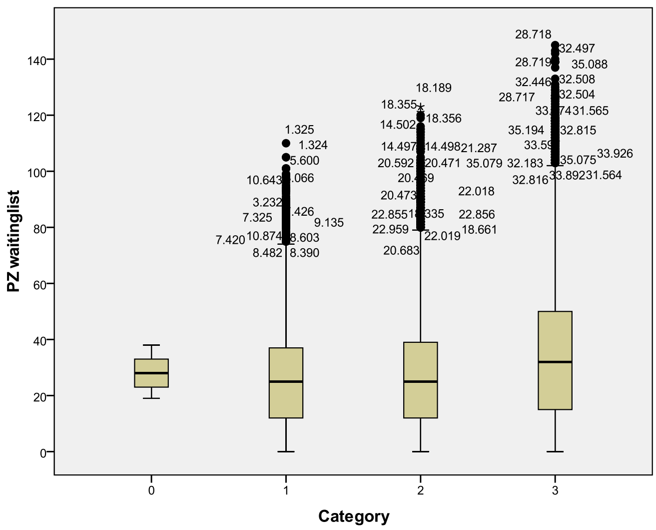
E.7.3 PZ withdrawal

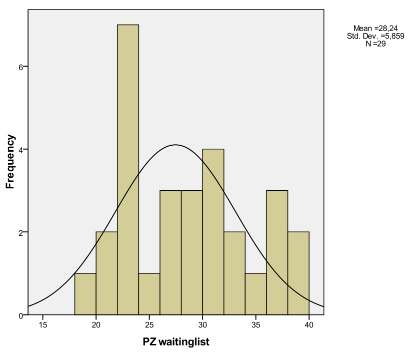

PZ withdrawal
Category

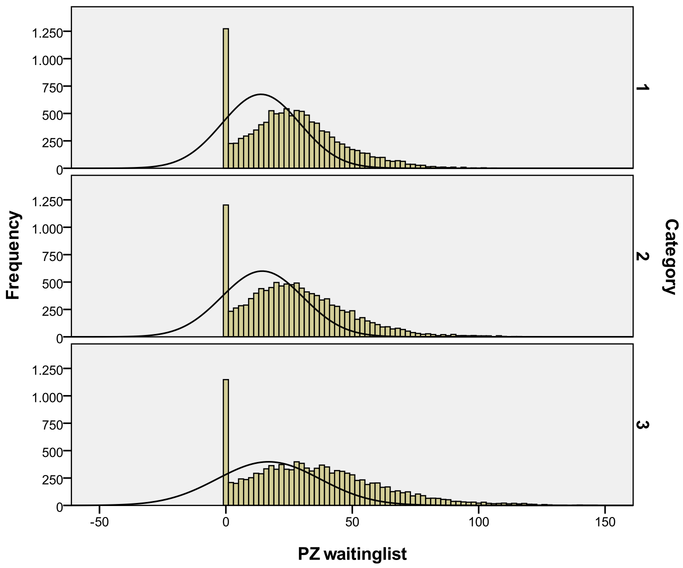

Frequency
PZ withdrawal
Category
Real system


Frequency
FIFO
Priority
Random
Category
PZ withdrawal

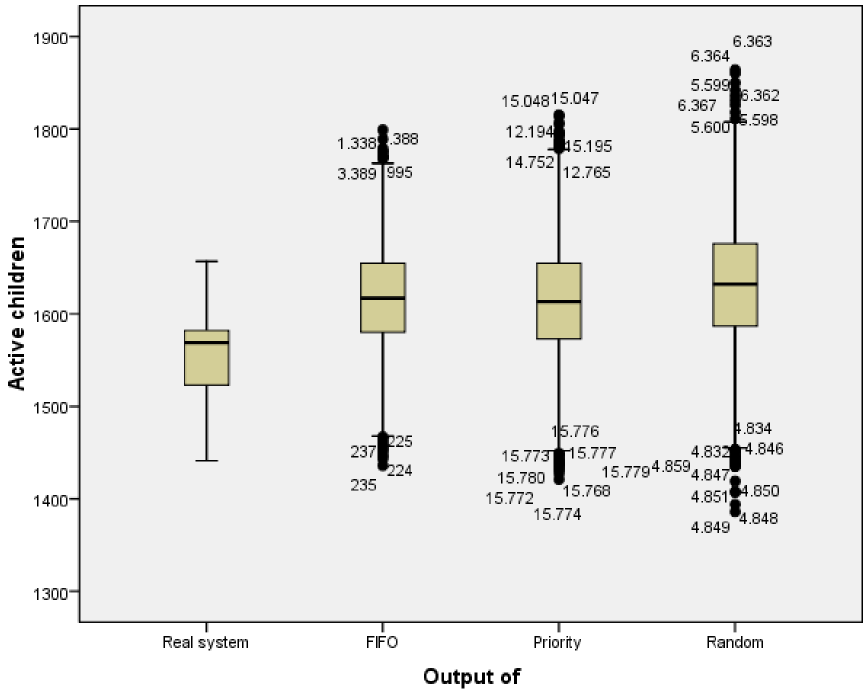
E.7.4 PZ waiting list

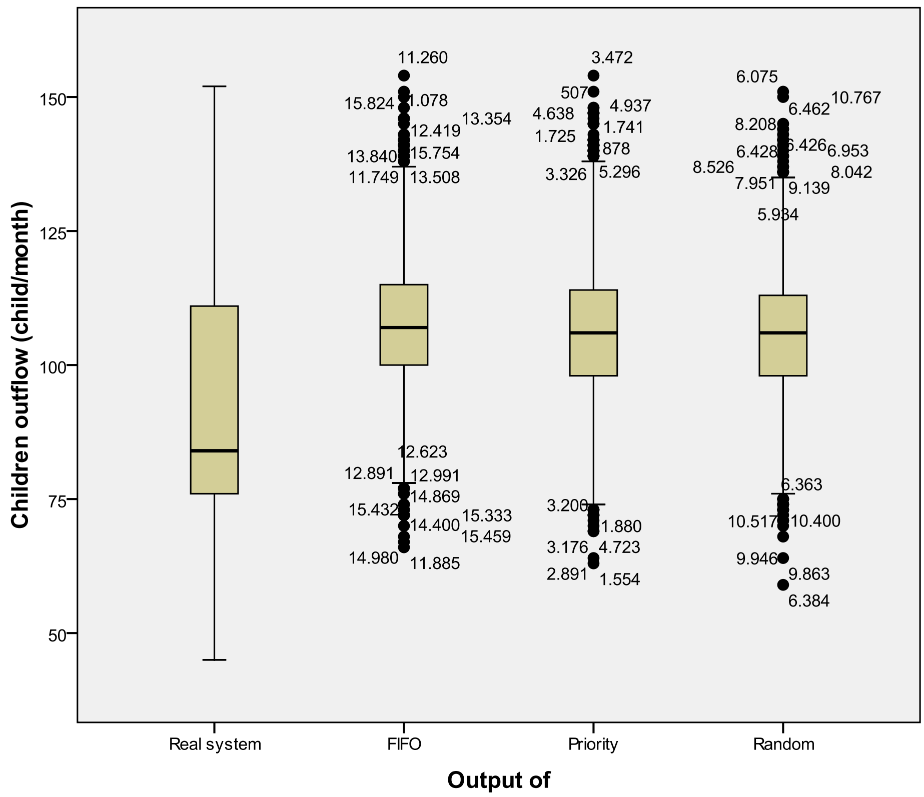


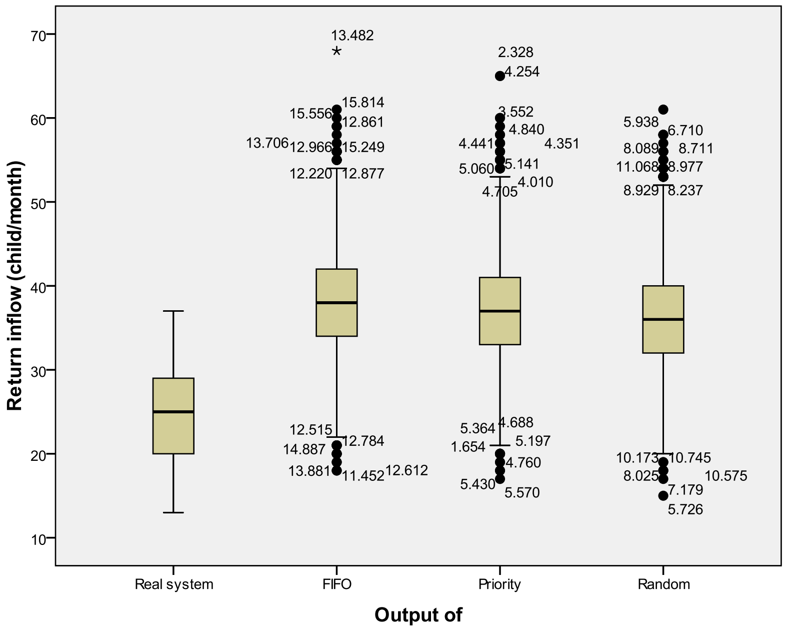




E.8 Validation child layer







Appendix F
Experiment runs

F.1 Scenario 10% increase children arrivals

Base= base case experiment
Exp.= Expirement 10% increase in children inflow
Units= Inflow (trj/month), withdrawal (trj/month), waiting list (trj), waiting time (wk)

		AH		DH		PZ		RH	
		base	exp.	base	exp.	base	exp.	base	exp.
SD	Inflow	228,1	252,5	13,1	14,5	22,6	25,0	29,7	32,8
	withdrawal	47,5	71,8	2,5	3,9	1,8	4,1	7,5	10,6
	Waiting list	363,0	463,4	32,5	44,0	25,5	42,3	64,2	81,6
	Waitingtime	6,8	7,9	10,7	13,0	4,8	7,3	9,3	10,9
FIFO	Inflow	230,2	254,3	13,1	14,5	24,6	27,0	32,4	35,6
	withdrawal	36,2	60,1	3,1	4,4	3,2	5,7	9,7	12,6
	Waiting list	368,9	618,8	33,4	56,7	26,9	46,6	87,8	131,0
	Waitingtime	7,0	10,6	11,1	17,0	4,6	7,3	11,6	16,1
Priority	Inflow	229,1	252,5	13,1	14,4	24,3	26,9	32,1	35,4
	withdrawal	34,8	58,3	3,1	4,4	3,1	5,6	9,4	12,9
	Waiting list	352,6	634,5	40,1	71,6	26,9	47,7	94,5	157,0
	Waitingtime	6,6	10,9	13,3	21,7	4,8	7,6	12,8	19,1
SIRO	Inflow	229,7	253,1	13,2	14,5	24,5	27,0	32,2	35,6
	withdrawal	35,8	59,0	3,1	4,4	3,2	5,7	9,6	13,0
	Waiting list	364,1	664,7	52,4	89,0	34,0	64,4	101,3	163,1
	Waitingtime	6,9	11,4	17,4	27,0	6,0	10,3	13,5	19,9