Sytze Jan Caminada

Game and Choice Based Simulation

The design of a methodological framework using the case of the Physical Internet inspired "Freight Transportation Game"

Master Thesis - Delft University of Technology

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The design of a methodological framework using the case of the Physical Internet inspired "Freight Transportation Game"

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by

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The painting shown on the cover page of this report is a, or inspired by, indigenous Australian dot painting. I was not able to, trace the source of the painting or photo.

Acknowledgements

Dear reader,

In front of you lies the result of my final project as a Master student at the Delft University of Technology. It is hard to imagine that the past six years as a student here in Delft have almost come to an end now. If I look back on this time I can see that I have developed myself in all kinds of ways. The people I met and became friends with, all the (non-)study-related activities, the trips to all sorts of places around Europe and even the world, the minor, the internship, and the periods of studying and travelling abroad in Indonesia and South East Asia, have been of great value for me. I'm grateful to end this precious chapter of my life with the interesting and enjoyable master thesis research I conducted. Staying in Paris for three months during the spring and summer, enjoying the city, having friends and family visiting you and on top of that working on an exciting topic with researches of a renowned institute gave me a lot of positive energy.

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Now it's time to see what the future holds for me!

Sytze Jan Caminada
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Executive Summary

When designing in socio-technical systems, developing products and services, or creating policies, a profound understanding of user behaviour, user demand, and the user response is desirable. Herefore, quantitative, statistically rigorous insights, beyond psychology are demanded (Chorus,2018). Choice models offer these insights as they can be used to understand and forecast (new) systems and predict the effects of policies. Conventionally the choice data by which theses choice models are estimated, is collected by means of the usually valid and reliable Revealed Preference (RP) method or the usually accurate and time-efficient Stated Preference (SP) method. A promising alternative for these methods could be the use of Serious Gaming to collect choice data. This Player Preference method could form a more valid and reliable method than SP and a more accurate and time-efficient method than RP. By estimating a discrete choice model (DCM) based on this collected game data, insight into the behaviour of players can be obtained. Additionally, the estimated choice model could be implemented into a simulation model that is based on the game. Herewith a simulation with modelled human decisions is conceived, creating a realistic simulation that incorporates the human dynamics of the system it represents. Eventually, the simulation model offers new possibilities for conducting experiments in a time-efficient and isolated way.

However, little is known about this methodology of combining Serious Gaming and DCM to gain insight into the behaviour and create a realistic simulation. To create more knowledge, experience and to evaluate this innovative Game and Choice Based Simulation (GCBS) methodology, this research endeavoured to design a methodological framework for GCBS. To explore and evaluate this GCBS methodology, a methodological framework for GCBS is designed using a combination of qualitative research and a modelling study that uses the GCBS methodology. The game that is used in the modelling study to apply the GCBS methodology is the Physical Internet (PI) inspired “Freight Transportation Game”.

Using defined design requirements and based on the argumentation of the introduction and the executed literature review, a first design of the methodological framework is created. This design is focused on opportunities and the structure of the GCBS methodology. Hereafter, the designed framework is used to conduct the modelling study. In this study, the bidding behaviour of players in the PI inspired “Freight Transportation Game” is captured and modelled using DCM. By analysing the gameplay and the estimated DCM, it was found that players have difficulties with the complexity of creating bundles and routes with multiple requests. Therefore a decision support tool that provides players with information about their most attractive bids, based on cost and reallocation possibilities, is created. This policy is tested by means of a simulation experiment. Based on the structure of the game and by imitating the bidding behaviour using the DCM, a realistic simulation of the PI inspired transportation market is created. In the simulation experiment, this simulation of the current situation was compared with simulation settings that represented the future policy situation and a centralised market situation. The results of the simulation experiment, showed that the tool caused a much more efficient and effective market performance, which is close to the situation of a central

market situation. Due to the tool, the filling rate increased, the price per allocated request decreased, more reallocations occurred, and almost no request remained unallocated. So it can be stated that the complexity of the market design has a significant impact on the bidding behaviour and market performance. However, in the real world, carriers could have other objectives besides making a profit (game objective) as well. Therefore, if implemented in a real the real world, the tool should be adjustable to a wider variety of carrier preferences. Nevertheless, a decision support tool for carriers in the complex PI inspired decentralised transportation market seems to be essential to reach an optimal market performance with a firm and "in control" position of the independent carrier.

Using the new insights obtained from this modelling study and by evaluating the first framework design, the final methodological framework for GCBS was created and presented. Additionally, the framework was validated using the design requirements. The main insights obtained from the modelling study were that a thorough understanding of the game structure and dynamics are needed because the choice situations and gameplay dynamics are given and not in control of the researcher. Additionally, a challenge could occur when the considered choice sets of players are unknown. Therefore theoretical based guidelines to generate these choice sets are created, and the use of extra attributes that could explain the creation of the real considered choice sets proved to be successful. Additionally, a way to deal with the situation where attributes that influence the behaviour of players are unknown is provided by this research and presented in the designed framework.

Concluding, it is discovered that the strength of using GCBS as a research methodology lays in the promising Player Preference data collection method, the explanatory and predictive power of DCM and the available modelled structure of the serious game. The methodology proved to provide valid quantitative and statistically rigorous insights into the behaviour of players performing in a futuristic environment. This helped to create a policy that could improve this situation. Additionally, the methodology succeeded in creating a realistic simulation of the (future) real world. This simulation was of valuable use for testing the defined policy in a time-efficient manner. To facilitate future research that suits the GCBS methodology, the methodological GCBS framework that is designed, practically explains when and how a GCBS methodology can be conducted. Eventually, more research needs to be done to test the (external) validity of the policy and to test and extend the methodological framework in order to increase its robustness.

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1. Introduction

1.2. Collecting choice data

Conventionally the choice data by which the choice models are estimated is collected using two methods (Krabbe, 2016). At first, the data is often gathered by observing choices in real life, so-called “Revealed Preference” (RP). Secondly, choice data is often retrieved by conducting advanced surveys; the so-called “Stated Preference” (SP) method. RP data portrays the world as it is, with all its complex and human interaction, and therefore usually results in reliable and valid choice data. However, because of these interactions, inherent relationships between attributes occur in the RP data. Additionally, the effect of nonexistent or future alternatives can not be observed using RP and often only one observation per respondent is possible, making it a time-consuming method (Louviere, Hensher, & Swait, 2000). On the other hand, using SP surveys, the effect of nonexistent alternatives can be studied, relationships between attributes can be controlled by the design of the survey and multiple observations per respondent is possible Louviere et al. (2000). However, because the recorded choices are only based on (perfect) information provided by the survey, complex interactions between individuals and their environment are neglected, and consequences of (nonexistent) alternatives are not felt. Therefore, respondents may show other behaviours than they would show if the choices were made in real life.

1.3. Combining Serious Gaming and Discrete Choice Modelling

A solution to the drawbacks the RP and SP data collection methods could be found by using an innovative data collection method; Serious Gaming. In Serious Games, a simplified representation of a complex (future) reality can be created (Duke, 1975) in which the human factor and dynamic relationships are addressed (Bradley, Hax, & Magnanti, 1977). Herewith choices are made in a real-life inspired experimental setting with interacting players and changing in-game environments. Additionally, nonexistent alternatives can be included, and multiple observations per individual are possible. This way of collecting data, therefore, has the potential to form a more valid and reliable method than SP and a more accurate and time-efficient method than RP.

By estimating a discrete choice model (DCM) based on this collected game data, insight into the behaviour of players can be obtained. Additionally, the estimated choice model could be implemented into a simulation model that is based on the game. Herewith a simulation with modelled human decisions is conceived, creating a realistic simulation that incorporates the human dynamics of the system it represents. So, herewith a game model of the real world is used to estimate a discrete choice model, which is then implemented into a simulation model (that uses the structure of the game model) to create a realistic simulation of that same world. Eventually, the simulation model offers new possibilities for conducting experiments in a time-efficient and isolated way.

However, little is known about this methodology of combining Serious Gaming and DCM to gain insight into the behaviour and create a realistic simulation. To the best of the author's knowledge, only Karampelas (2018) ones used DCM to create a simulation based on a serious game. However, his work focussed more on the multi-model approach (gaming, simulation and optimisation). Although his insights will be used, this research will focus more on the methodological combination of Serious Gaming and DCM, which will be further referred to as Game and Choice Based Simulation (GCBS). To create more knowledge, experience and to evaluate this innovative GCBS methodology, this research endeavours to design a methodological framework for GCBS. This will be performed and evaluated by the process of conducting a design cycle. To gain insights into and evaluate the methodological framework design, a modelling study that uses the GCBS methodology will be conducted. Eventually, this research endeavours to act as structured guidance and example for further research using GCBS methodology. The game that will be used to apply the methodology on is the Physical Internet (PI) inspired "Freight Transportation Game".

1.4. Application case

The current world of transport and logistics is inefficient and unsustainable (Montreuil, 2011). The innovative future concept of a decentralised, Physical Internet inspired, transportation market has the potential to increase efficiency and sustainability within the transport and logistics sector (Ballot, Montreuil, & Meller, 2014). To research the dynamics and performance of this non-existing market, the "Freight Transportation Game" is developed at MINES ParisTech - PSL (Lafkihi, Pan & Ballot, 2019). Experiences with game sessions show that the players behave sub-optimal, and the potential of the market can be utilised better. A DCM based on the game data will be created to gain insight into the behaviour of players. Using these insights, a policy to optimise the behaviour and system performance will be defined and tested in an experiment. The experiment will be conducted using a simulation based on the gameplay, at which players' behaviour is imitated through the DCM. One could argue that experiments can also be conducted by playing the game. However, in this research, it is chosen to use simulations based on the gameplay, because the aim is to create more knowledge about the innovative GCBS methodology. Additionally, DCM provides more insight into the attributes that affect people's decision making, which helps to find and endorse a policy that can improve this behaviour. By creating a simulation based on the game, a clean (ceteris paribus) comparison in performance between different settings of the simulation can be made as well. Finally, more game rounds can be simulated than in a typical game session, and multiple games can be simulated in far less time than by playing the game in real life.

1.5. Content of the document

In chapter two, the research questions will be presented, and the used research approach will be explained. In the third chapter, the core concepts of this research will be elaborated on in a literature review. After that, in the fourth chapter, a first version of the methodological GCBS framework will be formed. In chapter five, the application case of the GCBS methodology will be elaborated on. The sixth chapter describes the process of conducting the GCBS methodology. Hereafter, in the seventh chapter, the final design of the methodological GCBS framework will be created. Finally, in chapter eight, the conclusion including the: main findings, remarks, recommendation and contribution of this research are presented.

2. Research approach and methodology

2.1. Research questions

After introducing the problem statement, the research question and sub-questions will be presented in this section. The research question and sub-questions are related to the following identified gaps in the literature:

- Create more knowledge, experience and evaluate the innovative methodology of Game and Choice Based Simulation for understanding behaviour and creating a realistic simulation.

- Analyse the behaviour of players in the PI inspired “Freight transportation game”, and create and test a policy using the GCBS methodology.

The objective of this research, concerning the problem statement and the identified knowledge gaps are set as follows:

The research objective is to design a framework for the GCBS methodology to analyse players' behaviour and create a realistic simulation. By applying it on the case of the PI inspired “Freight transportation game” a policy should be defined and tested, and insights can be obtained for the framework design.

The associated research questions to this research objective are:

RQ1: *How can the methodology of Game and Choice Based Simulation, be used to create insight into players' behaviour and establish a realistic simulation that can be experimented with?*

RQ2: *How can the system performance of the PI inspired “Freight transportation game” be improved using the Game and Choice Based Simulation methodology?*

To answer the research questions in a structured way, the following sub-questions are defined:

- [SQ1] What are the opportunities of the GCBS methodology?

- [SQ2] What is the structure of conducting the GCBS methodology?
- [SQ3] Why is the case of the PI inspired “Freight Transportation Game” suitable for conducting GCBS methodology?
- [SQ4] How can game data and DCM be used to analyse people’s behaviour?
- [SQ5] What policy could optimise the system’s and player’s performance?
- [SQ6] How can a realistic simulation, based on the game and DCM, be created?
- [SQ7] What is the difference in performance between the current situation and the situation with policy intervention, according to a simulation experiment?
- [SQ8] What are the GCBS methodological insights obtained?

2.2. Research approach

As has been mentioned in the previous part, this research can be divided into two goals that synergise each other. Designing a framework for the “innovative methodology”, will be performed by conducting the other part of the research; analysing the player behaviour in the "Freight Transportation Game" based on which a policy for the game will be created and tested using a game and choice based simulation. To conduct this comprehensive research, a combination of a design cycle and modelling study will be performed.

2.2.1. Design Cycle

To structure the design of the methodological GCBS framework in this research, a straightforward design cycle is used. This consists of the following elements: investigate, design, create and evaluate. Using these elements, the methodological framework is to be created. A methodology can be seen as a guideline for solving a problem consisting of specific components such as methods, tools, techniques, tasks and phases. "Generally methodologies are comprised of the following four elements: providing an opinion of what needs to be solved, defining techniques on what has to be done and when to do it, advising on how to manage the quality of deliverables or products, as well as providing a toolkit to facilitate the process" (Ishak, & Alias, 2005). Eventually, the methodological framework should benefit the user by providing information to plan, review and control projects (Ishak, & Alias, 2005). Therefore, the framework should also provide information about the opportunities of the methodology, so users know in what situations they can use it. More specifically, the designed methodological framework should lead to the general advantages of DCM, which are explaining choice behaviour (Krabbe, 2016) and predicting or validly simulate choices. So, the framework should provide guidelines to systematically create a valid choice model of players' in-game behaviour and to create a realistic simulation. Based on the methodology elements of Ishak, & Alias (2005), these required properties are translated into design requirements, see Table 1. This will help to focus the design and evaluation of the framework.

Methodology elements (Ishak, & Alias, 2005)	**Design requirements for the methodological GCBS framework**
Providing an opinion of what needs to be solved.	1. Provide insight into the opportunities of the methodology 2. Help to provide insight into the behaviour of players.
Defining techniques on what has to be done and when to do it.	3. Provide structured guidance on how to conduct the methodology.
Advising on how to manage the quality of deliverables or products.	4. Contribute to the creation of a valid game based discrete choice model. 5. Help to create a realistic simulation based on the gameplay, including human behaviour.
Providing a toolkit to facilitate the process.	6. Use a combination of Serious Gaming, DCM and simulation

Table 1, Design requirements for the methodological GCBS framework

Using the requirements of Table 1 and based on the argumentation of the introduction and an extensive literature review, a first version of the methodological framework will be created. Hereafter the modelling study that uses the GCBS methodology will be performed. Using insights into this modelling study and by evaluating the first framework, eventually, an improved, final framework will be created. A visualisation of this design cycle used for this research is presented in Figure 2.

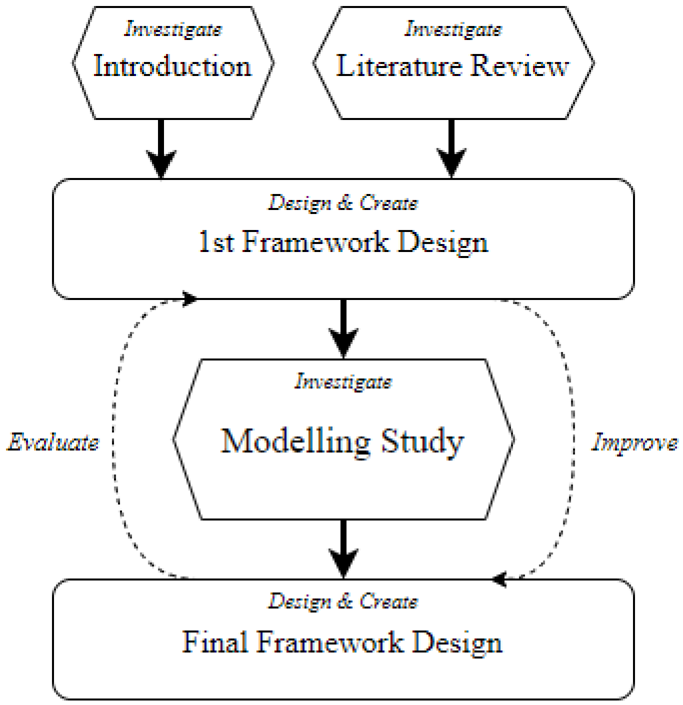


Figure 2, Design cycle for this research

2.2.2. Modelling Study

So the final design of the GCBS framework will, to a significant extent, be based on insights obtained from applying the GCBS methodology on the case of the "Freight Transportation Game". Applying the GCBS methodology on the game will mainly follow the structure of a modelling study. Using the game data and discrete choice modelling, the behaviour of players will be analysed. Together with practical and theoretical knowledge, this will form the basis of a new policy that could optimise the system's and the player's performance. The policy will be tested in a simulation experiment. Herefore, a simulation based on the gameplay will be created, at which DCM will be used to include the current behaviour of players. Eventually, the simulation experiment will generate results that can show to what extent the policy is a success. The modelling study is visualised in Figure 3.

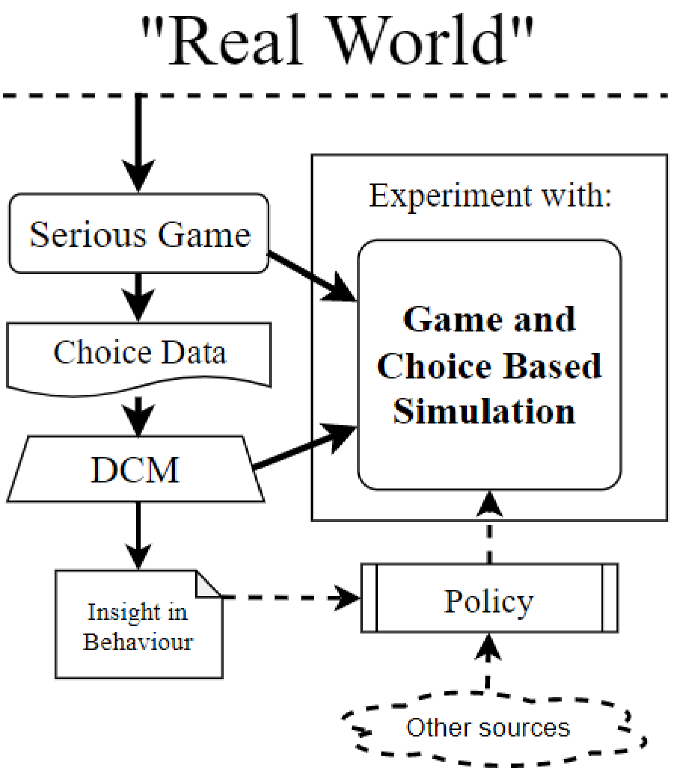


Figure 3, Modelling study of this research

2.2.3. Research plan

A more detailed elaboration on the research plan will be described step by step in this section.

At first, to get an extensive overview of the research concepts, a literature review consisting of two categories is performed. Imprimis, literature concerning the concepts of the GCBS methodology; discrete choice modelling, data collection methods, Serious Gaming and models. Secondly, literature about the case of the modelling study; innovations within the transport and logistics domain, the Physical Internet and information systems.

Subsequently, using the design requirements of Table 1 and based on the argumentation of the introduction and the executed literature review, a first version of the methodological GCBS framework will be formed. This will contain an elaboration on the opportunities if the GCBS methodology and a structure for conducting the GCBS.

So hereafter, the case of the modelling study will be introduced and elaborated on. The motive and a description of the "Freight Transportation Game" will be given in more detail, using literature and experience of playing the game. Hereafter, using this the GCBS framework, it will be argued for why this game fits as an application case for the GCBS methodology.

Hereafter, using the designed structure of conducting the GCBS methodology, the modelling study will be performed. The game will be analysed, and important player's behaviour will be modelled using DCM. By interpreting the DCM results, insights can be obtained and together with other sources; a policy will be defined. This policy will be tested by setting up a simulation experiment and creating a realistic simulation using the DCM. Eventually, conclusions about the policy can be drawn.

Finally, using the new insights obtained from the modelling study and by evaluating the first framework design, the final methodological framework for GCBS will be created and presented. Additionally, validation of the framework will be conducted using the design requirements.

3. Literature review

This literature review forms the knowledge base of the design study. At first scientific grounding on the to be designed methodological framework will be presented. This consists of literature about DCM, data collection methods, Serious Gaming and models. Hereafter literature concerning the application case is reviewed. Hereat, the current innovations in the transport and logistics domain, literature about the Physical Internet concept, the PI inspired transportation market, modelling and the role of information systems in transport and logistics will be presented.

3.1. Discrete Choice Modelling

Although he presented it in a different notation and terminology, Thurstone formulated the random utility model for the first time in the late 1920s. It was economist Marschak who introduced Thurstone's work into economics by stating that "when perceived values are interpreted as levels of satisfaction or utility, this can be interpreted as a model for economical choice in which utility is modelled as a random variable" (Krabbe, 2016). This was captured in a model by Marschalk and called the random utility maximisation hypothesis or RUM (Marschak, 1959). The RUM assumes that a decision-maker has perfect discrimination capability over alternatives but also has incomplete information, causing uncertainty (i.e. randomness) to be taken into account (Krabbe, 2016).

Discrete choice models (DCM) are based on this RUM hypothesis and have their roots in the work of Nobel Prize laureate in economics McFadden (McFadden, 1974). He developed the first version of the multinomial logistic model (MNL model) and a computer program that allowed him to estimate this model. McFadden made a link to the economic theory of choice behaviour by proposing an econometric model in which the value of alternatives would depend on the weights assigned to their attributes (McFadden, 2001). Herewith, two essential functions are included in the paradigm of discrete choice modelling. First, given the values of certain alternatives, a statistical model describes the probability of ranking an alternative as better than another. Secondly, the utility value of a given alternative can be related to a set of explanatory values by means of a function (Krabbe, 2016). Together with the development of improved computational power, more sophisticated derivatives of the MNL model have been created.

Examples are the Mixed Logit Model (able to capture nesting effects, taste heterogeneity, panel effects) and a Random Regret Minimisation (regret minimisation instead of utility maximisation) (Chorus, 2018).

Discrete choice modelling is focused on explaining choice behaviour. By using the modelling technique, the relative merit of a phenomenon can be computed as it makes it possible to estimate the relative importance of these attributes and even to estimate overall value for different combinations of attribute levels (Krabbe, 2016). DCM is applicable when individuals can choose between two or more distinct ("discrete") alternatives. Because this conceptual requirement is common in our daily life (everyone makes choices between distinct alternatives every day) and because of its explanatory and predicting power DCM is a popular method used in all kinds of sectors (see introduction).

3.2. Data collection methods

3.2.1. Revealed Preference and Stated Preference

At first choice models had been used to analyse behaviour that was observed in real life/market contexts, the so-called revealed preference method (RP). Due to the contribution of Louviere et al. (Louviere and Woodworth, 1983, Louviere et al., 2000) choice models were applied to choices which were collected from respondents who got presented choice sets with hypothetical alternatives; what they called "simulated choice situations". So Louviere modelled choices made by respondents in carefully constructed experimental studies instead, which is now best known as the stated preference method (SP). Herewith the prediction of values for phenomena that could not be measured in the real world became possible as well (Krabbe, 2016).

Using RP, choices are observed in a real-world context, herewith complex interactions between individuals and their environment are taken into account. This usually results in reliable and valid data. However, these interactions also cause a lot of inherent relationships between attributes making it hard to predict uncorrelated parameters. Using the carefully designed experimental surveys that usually form the basis of SP data, the correlations between attributes can be controlled by design, making it easier to estimate values for independent attributes. Additionally, SP is normally a much more time-consuming data collection method as taking a survey is easier than observing the behaviour and multiple choices can be observed per respondents.

As has been argued for in the introduction, using Serious Gaming data for discrete choice modelling could be an elegant method to combine the advantages of both RP and SP. By being a more valid method than SP and a more accurate and time-efficient method than RP. To the best of the author's knowledge, the method of applying a discrete choice model on choices made by players in a Serious Gaming can be seen as an unexplored scientific territory only visited by Karampelas (2018). For his study, Karampelas created multiple simulations of a board game about multimodal transport from port to hinterland, where players had to choose between different modalities. Central to his study was the aim to evaluate cooperation policies and the concept of creating (optimisation) simulations of the board game (multi-model approach). DCM was used to model the modality choices within the simulation of the gameplay. In contrast to this study, Karampelas's research was less focussed on the methodological combination of Serious Gaming and DCM and more focused on the opportunities of modelling a serious game.

3.2.2. Serious Gaming

The use of serious games or simulation games is a rather new but commonly used method in the field of transport and logistics (Kourounioti, Kurapati, Lukosch, Tavasszy, & Verbraeck, 2018). Since the integration of military games, operational research and computer science in the 1950s, a modern era of simulation games has come up (Wolfe, 1998). Within these games, players have the objective to win the game by managing their limited resources within the boundaries of certain rules (Greenblat, 1975). Simulation games are valuable as they provide the opportunity to effectively study complex systems that are future-oriented (Duke, 1975). Compared to experimenting in reality, gaming is a relatively easy and cheap way to study and experiment with a problem. Additionally, it makes a particular phenomenon more visible for observation and allows for the design of controlled experiments in a safe environment (Kurapati, Kourounioti, Lukosch, Tavasszy, & Verbraeck, 2018). An advantage compared to a simulation model and an analytical model is that games take into account part of (important) human interactions that exist in the real world (Bradley et al., 1977).

Games were and still are often used as a learning device for developing an understanding of complexities (Bradley et al., 1977). However, games could also be used as a tool to understand human behaviour better. A digital game could even be a potential source of loads of quantitative data (Lukosch, H. K., Bekebrede, Kurapati, & Lukosch, S. G., 2018). This data can be used to model the decisions of players as has been proposed by Kourounioti et al., (2018). So herewith serious games can obtain a new valuable function as data collection instrument for discrete choice modelling, helping to analyse and simulate behaviour.

3.2.3. Comparing data collection methods

Table 2 shows the characteristics of the three methods, revealed preference, stated preference and player preference (a notion created for this thesis). The revealed preference and stated preference columns are based on Louviere et al. (2000). The most player preference column is created for this thesis and is based on logical reasoning and experience from this thesis research. The final row shows that the player preference shares the validity and reliability characteristics with the revealed preference method and the accuracy and efficiency characteristics with the stated preference method. This way, one could argue that the player preference method is a data collection method positioned in between the two other methods, which yields a method with advantageous characteristics of both other methods.

Revealed Preference	**Player Preference**	**Stated Preference**
Portrays the world as it is	Portrays decision within the boundaries of the gameplay	Described hypothetical and virtual decisions context
Consist of inherent relationship between attributes	Consist of relationships between attributes	Control relationships between attributes
Only existing alternatives as observables	Including existing and/or proposed and/or generic alternatives	Including existing and/or proposed and/or generic alternatives
Represent market & personal limitations on decision-maker	Represent in-game market & player limitations	Does not represent changes in market & personal limitations effectively
High reliability & face validity	Assumed to be reliable when game is well designed, players understand the game and feel committed to the gameplay	Appears reliable when respondents understand, commit to and respond to tasks
Yield one observation per respondent	Yield multiple observations per respondent	Yield multiple observations per respondent
Valid & Reliable		**Accurate & Efficient**

Table 2, Data collection methods, based on Louviere et al. (2000)

Table 2 shows that Player Preference can be seen as a distinctive method which has corresponding characteristics, but as a whole differs from the RP and SP methods. Because the positive characteristics of RP and SP are fused in the Player Preference method, it forms an interesting data collection method to investigate.

3.3. Models

As mentioned before, using and creating models is an essential part of this research. A discrete choice model will be used to gain insight into players' behaviour and helps to create a realistic simulation model which will be used to test a policy. The basis of this all is the "Freight Transportation Game", which is itself also a model. To get a better overview, this section will elaborate on different types of models and the concept of multi modelling.

3.3.1. Model types

The application case in this research is inspired by the concept of the Physical Internet, which is new and innovative. Therefore, it is not fully implemented (on a large scale) yet. Additionally, there is much complexity within the actual freight transport market which is very dynamic. Therefore analysing the behaviour of actors within this new transportation market environment in a real-life case study could be very difficult and time-consuming. A way to deal with this is by creating a model of reality as has for example been conducted in the paper of Holguín-Veras, Xu, De Jong, and Maurer (2011) and by researchers of the "Freight Transportation Game" which is central to this research.

There are several ways to model the real world. These types can be categorised on the degree of realism that they achieve in representing a situation (see figure 4) (Bradley, Hax, & Magnanti, 1977).

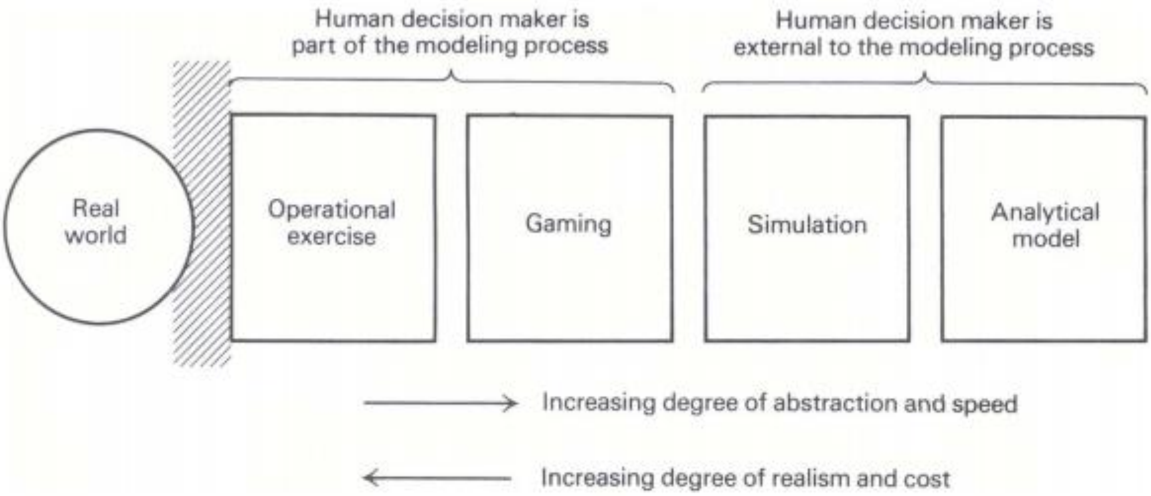


Figure 4, Types of models (Bradley et al., 1977)

The new Game and Choice Based Simulation as proposed in this thesis research is visualised in terms of modelling types in figure 5. Using the GCBS methodology a game is used based on the (future) real world (1), hereafter a DCM is created based on choice data from the game (2), then a simulation of the game is made (3) at which the DCM is used to imitate people's behaviour (4). In this way, the human decision-maker is part of the simulation (in contrast to the situation shown in Figure 5) creating a modelling method with an increased degree of realism. So a Game and Choice Based Simulation can be seen as a more realistic simulation type which retains its time-efficiency quality.

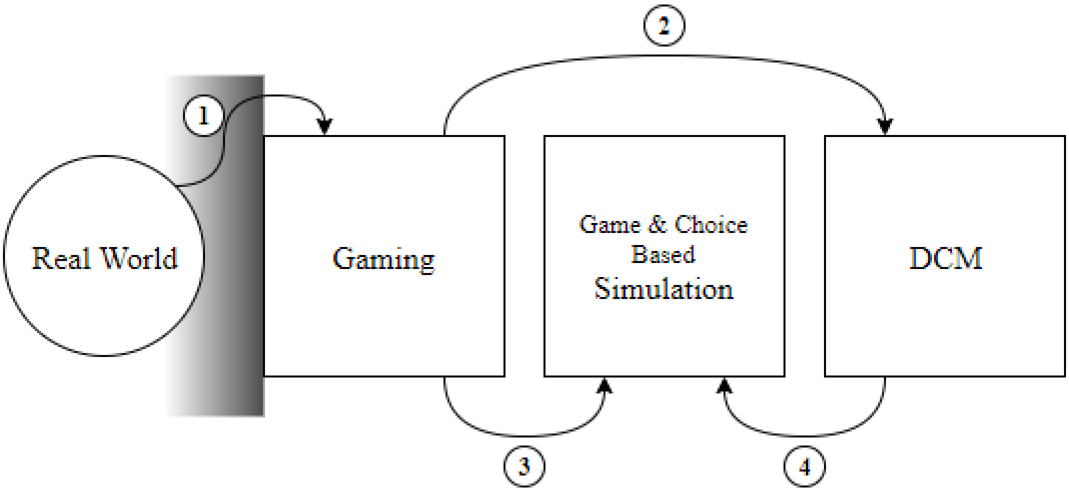


Figure 5, GCBS in terms of modelling types

3.3.2. Combined modelling

The use of a combination of modelling types is a rather new approach in the field of modelling. There is still little known about this topic; however, there is some literature that does describe combinations of modelling.

In research of Kurapati et al., (2017), about the exploration of “challenges and solutions for container transportation using rail”, a combined modelling method has been used. The approach consists of a combination of simulation and gaming. The game is used to “gather insights into the behaviour of the main stakeholders and their decision making for rail utilisation” (Kurapati et al., 2017). Additionally, the game was used to maximise the facilitation of stakeholder engagement to obtain valid insights. To overcome the challenges of limited scalability for data collection and the demanding process of incorporating changes in the game, a simulation model was used. Observations about the behaviour of players, together with quantitative data, were used to define parameters values. These parameters were then inserted into the simulation model. With the use of this simulation model, the effects of decisions on the performance of the system is quantified. The combination of the two methods was considered as a "unique tool that instantly shows how each decision can affect the results of the model” (Kurapati et al., 2017). Eventually, Karampelas (2018) went on with this study by implementing modelled behaviour using DCM. The multi-model GCBS methodology chosen for this research is, therefore, to the best of the authors' knowledge, only executed by the research of Karampelas in 2018, as part of his Master Thesis research. As mentioned in the introduction, he used a combination of modelling types to maximise the quality and efficiency of a modelling study.

A known approach that uses a combination of different types of models is Companion Modelling. This is a “participatory approach used to support and accompany collective decision-making processes” (Simon & Etienne, 2010). It is based on the idea that the participation of stakeholders is important by developing models. Therefore this approach uses role-playing games to acquire knowledge, build a simulation model (often agent-based simulation models (ABM)), validate the model and use it in the decision-making process (Bousquet, Barreteau, d’Aquino, Etienne, Boissau, Aubert, ... & Castella, 2002). With this bottom-up modelling approach, it is tried to stimulate understanding of how social and ecological systems function to facilitate collective learning and support decision-making (Moreau, Barnaud, & Mathevet, 2019).

One could argue that the methodology of GCBS can be seen as a specific kind of companion modelling. As with GCBS, a game is used to acquire data (potential knowledge), and DCM is used to obtain knowledge about players behaviour and build a simulation model. However, companion modelling can better be interpreted as a participatory approach using ABM to facilitate and enhance shared learning in social and ecological dynamics (Simon & Etienne, 2010), rather than a multi-model umbrella term that can be linked to a specific methodology as GCBS.

3.4. Innovation in transport and logistics

Because the serious game ("Freight transportation game") that is central to this thesis research is embedded in the world of transport and logistics a concise overview of the new developments within this sector is desirable. Current innovations in the world of transport and logistics are to a great extent related to IT developments or as can be argued; part of the "fourth industrial revolution". Professor Klaus Schwab first introduced this idea of the fourth industrial revolution. He argues that this revolution is fundamentally different from former industrial revolutions as it is characterised by a range of new technologies that are fusing biological, digital and physical worlds, which has the potential to impact all industries, economies and disciplines (Schwab, 2017).

In a transport and logistics trend book made by PWC in 2018 four of the five mentioned trends that transform transport and logistics (T&L) can be linked to this revolution: digitalisation, software-driven process changes, changes in markets' domestic commerce, and machine-driven process changes. At first, digitalisation is seen as the most impactful trend over the coming years, reshaping entire businesses. It allows for new: business models, processes, marketplaces, services/revenue sources, and transaction types and places. Secondly, the opportunities in software-driven process changes are expected to grow dynamically in the coming years but still need to find their way into the mainstream. For example, the implementation of freight management systems and software automation due to the development of artificial intelligence and blockchain are promising but not yet fully enhanced.

Thirdly, the changes in markets' domestic commerce are highly likely to create a push for sharing economy and value chain integrations between T&L companies, eCommerce and producers. This due to the growth of eCommerce across regions, coupled with increasing levels of optimisation in T&L. Finally, machine-driven process changes like, robotisation, electromobility, support of AR and VR and last-mile delivery optimisation, can among others, increase the efficiency of deliveries and warehousing.

3.5. Physical Internet

The Physical Internet can be seen as a more comprehensive vision in accordance with the previously mentioned T&L trends and innovations. It embraces the digital innovations to, e.g. create marketplaces or open services and standardised transactions. Additionally, innovative concepts as freight management systems and the sharing economy are rooted in the vision of the PI.

3.5.1. Concept of the Physical Internet

The concept of the Physical Internet (PI) was first mentioned by Markillie in 2006 on the front page of The Economist. After a few years, it was picked up by a group of researchers consisting of Professor Benoit Montreuil, Professors Éric Ballot and Russell Meller, who pioneered the research on PI by leading and initiating high-impact research projects starting in 2009 (Pan, Ballot, Huang, & Montreuil, 2017). They defined PI as an open global logistics system founded on physical, digital and operational interconnectivity through encapsulation, interfaces, and protocols for increased efficiency and sustainability (Montreuil, 2011) (Ballot, Montreuil, & Meller, 2014).

The PI could have a promising effect on social, economic and environmental aspects of the transportation market. An example of how this could work in practice is pointed out by a publication of Fazili, Venkatadri, Cyrus, & Tajbaksh (2017) in which the advantages and disadvantages of PI from a truck and driver routing perspective are analysed. They conclude that PI reduces driving distance/time, causing more efficiency and less pollution, and a reduced social cost of truck driving. Additionally, the number of drivers who can go back home at the end of a workday is high due to PI. These results are achieved because a trucks' riding time no longer depends on the final destination of its load. In PI, a drivers' trip time can be reduced by making use of pooled warehouses and transport fleets, whereat long-distance trips, are being replaced by a series of short hauls (Mervis, 2014). Figure 6 shows the potential advantages when contrasting current point-to-point transport and a Physical internet-enabled distributed transport.

Figure 6, Contrasting current and proposed PI transport (Montreuil, 2011)

Because the concept of PI is quite new, the form of implementation is still somewhat uncertain. However, the Alliance for Logistics Innovation through Collaboration in Europe (ALICE) came up with a roadmap about how PI could increasingly change today's logistics, based on the idea that it will gradually replace certain aspects of current logistics (see figure 7). As can be seen in figure 5, the PI is a comprehensive term that concerns a broad range of transport and logistic facets. In the end, the PI will be a system with all logistic services interconnected (Ballot, 2019).

Because the PI vision is still in a premature state of its development, a lot of research, initiatives, and projects need to take place to shape the vision and give it more flesh (Montreuil, 2011). Additionally, some significant challenges for adopting the PI by critical actors are still to be solved; e.g. about the incentive for logistics service providers to engage in PI.

Policymakers and other interested parties need to solve these critical issues to encourage and stimulate the adoption and development of the PI (Sternberg & Norrman, 2017).

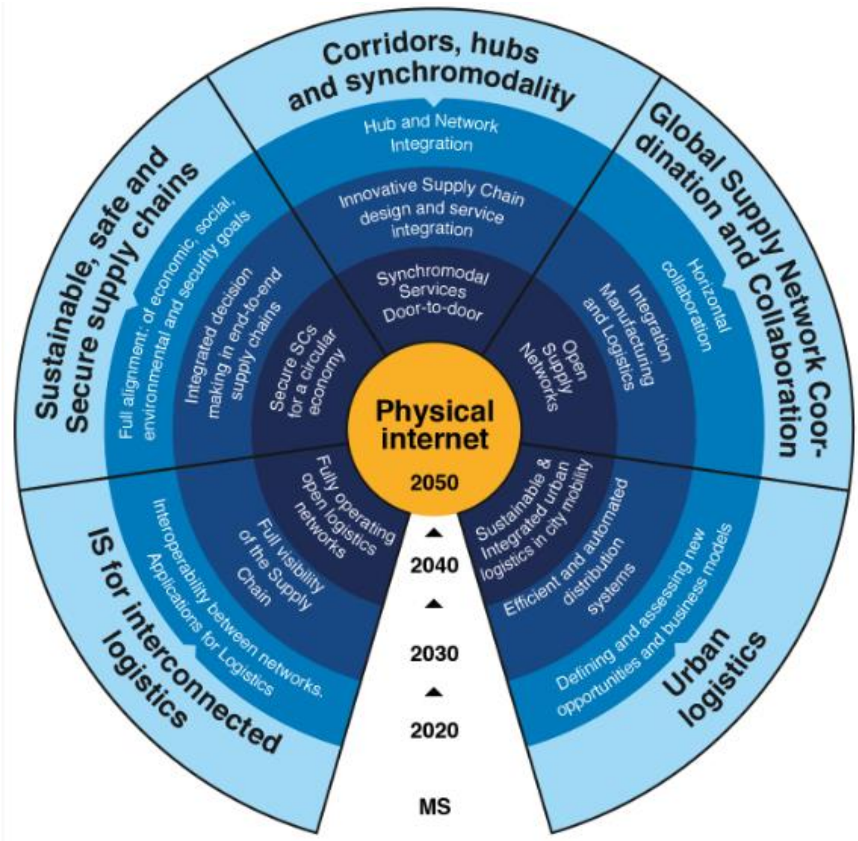


Figure 7, Roadmap towards Physical Internet (ALICE, 2018)

3.5.2. Physical Internet transportation market

The working of a Physical Internet transportation market as described by Ballot (2019) works as follows. In a Physical Internet situation, the transport of standardised (handling) containers is conducted by an interconnected system of carriers, physical hubs and a marketplace, supported by shared information. The hub and carrier take care of physical distribution, and the market place arranges the allocation of services. The market place combines shipments to create the best composite offers, based on specific requirements, e.g. lead time, delivery date and costs. This process of interconnection is possible and supported by the ability to share real-time physical and service information. The offers are allocated optimally by the marketplace, using an auction mechanism. As described by Pan, Xu and Ballot (2014), new transportation requests will be assigned to the carriers who offer the lowest price after auctioning. Thereby, the network of the PI enables shippers to exchange their capacity via spot market-based reallocation in the PI-hubs. Besides prices, the auctioning could also be based on the carrier's service quality performance (Othmane, Rekik, & Mellouli, 2014).

This auction mechanism is a decentralised system with independent carriers bidding for the transportation requests, so a centralised party does not plan the allocation. Decentralised logistics enables an agile and sustainable service, as carriers can quickly and in a flexible way to adapt to new offers to optimise their routing and individually maximise profit and minimise costs. However, in a centralised system, a centralised authority optimises transportation for all carriers involved, which could lead to a better performance in terms of effectiveness and efficiency (Lafkihi, Pan & Ballot, 2019).

3.6. Information Systems

As mentioned before the PI is a system that is supported by shared information. For example, real-time information about the offered goods (the type of goods, quantity of goods, their origin and destination, reallocation points, etc.) needs to be available for all transporters to create an open, transparent marketplace and a resulting price for the service. Additionally, this increased information flow needs to be made practical and understandable for users to facilitate rational choices to, e.g. bid or not bid on a request.

3.6.1. Definition of information

Information is an ambiguous term; it does not have a single, uniform definition. However, it is often linked to the terms: data and knowledge. The famous hierarchical DIKW (Data - Information - Knowledge - Wisdom) explanation introduced by (Ackoff, 1989), gives definitions to these terms and explains how these terms are interrelated to each other. "Data are symbols that represent the properties of objects and events. (...) Information is contained in descriptions, answers to questions that begin with such words as who, what, when, where, and how many. Knowledge is conveyed by instructions, answers to how-to questions. (...) Wisdom deals with values. It involves the exercise of judgment." (Ackoff, 1989). The definitions and relations Ackhoff describes in his model provide a structure to analyse information systems.

3.6.2. Information management systems

Whether it is data, information, knowledge or wisdom (DKIW), it needs systems to collect, process, interconnect etc. it, in other words, a management system. Rowley (2007) mapped the DKIW model to different types of information management systems in the following way:

- Data is related to transaction processing systems.
- Information with information management systems.
- Knowledge with decision support systems.
- Wisdom with expert systems.

This gives an overview of what type of management system is needed. Therewith it shows that information management systems do not self-evidently provide knowledge or wisdom. This shows that in a decentralised (PI) transport market, where decisions are not made by a central controller but by multiple individual transporters, providing information is not enough to utilise the potential of such a transport system. Truckers also need decision support systems that process the information for them to make the best individual trade-off. In other words, they need an answer to the question, how do I maximise my profit (and social comfort), given all the information I have? Therefore, the aim to provide truckers with decision-support could be a fruitful knowledge base for the creation of a policy intervention.

3.6.3. Decision support system

In literature, numerous examples of all kinds of decision support systems within the world of transport and logistics are known. These are mainly software-driven systems that help with all kinds of challenges within the sector, with subjects concerning policy support, network design, (intermodal) routing, operations, and so on.

4. Methodological GCBS Framework

Based on the argumentation of the introduction and the information of the literature review, a first version of the methodological GCBS framework will be created in this chapter. The design requirements of Table 1 will be leading for the methodological design. However, in this section, the requirements: 1. Provide insight into the opportunities of the methodology and 3. Provide structured guidance on how to conduct the methodology, will be focused on mainly. So the first design will contain an elaboration on the opportunities of the GCBS methodology and a structure for conducting the GCBS.

4.1. Opportunities of the GCBS methodology

4.1.1. Define the opportunities of the GCBS methodology

Gaming makes it possible to collect data with a so-called "players preference" method, which forms an alternative to the conventional revealed preference and stated preference methods. The player preference method yields advantageous characteristics of both other methods. At first Serious Gaming makes it possible to gather data about human behaviour validly and reliably as players, to a certain extent, feel connected to the system situation the game is representing. Additionally, a serious game takes into account interactions between people and their (game) environment. Especially when these interactions are important for the decision-making process of people, it should be included in the data collection method. Secondly, using the player preference method, accurate data can be gathered in a time-efficient way. Because a serious game makes it possible to control the setting in which choices are made. This means a more experimental setting than real life is created, making it less likely that disturbing inherent relationships in the data occur, resulting in an accurate data collection method. A controlled setting also means a possibility to observe and analyse the behaviour in future environments, or real-life behaviour that is hard to observe in an efficient way (costly and complex). Using serious games, especially a digital one, multiple choices per player per round can potentially be collected and transformed into usable data, making it much more efficient than RP and when using digital games maybe even faster than SP.

By estimating a DCM based on this player preference data collection method, quantitative and statistically rigorous insight into the choice behaviour of these players can be obtained. This will help to obtain a thorough understanding of the system being analysed. Additionally, the insights could form a basis for a policy or intervention that could optimise the performance of human behaviour and the system.

Finally using the estimated DCM a realistic simulation based on the gameplay, including human behaviour, can be made. The ability of DCM to predict choices can be used to simulate human choice behaviour. Because a game is already a model of reality, a simplified structure of the system is given already. This makes it relatively easier to construct a simulation of the real world. Eventually, based on the structure of the game and the estimated DCM, a realistic simulation of the real world can be created. This simulation then makes it possible to quickly test and evaluate interventions or policies in a simulation experiment. In this experiment, a clean (ceteris paribus) comparison in performance between different settings of the simulation can be made over much more rounds than in real gameplay.

4.1.2 Design of the sub-framework: opportunities of the GCBS methodology

The discussed opportunities are eventually summarised and designed as a framework, which is shown in Figure 7.

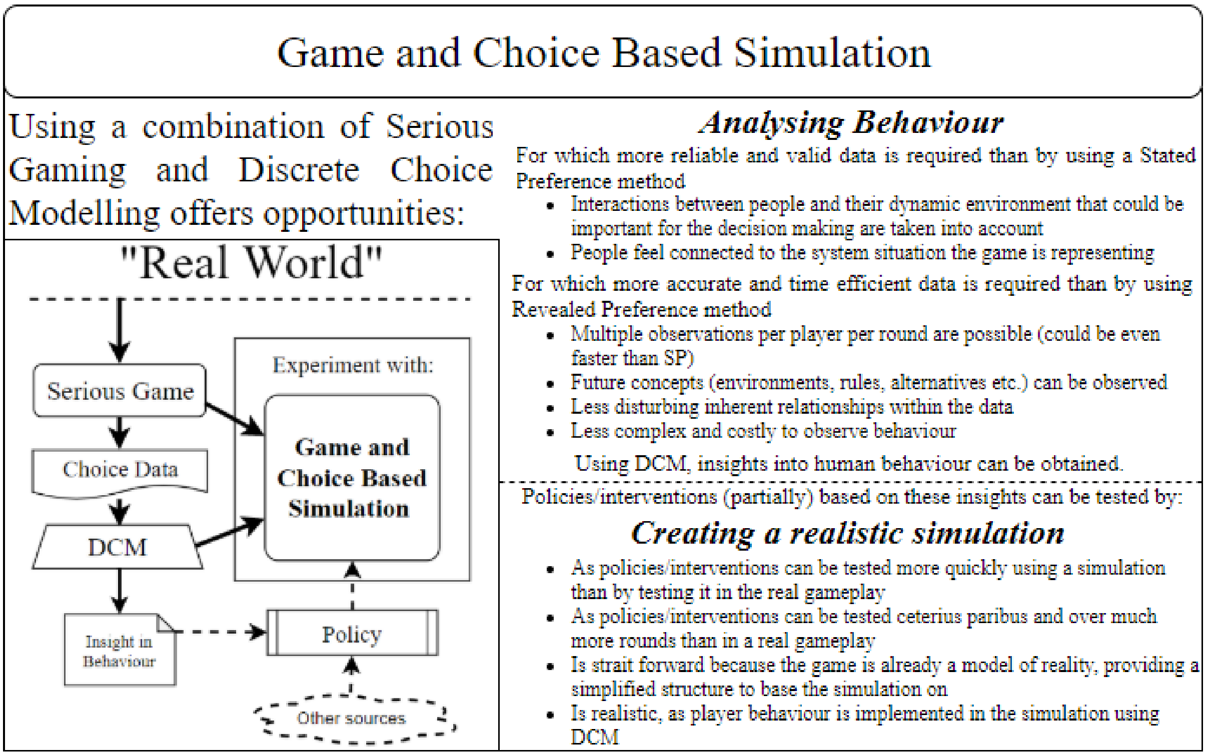


Figure 7, First design of the sub-framework, showing the opportunities of the GCBS methodology

4.2. Structure for conducting the GCBS methodology

This section will provide structured guidance on how to conduct the methodology by defining phases that are essential for performing the methodology. These phases will also guide the conduction of the GCBS methodology on the application case (modelling study). On the other hand, the application case will also be a source of reflection and improvement on the methodology as it is impossible to know how certain specific challenges can be handled before the methodology is conducted. Therefore, the methodological phases elaborated on in this section will be slightly abstract. However, if possible, matters that need to be clarified or worked out more precisely during the modelling study will be identified in this section and reflected on during the design of the final methodological framework.

4.2.1. Define structured guidance on how to conduct the methodology

Before the methodology is conducted, it should be argued for why the research case fits with the GCBS methodology. So a convincing motivation for a case, where GCBS can help to analyse behaviour and evaluate a policy/intervention using the simulation, should be performed. Herefore, the opportunities set out in the previous section can help.

In the first phase of conducting the GCBS methodology, a profound understanding of the structure of the game needs to be obtained. The game steps and game dynamics need to be researched to create a comprehensive understanding and to be able to select important choice situations in the game. Eventually, a choice situation that is interesting to gain insight in and important for the gameplay dynamics needs to be chosen. A clear definition of this choice situation and its alternatives needs to be created because a DCM is only applicable when a choice situation is created at which a choice is made between two or more distinct ("discrete") alternatives.

In the second phase, a valid DCM should be created that captures the selected choice behaviour and produces quantitative and statistically rigorous insight into this behaviour. Conventionally, a researcher defines a certain choice or trade-off situation and attributes that could influence it before analysing it using DCM. However, now a choice situation is given by the game design and a DCM should be created to capture this situation in a model. This reverse way of modelling brings some challenges with it; the choice situation needs to be captured in a way that it is possible to be analysed using DCM, the choice sets of players need to be defined and attributes that influence these choices need to be selected. Together this should lead to a valid DCM that imitates the choice situation as well as possible. So the following questions need to be answered by means of the modelling study:

- How can a choice situation be defined in order to be able to capture it using a DCM?
- How can the choice sets be created?
- How can attributes that influence the choice be selected?

Eventually, the required data needs to be collected, and DCM should be estimated. The DCM should be checked to verify if the choice situation is modelled in a valid way. A conventional method to assess the validity, especially when the aim is to predict choices, is an out-of-sample hit rate calculation (Boughanmi, Kohli, & Jedidi, 2016). If the DCM appears to be valid, conclusions about a player's behaviour can be drawn based on the estimated parameters of the choice model.

In the third phase, a realistic simulation that is based on the gameplay and uses the DCM to imitate human behaviour should be created. To create this game and choice based simulation, the game steps should be simulated using mathematical rules (e.g. if, then, else) at which the earlier obtained structural insights of the game can be used. The player's behaviour can be simulated using the estimated DCM. So for each choice situation, the simulation generates the corresponding choice set, calculates the utilities per alternative after which the alternative with the highest total utility is chosen. When the GCBS is completed, experiments can be conducted with it to test policies or interventions. Using pre-defined KPIs, the simulation results of the experiment can be interpreted.

4.2.2. Design of the sub-framework: conducting the methodology

Using the description of the methodological phases, a first design of the sub-framework showing how to conduct the GCBS methodology is shown in Figure 8.

Conducting the methodology	
Phase 1	**Create understanding of the structure of the game** • Game steps • Game dynamics • Select important choice situation(s) that are interesting to gain insight in and/or are important for the gameplay dynamics • Create a clear definition of the choice situation and alternatives of that situation
Phase 2	**Create a DCM of the selected choice situation** • Frame the choice situation in order to capture it using DCM • Define the choice sets of players • Select attributes that influence the choices • Extract the required data and prepare for estimation • Estimate the choice model • Validate the model • Draw conclusions about players' behaviour based on DCM
Phase 3	**Create a Game an Choice Based Simulation to test policies/interventions** Create a simulation experiment to test the policy/intervention Define KPIs to measure the results of the simulation performance Create a simulation of the gameplay 1. Simulate the game steps using mathematical rules (e.g. if, then, else), based on Phase 1 2. Simulate the (important) player behaviour using DCM • Calculate utilities of the alternatives based on the utility function of DCM and attribute values in the game • Base the choices on the calculated utilities Create other versions of simulations needed for the experiment (simulation with intervention or implemented policy) Conduct the experiment and interpreted the results

Figure 8, First design of the sub-framework showing how to conduct the GCBS methodology

5. Application of the Game and Choice based Simulation

5.1. The Freight Transport Game

As mentioned before the game that is used in this thesis research to apply the "innovative methodology" is the "Freight transportation game". This section will elaborate on the context and the motive of the game, the working of the game, and why there is a need for a policy to optimise the performance of the system.

5.1.1. Context and motive of the game

The world of transport and logistics (T&L) is an unsustainable societal, economic and environmental industry (Montreuil, 2011). Freight and transport account for seven per cent of global greenhouse gas emissions. Uncertainties in numerous factors cause inefficiencies and cost efficiency is often realised by drivers working under poor social conditions (Sternberg & Norrman, 2017). Additionally, the fundamentals of supply chain management have changed remarkably little in history; "The aversion to innovation has left the current global supply chain riddled with practices that waste space and energy, delay deliveries, endanger workers, increase road congestion, and pump out vast quantities of carbon dioxide." (Mervis, 2014).

However, the industry of transport and logistics is also changing. New trends and innovations have the opportunity to (partly) solve the sustainability challenges in the logistics industry. Current innovative forces that transform the T&L segment are digitalisation, software-driven process changes, changes towards digital markets and machine-driven processes (PWC, 2018). An innovative vision that incorporates a lot of these innovative concepts and trends is the Physical Internet (PI). The vision of PI is a rather new developing concept that uses the Digital Internet as a metaphor for designing an interoperable, sustainable and collaborative logistic system (Sternberg & Norrman, 2017). Just like an e-mail is sent and received without a fixed and predetermined combination of internet cables, data centres, and other infrastructure, the physical goods in the Physical Internet vision, travel similarly; using the most efficient combination of logistic services. By using an open global logistic system with interconnected logistic networks, standardised protocols, modular containers, and smart interfaces, the PI has the potential to increase efficiency and sustainability within the world of transport and logistics.

The transportation market within the PI is decentralised, with independent carriers bidding for transportation requests. It roughly consists of hubs, carriers and a marketplace. The marketplace combines shipments to create the best composite offers, based on specific requirements, e.g. lead time, delivery date and costs. The offers are allocated by the marketplace, using an auction mechanism (Ballot, 2019). After auctioning the request is assigned to the carrier offering the lowest price and best service.

Additionally, carriers have the option to exchange their cargo on a reallocation hub via the same open spot market principle (Pan, Xu and Ballot, 2014). This mechanism of decentralised auctioning with independent carriers enables an agile and flexible service, where carriers respond quickly to new market demand. However, because the allocation is not carried out strategically by a central party, the decentralised system may not result in the most efficient and effective global service (Lafkihi, Pan & Ballot, 2019). Efforts to increase the global efficiency and effectiveness could be difficult due to carriers who could be afraid of losing control (Ballot, 2019), show bounded rationality (not able to oversee all the possibilities, especially due to the new option of reallocation within the PI) or show opportunistic behaviour (they do not care about a global optimisation, they just want to maximise their own profits) (Williamson, 1975, 1995). Therefore, it is important to gain insight into the behaviour of carriers and investigate possibilities to utilise the potential of a PI inspired decentralised transportation market better and to increase its global effectivity and efficiency. This should, however, not come at the expense of the benefits as mentioned earlier (agile and flexible service) of the decentralised PI market.

To investigate this future PI inspired market in real practice the "Freight Transportation Game" is developed at MINES ParisTech - PSL. It is a digital simulation game that allows to analyse player decisions, behaviour and analyse barriers to the best strategies. Herewith, it provides the opportunity to study the future-oriented PI decentralised transportation market effectively. By playing it with students, people from the industry, policymakers etc. it is also used as a learning device for stakeholders to develop an understanding of the complexities of the system.

As has been mentioned before thesis research focuses on the behaviour of people in this new environment created by the game. Herefore, the game will be used as a data source and basis for the to be created simulation but also as a tool to understand the dynamics of the PI inspired decentralised transportation market. Therefore, the game will be played multiple times by the author and close collaboration with the researchers and developers of the game is performed for this research.

5.1.2. Description of the Freight Transportation Game

The "Freight Transportation Game" is a digital simulation game developed at MINES ParisTech - PSL. The game is about an industrial distribution system where players play a role as a carrier. The objective of the game is to optimise the allocation of resources in a way that the costs of the transport market are minimised, taking into account the interest of each player (Lafkihi, Pan & Ballot, 2019).

The game contains some crucial elements that relate to the Physical Internet transportation market. It has an open spot marked where players offer their own prices for requests. There is a central transit node and reallocation is possible on that node (see table 3). With these elements, the game represents the future PI transportation market.

Current market	**Physical Internet market**
No transit nodes	A central transit node
No reallocation possible	Reallocation possible
Players offer their own rates	Players offer their own rates

Table 3, game elements in the current and PI market situation.

The game has been played multiple times already with characteristics of the current market and of the PI market. From a conversation with developers and researchers of the game (E. Ballot, M, Lafkihi April 2019) and as described in the working paper (Lafkihi, in press) it is known that the scenario with the PI setting outperforms the scenario of the current market. However, players still do not use the full potential of reallocation and are not able to reach the market performance of a centralised market (representing the most efficient allocation of request over the carriers, executed by a central authority).

The "Freight Transportation Game" works as follows. There is a simplified geographical map on which nine nodes (cities) are displayed. Each move to a neighbouring node takes one playing round. Four players (carriers) start with their imaginary truck with a capacity of four units on the central node 9 (see figure 9).

Figure 9, starting point and map of the game

Each round the game generates three requests with the following details:

- Origin (the pick-up node)
- Destination (the drop-of node)
- Volume (number of units per request, 1 or 2)
- Lead Time (the number of rounds after which the request should be delivered. Otherwise the carrier pays a penalty)

Each round the players can bid on a request bundle (one or more requests) and set a price. This is only possible if the player finds a route that contains all the pick-up and drop-off nodes of the load, and for each move does not exceed the maximum capacity of four units. After each move, the delivery lead time decreases by one, and each delivery delay generates a penalty of $5,00. At the end of a round, the prices proposed by the carriers are analysed, and the requests are allocated to the winners by means of minimising the total price.

When a carrier arrives at node 9, their requests are offered for reallocation. These so-called “reallocation requests” are then visible for other carriers to bid on. A request can be taken over by another carrier if he bids a price lower than the former transportation costs. This creates a win-win situation as the former carrier receives his money for the transport until reallocation and gains the free capacity to bid on other requests, and the new carrier gets the new request with associated profit. Additionally, globally, the full transport of such a request is executed in a more efficient way when reallocation is involved, again showing the potential of such a transport system.

5.2. Fit between GCBS methodology and the application case

This section will explain why the application case is chosen to conduct, create and evaluate the GCBS methodology. This will be conducted by referring to the opportunities of the GCBS methodology (section 4.1.) and the characteristics of the "Freight Transportation Game" as have been mentioned in the previous section 5.1.

Based on the context and motive of the "Freight Transportation Game" as explained in section 5.1.1., possibilities to utilise the PI inspired transportation market better need to be investigated. Using the "Freight Transportation Game" dynamics of the future transportation market can be investigated. However, it provides little (quantitative) insight into why players (carriers) behave in a certain way. Played game sessions show that the current behaviour is not optimal, so there is a need to get more insight into the behaviour of players. DCM provides a way to analyse the behaviour by estimating parameters for attributes that influence choices people make. Estimating a DCM based on choice data of "Freight Transportation Game" (player preference data collection method) is a valid, reliable and efficient method in this case. This is because real-life observation using an RP method is not possible due to the future (not yet existing) concept of the PI inspired transport market. Additionally, the interaction between players (competing market) and interaction with their changing environment (reallocation of request to other players) likely influences the behaviour of players. So using a "flat" survey SP method is unsuitable for this case as crucial information about this dynamic behaviour may be missed. Finally, the game provides a researcher already with an experimental setting and a simplified representation of reality (model), so choices are less likely to be influenced by all kinds of disturbing factors. This model also provides a simplified structure of the system its representing, making it relatively straightforward easy to create a simulation based on the game. With implemented discrete choice modelling to simulate the player's behaviour, this simulation can be used to test and evaluate policies in a realistic way and in addition more efficiently than by testing the policy in the game. Playing a game session takes about two hours and simulating a game session is a matter of seconds or minutes.

The methodological choice to use the gaming data to analyse and simulate players behaviour is also motivated by recommendations given by researchers of the game, Lafkihi, Pan and Ballot (2019): “the developed game provides an efficient way to gather data for the future research work, for example, to test hypotheses in collaborative mechanism or to gather data to empirically study carriers’ behaviour”.

6. Conducting the GCBS methodology

In this chapter, the GCBS methodology will be conducted using the designed phases of section 4.2. So, the structure of the PI inspired “Freight Transportation Game” will be further investigated and elaborated on. Herewith important behaviour and decisions of players in the game can be identified. This behaviour will then be analysed using DCM. The eventually created model and estimated parameters for the attributes will give more insight into players behaviour.

6.1. Phase 1; Create understanding of the structure of the game

6.1.1. Mathematical simulation of the game

Currently, the researchers of the game have already created a model of the game as is described in a working paper (Lafkihi, in press). This model follows the same steps as the game. It mathematically simulates the game rounds without human (or modelled human) choices. In the working paper, this simulation is used to evaluate the performance of proposed collaborative rules and to analyse their impact on the decentralised PI inspired transportation market. This is done by varying two significant factors; the network characteristics (i.e. supply and demand) and carriers’ competitiveness. In the end, the results are compared with the result of the market without collaboration (Lafkihi, in press). The mathematical simulation will be used as a starting point for investigating the game structure. Additionally, it will serve as the basis for the game and choice based simulation (with discrete choice modelling implementation), which will be elaborated on and experimented within the next chapter.

In the mathematical simulation, each round starts with the pool of requests. This pool consists of the three randomly generated request per round and the reallocation requests. Hereafter, the feasible request bundles (one or more requests) and corresponding feasible route(s) per carrier are calculated. The possibility of combining a request bundle and route is bounded by the capacity and already set routing obligations of previously won bundles. The transportation cost and penalty cost of each unique feasible bundle of request(s) and route are calculated using the cost function also used in the game. Hereafter a price is set for these bundles based on a function with costs. These price functions are set according to the to be represented market type. In a centralised market, the price functions of the carriers are the same, and in a decentralised market model setting the price, functions differ, so then carriers set different margins Lafkihi (2019). Hereafter the requests are allocated to the winners by minimising the total cost, just as in the game. A visual representation of one modelled round is presented in figure 10.

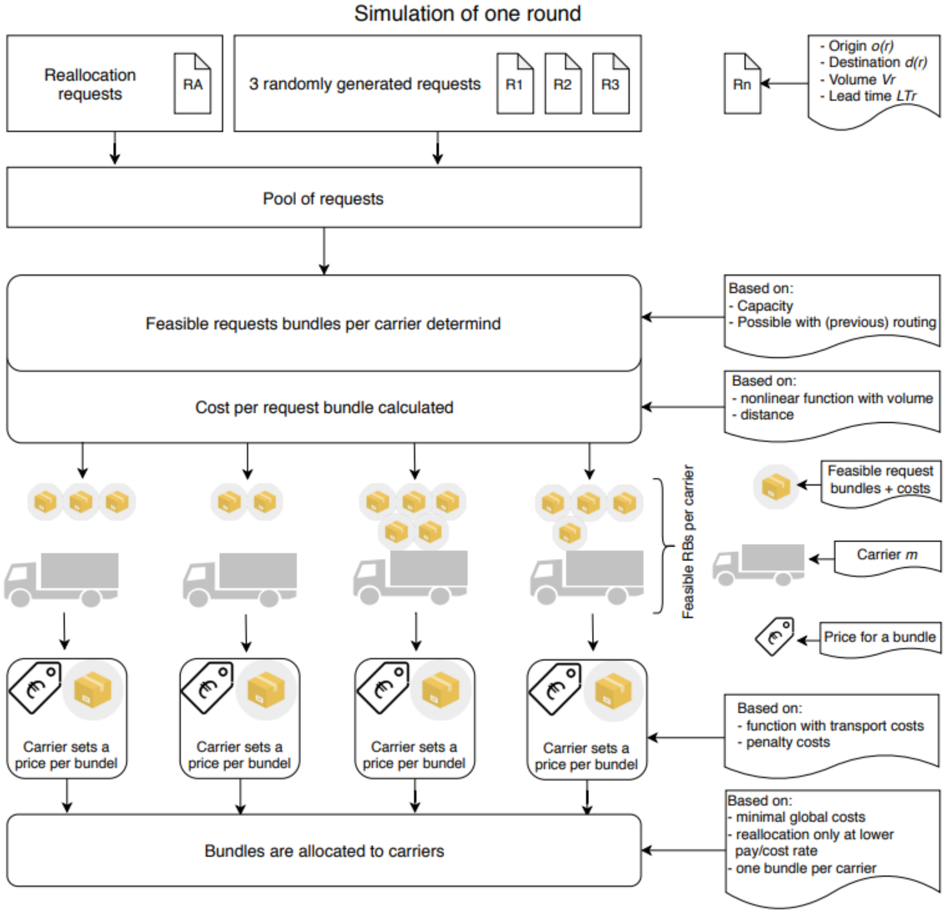


Figure 10, Current mathematical model of the game.

6.1.2. Human decisions in the game

The difference between the game and the mathematical model lay at the bidding and price-setting processes (see table 3). In the game, players select one or more requests, try to make a route that fits with the requirements and decides to bid or not bid on that bundle. In the mathematical simulation, all feasible request bundles and possible routes for that bundle (and current transporting load) are bid on. Additionally, in the game, players can set a price based on all kinds of aspects. In the mathematical simulation, a price is set just by putting a margin on top of the costs.

	Game	**Mathematical Simulation**
Bidding	Players do not bid on all feasible request bundles	Players bid on all feasible request bundles
Price setting	Players set a price based on several aspects	Players set a price based on a predetermined cost function

Table 4, Key differences between gameplay and the mathematical model

So there are two critical aspects of the differences between the game and the mathematical model. It is decided that this research will further focus on the bidding process, as this part requires a lot of information processing for players. It is interesting to get more insight into this complex "bidding behaviour", and it has significant potential to be improved by a policy. Additionally, setting prices is a more strategic consideration, that is essential for the gameplay and harder to improve without interfering with the idea of an open market. Therefore the bidding behaviour of players will be analysed (and later on simulated) using DCM.

6.1.3. Definition of choice situation

In order to create a DCM, a clear definition of the choice situation and alternatives of that situation needs to be created. In the game, the bidding behaviour consists of two choices; selecting a bundle of one or more requests and selecting a route to transport these requests. Because a DCM can only be created when a choice situation is defined at which a choice is made between two or more distinct ("discrete") alternatives, this bidding behaviour and its choices need to be redefined. Inspired by the mathematical simulation, where these two choices are combined and because modelling two consecutive choices using DCM is too complex, the two choices and their alternatives are combined. So, the alternatives used for capturing the bidding behaviour are defined as all the unique possible combinations of requests and routes a player has in a certain round. For example, if a player in a certain round can select request B and transport this using six different routes (keeping in mind the requirements of the current load of the player), these are considered as six feasible alternatives. Because a player often can select multiple requests and combine them, the list of feasible alternatives per player (choice set) could be large.

6.2. Phase 2; Create a DCM of the selected choice situation

In order to capture players' bidding behaviour into a discrete choice model, choice sets need to be generated based on the game data and attributes must be identified. Eventually, it will be attempted to create a discrete model that imitates the bidding behaviour as well as possible. To check this, a validation of the DCM is carried out eventually.

6.2.1. Creating choice sets from game data

To create a discrete choice model, a choice set should be collectively exhaustive, mutually exclusive, and the sets should contain a finite number of alternatives. At first, for this research, it is possible to collect all possible alternatives players have (collectively exhaustive), because the required information for this is digitally stored during game sessions. Secondly, players can choose multiple alternatives which does not meet the mutually exclusive requirement, however by considering each alternative as a binary choice set this requirement can still be met (this will be elaborated on further at the end of this section). Finally, the number of alternatives players can choose from is large but finite.

The dynamic choice sets of the game should be generated based on the game data. Because the approach of using a serious game to obtain choice data is new, no literature is available about how to generate choice sets from game data. Choice sets in a game are dependent on the game environment, just like real-life choices are dependent on their real-world environment. Therefore literature of empirical-based choice set generation is used. The Doctoral dissertation "Choice Set Generation in Multi-Modal Transportation Networks" from Fiorenzo-Catalano (2007) describes the theoretical basis for generating route choice sets based on real-world routing observations (Revealed Preference). This theoretical basis will be used and translated to the situation of generating choice sets based on Serious Gaming observations (Player Preference).

In her work, Fiorenzo-Catalano introduces the important conceptual difference between:

1. Actual, observed and generated choice sets
2. Traveller's viewpoint and researcher's viewpoint.
3. Analysis, estimation and prediction applications

So it is important to distinguish between actual choice set considered by players in their decision-making process, observed choice sets as obtained using the game data, and generated choice sets established by a researcher. Additionally, there is an important difference in the perspective of a player and the perspective of a researcher. Finally, it is important to consider the purpose for which the choice sets formation are needed. In this case, the purpose is to estimate parameters for a choice model (in order to derive insights into the bidding behaviour) and to predict choice outcomes for the game simulation using these parameters.

As well in real life as in the gameplay, often the number of feasible routing alternatives is large for a person. This set of feasible alternatives is called the subjective choice set. A player usually has a lot of feasible combinations of routes and requests to bid on. However, only a subset of them is known to the player and considered in his choice process. These considered alternatives of a player are called his/her considered choice set. In reality, but also in the game, a person's choice set formation largely follows an experimental process of trial-and-error of route use and information acquisition (Fiorenzo-Catalano, 2007). In the game, a player selects a request (bundle) and tries to create a route that satisfies the requirements of his/her current and the new load. Eventually, one or more alternatives of the considered choice set are chosen to bid on. As a researcher, it is almost impossible to know someone's considered choice set when researching empirical data (Fiorenzo-Catalano, 2007). The same counts for the considered choice sets in the game. It is not possible to track down the alternatives a player has considered by him or herself in a particular round of the game. Therefore these considered choice sets need to be generated in some way. The generation of these considered choice sets will be executed based on the theoretical guidelines of Fiorenzo-Catalano (2007).

So, for a researcher, the subjective choice set, with all the feasible alternatives per player per round, is observable using the historical game data. Additionally, the chosen alternatives are known to the researcher. However, the considered choice set, that "sits in between" these two sets, is not known by the researcher. As the choice sets will not only be used for attribute estimation but also for choice predictions, precise and valid measurements are demanded. Therefore, the considered choice set is not just considered to be equal to the subjective choice set. Additionally, "the choice sets should include all realistic and reasonable alternatives; otherwise computed route choice probabilities may produce wrong predictions" (Fiorenzo-

Catalano, 2007). The choice sets must include at least all attractive routes but may miss some routes of less attractiveness (Fiorenzo-Catalano, 2007). Almost all route set generation approaches analysed by Fiorenzo-Catalano (2007) are based on shortest path search. So the "attractiveness" of a route is mainly based on minimising criteria such as minimum distance and time.

Considering these insights, it is chosen to include all the feasible request bundles a player can bid on, into the considered choice set. However, when the request bundle (and current load) can be carried using several different routes, only the one with the shortest route is included in the considered choice set. This incorporates not only the idea of including only the shortest routes but also the routes that take the least time, as one unit of distance is fulfilled in one unit of time (round). When a feasible request bundle has several potential routes with the same (shortest) length, only the one with the lowest costs is included in the considered choice set. This theoretical approach is also consistent with the practical experience of the game, as players usually try to search for transportation opportunities using the shortest route. The full visualisation of the theoretical framework for choice set creation of the gameplay choices is visible in figure 11.

Eventually, as mentioned before, it is assumed that the generated considered alternatives will be constructed as a binary choice set. So for each considered alternative, there is an observation whether a player bids on that alternative or does not bid on that alternative. This is done because players can choose to bid on multiple alternatives in the game, so including all alternatives in a choice set would ignore the DCM requirement of creating a mutually exclusive choice set (choosing one alternative, means not choosing any other alternative from the choice set).

6.2.2. Attribute selection for the DCM

As can be seen in figure 10, the "generated considered choice set" is created as a subset of the "objective choice set" using assumptions based on the work of Fiorenzo-Catalano (2007). However, it is still assumed that this "narrowed down" choice set does not fully grasp the real considered choice set of a player in a game, as it remains a too extensive set for that. Players are not able to find all these alternatives due to complexity and their bounded rationality. Therefore, the "gap" between the real considered choice set and the considered choice set, which is highlighted in figure 9 by the purple part (middle right square), needs to be "filled" with "information" to imitate the real choice behaviour. This is done by including attributes that are assumed to provide information about the "complexity to find a feasible alternative" into the utility formula of the discrete choice model. Additionally, the eventual choice process to bid or not bid on the alternatives a player considers is imitated. This is done by including attributes that are assumed to (partially) explain these choices.

Herewith, all the means to imitate the choice behaviour using DCM are defined. This process is visual in Figure 10. At first, a considered choice set is generated using a theoretically based assumption (see section 6.2.1.) of including all relevant and chosen alternatives (shown by the top right blue square in Figure 10). Because these generated considered choice sets are still not representative for the real considered choice sets, attributes that could explain the creation of considered choice set will be formulated (middle right purple square in Figure 11) and finally attributes that could explain the consideration players make when choosing an alternative are formulated, as visualised by the bottom right (yellow) square in Figure 11.

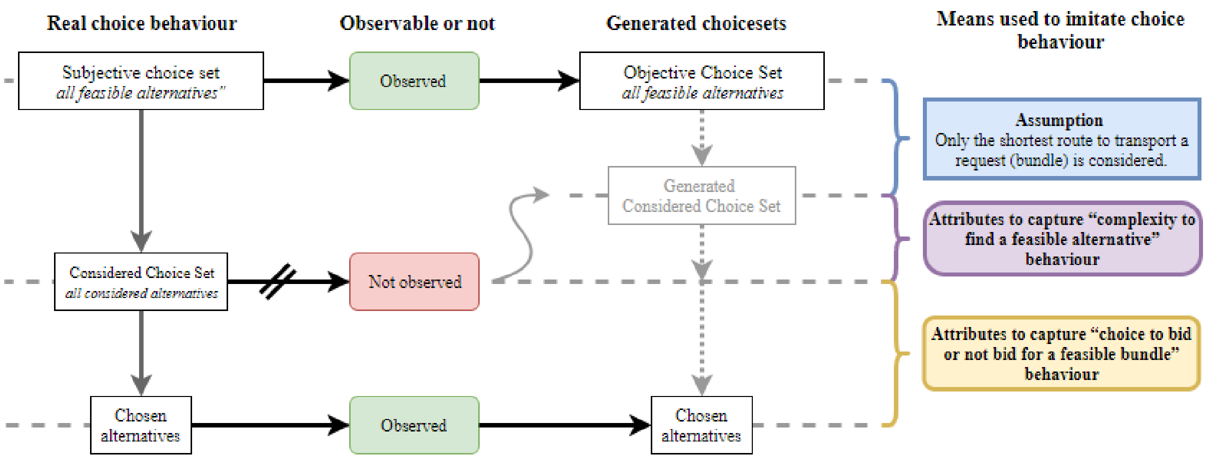


Figure 11, Theoretical framework for imitating choice behaviour

<u>Attributes to capture "complexity to find a feasible alternative" behaviour</u>

As mentioned before, a player's considered choice set formation depends on his/her ability to find a route that satisfies the requirements of his/her current and the new load. In the game a player, just as Fiorenzo-Catalano (2007) mentions in her work, finds these opportunities by an experimental process of trial and error. In a game round, several routes in combination with the limitations of the current load and new request (bundle), are tried by players. Sometimes these trials are successful, and sometimes these trials will not result in a feasible combination of bundle and route.

The aspects that make it hard to find a feasible alternative for a player are the requests' lead time, the origins and destinations (O&D), and the route that combines this all. For a player, it is easier to find a feasible route to bid on if the amount of requests to consider is small. However, the more requests a player needs to consider; the more complex the potential route will be. If for example, a player is already carrying one request, he is executing his route by first going to the origin of the request and thereafter going to the destination of the request within the given lead time. When, in the next round, he/she considers to bid on a bundle of two requests he needs to create a route that passes by the O&D of the current load but also passes by the O&Ds of the requests in the bundle (all in the right order). Additionally, all these requests need to be delivered within their own lead time to avoid a penalty. In conclusion, it can be said that the number of requests a player needs to consider is a good indicator of the complexity of finding the feasible bundle. Herewith, the total number of requests (current and new load) or only the new load (number of requests in the bundle) could be included as an attribute in the utility formula of the discrete choice model. Both attributes will be used to see which one performs best in the DCM.

Additionally, it can be argued that the length of a feasible route, that successfully connects the current and the bundle request(s), could be an indicator for the complexity of finding the feasible bundle as well. Because the longer this feasible route is, the more difficult it is to find for a player. However, the indicator route length does not contain the "complexity information" of taking into account several O&Ds and lead times as precisely as the indicator total route number of requests does. Both attributes will be estimated to see if they have a significant influence on the bidding behaviour.

Eventually, the considered set of alternatives may differ strongly between individuals even under the same conditions (Fiorenzo-Catalano, 2007). In the game, this effect is also plausible because some players perform better in finding feasible routes than others. In DCM literature this effect is known under the term "panel effect". This is the effect that observations of the same individuals carry less unique information than observations of different individuals

(Chorus, 2018). Therefore, eventually, the model will be tested as a Panel Mixed Logit model which captures the panel effect.

Additionally, there could be an integrated effect of players who learn to play the game while playing it (Ryu, 2013). It is plausible to assume that, due to practice, players will become better at finding feasible alternatives during the game. However, as the game processes, finding alternatives will likely become more difficult as players need to process more information. Therefore, a game round attribute will be included in the utility function, to test if it influences the bids made.

Attributes to capture "choice to bid or not bid for a feasible bundle" behaviour

This section will present the attributes that will be used to imitate the choice process of bidding or not bidding for a considered alternative. So it is assumed that a player has found a considered set of alternatives to bid on, and now the question is: which of these alternatives will he/she eventually bid on and which not? In literature, information is available about simulations of transport market auctions and what factors influence the bidding behaviour.

The PI inspired transportation market used in the game shows the characteristics of a "First price sealed bid" auction. Within this auction type, bidders secretly bid for an item after the deadline, the bids are opened simultaneously, and the highest is declared the winner. There is no chance to update a bid once submitted, and the winner pays the price bid (Van Duin, Tavasszy & Taniguchi, 2007). Therefore no interaction effect between players, or between player and auctioneer are assumed in the bidding process. However, presumably, players are influenced by other factors when choosing to bid or not bid on a request bundle. Van Duin, Tavasszy and Taniguchi (2007) name the profit to be made and the profit already won, as factors that influence bids.

At first, only profit can be made from an alternative when a player bids on this alternative, so bidding means a chance to make a profit. To imitate this effect a constant for bidding is included in the utility formula. Additionally, the profit to be made is highly dependent on the total cost (route and penalty costs) of an alternative. It is plausible that alternatives with a low total cost are more attractive to bid on than alternatives with a high total cost because players can set more competitive bids and a higher margin when the costs are low. Although players can set as many bids as they want, they may think bidding is reasonless when the costs are high. Especially because they are operating in a tight market where the supply of request is lower than the capacity of the carriers (players). To capture this effect, the cost of an alternative will be included in the utility function as an attribute. Herewith the total cost of an alternative could be the attribute (this exists of transportation cost and penalty cost). However, the penalty cost could be a useful attribute as well because the main factor that creates a really high (unacceptable) total cost is the penalty costs. Additionally, penalties are directly linked to delays of requests, and players are presumably trying to prevent delays as much as possible using the penalty costs as their main indicator. So both attributes (total cost and penalty cost) will be used to see which one performs best in the DCM.

Secondly, the aspect of the profit already won can be interpreted in two ways. Van Duin, Tavasszy and Taniguchi (2007) mention the effect as a player whose truck is far from full causing him/her to probably be greedy to attract new loads as his current earnings can be increased. On the opposite side, when a player's truck capacity is almost fully utilized he/she will be less eager to place a bid as earnings are already being made and it could bring extra restrictions for next rounds in which better bids could be won as well.

Additionally, the "profit already won" can be interpreted as the profit already won during the whole gameplay compared to others. Normally carriers are not aware of each other's profit figures. However, in this game environment, players are shown a competitive podium ranking of their profit made so far. This is done after each round, to create the competitive game element as eventually the one with the most profit wins the game. So players know if they performed well in terms of making a profit or not. Therefore there could be an effect that players who, after a certain round, are on the lower ranks of the podium, are more eager to place bids in the next round to increase the chance to make a profit.

6.2.3. Discrete Choice Model Estimation

In this section, different models with different utility functions and composition of attributes will be estimated to check whether evidence can be found if the previously mentioned attributes (that theoretically could influence players' choice behaviour) really do have their effect on the bidding behaviour. This iterative estimation process will be conducted using a prepared database of 485 "observed choices" (n = 485). Eventually, the aim is to construct a model that is valid and therefore, should explain the choice data as good as possible. This so-called model-fit is measured using the Rho Squared value. This is a statistical measure of how close the choice data are to the fitted regression line. Rho Squared can be interpreted as the percentage of the response variable variation that is explained by a linear model. Although there is no consensus about what is a good model-fit is, some say that studies which are trying to explain actual human behaviour generally have values less than 50%. Another statement found is that a model with Rho Squared greater than 0,2 is generally considered to have a statistically significant amount of variation in consumer behaviour (Oppenheim & Fry,1998). These allegations will be kept in mind but not be strictly adhered to in this research. Additionally, it is the aim that the model consists of parameters of which statistical evidence can be found that they have an influence on the bidding behaviour. So estimated parameters that appear to be really insignificant will be left out. Additionally, parameters that can replace another attribute and that have a greater estimated value (and equally as significant) will be preferred as they have more explanatory power. Finally, the composition of the utility function should be well explainable and aligned with the theoretical reasoning and construct described in section 6.2.2.

The attributes that are argued for in the previous two sections are visual in figure 12. The model will be estimated using two utility formulas, one for the option "to bid" and one for the alternative to "not bid" on an alternative.

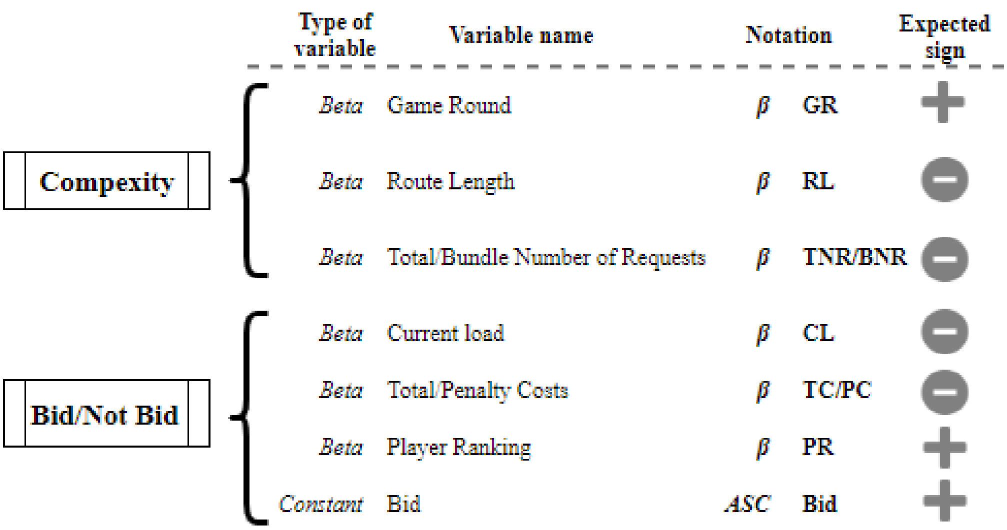


Figure 12, attributes that could theoretically influence players' choice behaviour

The attributes (GR, RL, TNR) that have been argued for being indicators of "the complexity to find a feasible bundle" will only be included in the utility function of bidding. This is done because these indicators are expected to make it more difficult to find a feasible request bundle. However, they do not affect the utility of not bidding as not bidding means going on with the current requests and routing. These requests and routing have already been determined in previous rounds, so do not affect the utility in the current round. On the other hand, the attributes (CL, TC, PR and ASCBid) that have been argued for being indicators of the Bid/Not Bid behaviour, do affect both of the utility functions (Ubid and UNotBid) and are therefore included in both functions.

Estimation Model 1

The first model that is estimated contains all the attributes mentioned in Table 5 in the following way:

- $U_{bid} = \beta_{GR} * GR + \beta_{RL} * RL + \beta_{TNR} * TNR + \beta_{CL} * CL + \beta_{TC} * TC + \beta_{PR} * PR + ASC_{Bid} + \varepsilon$
- $U_{NotBid} = CL + \beta_{CL} * CL + \beta_{TC} * TC + \beta_{PR} * PR + \varepsilon$

Rho square: 0.159

Name	Value	Std err	t-test	p-value		Robust Std err	Robust t-test	p-value	
ASC_Bid	0.355	0.436	0.81	0.42	*	0.448	0.79	0.43	*
B_CL	-8.91e-015	1.80e+308	0.00	1.00	*	1.30e+005	-0.00	1.00	*
B_GR	-0.00106	0.0421	-0.03	0.98	*	0.0443	-0.02	0.98	*
B_PR	7.28e-016	1.80e+308	0.00	1.00	*	2.69e+005	0.00	1.00	*
B_RL	0.00307	0.120	0.03	0.98	*	0.120	0.03	0.98	*
B_TC	-0.00856	0.0148	-0.58	0.56	*	0.0166	-0.51	0.61	*
B_TNR	-0.403	0.152	-2.66	0.01		0.162	-2.49	0.01	

Table 5, parameter estimations of Model 1

Estimation Model 2

The second model is similar to the first one; however, TNR is replaced by BNR and TC is replaced by PC to see if these attributes lead to a better performing model.

- $U_{bid} = \beta_{GR} * GR + \beta_{RL} * RL + \beta_{BNR} * BNR + \beta_{CL} * CL + \beta_{PC} * PC + \beta_{PR} * PR + ASC_{Bid} + \varepsilon$
- $U_{NotBid} = CL + \beta_{CL} * CL + \beta_{TC} * TC + \beta_{PR} * PR + \varepsilon$

Rho square: 0.256

Name	Value	Std err	t-test	p-value		Robust Std err	Robust t-test	p-value	
ASC_Bid	1.61	0.498	3.24	0.00		0.513	3.14	0.00	
B_BNR	-1.21	0.163	-7.39	0.00		0.201	-6.00	0.00	
B_CL	1.87e-014	1.84e+005	0.00	1.00	*	1.80e+308	0.00	1.00	*
B_GR	-0.0136	0.0412	-0.33	0.74	*	0.0412	-0.33	0.74	*
B_PC	-0.0197	0.0150	-1.31	0.19	*	0.0140	-1.41	0.16	*
B_PR	7.23e-015	1.80e+308	0.00	1.00	*	970.	0.00	1.00	*
B_RL	-0.0496	0.105	-0.47	0.64	*	0.108	-0.46	0.65	*

Table 6, parameter estimations of Model 2

As can be seen in Table 6, the values of the betas of BNR and PC are higher and more significant than the ones of TNR and TC. Additionally, the Rho square improved a lot using the new model specification. Therefore, from now on, BNR will be used as the attribute for the number of requests to consider, and PC will be used as the attribute for costs of a bid.

<u>Estimation Model 3</u>

As can be seen in Table 6, CL and PR appear to have no significant effect on the bidding behaviour. Therefore in the new estimation, these attributes are left out.

- $U_{bid} = \beta_{GR} * GR + \beta_{RL} * RL + \beta_{BNR} * BNR + \beta_{PC} * PC + ASC_{Bid} + \varepsilon$
- $U_{NotBid} = 0 + \varepsilon$

Rho square: 0.256

Name	Value	Std err	t-test	p-value		Robust Std err	Robust t-test	p-value	
ASC_Bid	1.61	0.498	3.24	0.00		0.513	3.14	0.00	
B_BNR	-1.21	0.163	-7.39	0.00		0.201	-6.00	0.00	
B_GR	-0.0136	0.0412	-0.33	0.74	*	0.0412	-0.33	0.74	*
B_PC	-0.0197	0.0150	-1.31	0.19	*	0.0140	-1.41	0.16	*
B_RL	-0.0496	0.105	-0.47	0.64	*	0.108	-0.46	0.65	*

Table 7, parameter estimations of Model 3

As can be derived from the Rho Square value, the model with a reduced set of parameters performs equally as good as the one of the 2nd model estimation. However, as can be seen in Table 7, the values and significance of the estimated parameters did not improve.

Estimation Model 4

Because GR and RL appear to have no significant effect on the bidding behaviour, these attributes are therefore left out of the new model estimation.

- $U_{bid} = \beta_{BNR} * BNR + \beta_{PC} * PC + ASC_{Bid} + \varepsilon$
- $U_{NotBid} = 0 + \varepsilon$

Rho square: 0.256

Name	Value	Std err	t-test	p-value		Robust Std err	Robust t-test	p-value
ASC_Bid	1.37	0.282	4.87	0.00		0.313	4.40	0.00
B_BNR	-1.22	0.161	-7.57	0.00		0.196	-6.24	0.00
B_PC	-0.0242	0.0126	-1.93	0.05	*	0.0118	-2.06	0.04

Table 8, parameter estimations of Model 4

As can be derived from the Rho Square value, the model with a reduced set of parameters performs equally as good as the one of the 2nd and the 3rd model estimation. Additionally, as can be seen in Table 8, the value of B_PC increased, and its significance improved.

Estimation Model 5

The model can also be constructed by estimating betas for different levels of BNR, as players presumably have different coefficient values for different amounts of requests. So to analyse this the BNR value is split up as follows (based on analysing the data):

  - BNR_1 = 1 request
  - BNR_2 = 2-3-4 requests
  - BNR_3 = >4 requests

- $U_{bid} = \beta_{BNR\_1} * BNR\_1 + \beta_{BNR\_2} * BNR\_2 + \beta_{BNR\_3} * BNR\_3 + \beta_{PC} * PC + \varepsilon$
- $U_{NotBid} = 0 + \varepsilon$

Rho square: 0.256

Name	Value	Std err	t-test	p-value		Robust Std err	Robust t-test	p-value	
B_BNR_1	0.153	0.160	0.96	0.34	*	0.159	0.96	0.34	*
B_BNR_2	-1.22	0.162	-7.54	0.00		0.196	-6.20	0.00	
B_BNR_3	-7.05	127.	-0.06	0.96	*	0.726	-9.71	0.00	
B_PC	-0.0242	0.0126	-1.92	0.05	*	0.0118	-2.05	0.04	

Table 9, parameter estimations of Model 5

Table 9 shows that there appears to be a different coefficient value between 1 request or 2 to 4 request requests in a bundle. However, when taking a closer look Model 4 and Model 5 are actually similar as ASC_bid+BNR in Model 4 is equal to BNR_1 in Model 5, BNR and BNR_2 are the same and BNR_3 is very insignificant, and PC estimates are the same.

Model 4 is, however, more simple than Model 5 (less estimated parameters). Additionally, Model 4 is well explainable and aligned with the theoretical reasoning of section 6.2.2.; ASC_Bid represents the utility derived from the potential profit that could be made when making a bid. Beta BNR stands for the increasing difficulty of finding feasible request bundle when the request in the bundle are increasing (so a decreasing utility for bidding). Furthermore, beta PC stand for the decreasing utility of bidding for a feasible request bundle when the penalty costs of a bundle increase. Therefore Model 4 will be used to in further.

6.2.4. ML model for capturing panel effects, nesting effects and beta heterogeneity

Because in the MNL model, the parameters are estimated without taking into account the effect that preferences and betas vary across players, a Mixed Logit model for panel effects is estimated. Herewith the complete sequence of choices made by an individual is the unit of observation. The parameters and random values are estimated using the Python Biogeme software, with a Monte Carlo simulation with 500 draws for the random distributions. Eventually, these efforts are made to improve the model-fit of Model 4 of the previous section.

<u>Estimation Model 6</u>

In this model estimation, ASC_Bid is randomly distributed, the mean and standard deviation of the Normal distribution are estimated, see Table 10. Herewith, the effect of alternative specific preferences across players can be investigated. This model is estimated by taking into account the possible panel-effect.

Rho square: 0.256

Name	Value	Std err	t-test	p-value		Robust Std err	Robust t-test	p-value	
ASC_Bid_mean	1.37	0.282	4.87	0.00		0.546	2.52	0.01	
ASC_Bid_std	0.000743	0.135	0.01	1.00	*	0.000522	1.42	0.15	*
B_BNR	-1.22	0.161	-7.57	0.00		0.295	-4.14	0.00	
B_PC	-0.0242	0.0126	-1.93	0.05	*	0.0150	-1.61	0.11	*

Table 10, parameter estimations of Model 6

As can be seen in Table 10, the standard error of ASC_Bid is not significant. Additionally, its value is very small so, using this reasoning, it can be said that apparently, there is evidence found of individual-specific variation in unobserved preferences for bidding or not bidding.

<u>Estimation Model 7</u>

As has been discussed in section 6.2.2. the constructed considered choices differ between individuals. In the situation of this game, the number of requests in a potential bundle (BNR) could possibly indicate this. Because for some players it might be easier to create a feasible alternative with a high number of BNR than for other players. Therefore, the coefficient of BNR could vary across people. To test this it mean and standard deviation estimated by simulating and drawing from Normal distribution. See the results in Table 11.

Rho square: 0.256

Name	Value	Std err	t-test	p-value		Robust Std err	Robust t-test	p-value	
ASC_Bid	1.37	0.282	4.87	0.00		0.546	2.52	0.01	
B_BNR_mean	-1.22	0.161	-7.57	0.00		0.295	-4.14	0.00	
B_BNR_std	0.00183	0.252	0.01	0.99	*	0.0104	0.18	0.86	*
B_PC	-0.0242	0.0126	-1.93	0.05	*	0.0150	-1.61	0.11	*

Table 11, parameter estimations of Model 7

As can be seen in Table 11, the standard error of ASC_Bid is not significant. Additionally, its value is very small, so no evidence is found for the existence of a panel effect in this case.

Final DCM model

Because the estimated standard deviations are insignificant, the ML model performs equally as good as the MNL Model 4 (see the Rho Square values). The MNL model is prefered to continue with as it performs equally as good as the more advanced ML models and creating simulations with MNL is less complex. Additionally, the discrete choice model well explainable and is used for simulation purposes. It is not the aim of this study to generate perfect choice predictions but to gain insight into behaviour and to imitate the choice behaviour as good as possible in the simulation using DCM. Finally, using a MNL model for simulation is a relatively straightforward process and less complex than simulating a ML model.

6.2.5. Validation of the DCM

To check how reliable the MNL Model 4 is considering its ability to predict the right choices, a validation of the model is carried out. Herewith, it is calculated what percentage of choices is predicted right by the model (hit rate). This validation consists of calculating the hit rate using out-of-sample testing. Herefore, the data-set of 485 observations is split into two parts. The first ⅔ of the observations is selected randomly to estimate the model on. Then this model is applied to the remaining ⅓ of the observations. The percentage of correctly predicted choices is the hit rate. To reach robust results, the hit-rate is calculated ten times, each time with another randomly selected estimation- /data-set. For MNL Model 4, the hit rate is quite stable over the ten validations, and on average, 73% see figure 12. To put this into perspective; if bids were set on all the request bundles of the generated considered choice sets, the hit rate would be 29%. If bids were set on all the request bundles of the objective choice sets (which is the case in the mathematical simulation), the hit rate would be only 1%. Therefore the calculated hit rate of 73% is considered to be a good validation-score for the model. As herewith, the bidding behaviour can be (far more) realistically imitated.

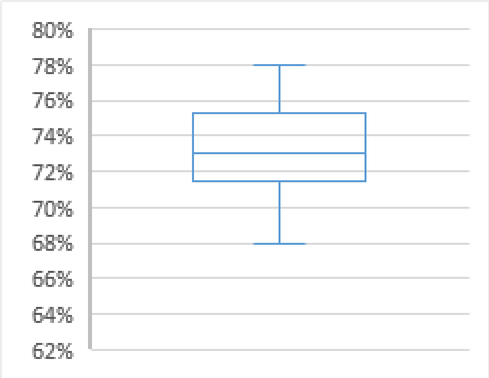


Figure 12, Boxplot of ten hit rates of Model 4

6.2.6. Conclusions about the behaviour of players based on the DCM

Based on the estimated parameters of the final chosen model (model 4), some careful conclusions can be drawn about the bidding behaviour of players. It can be stated that players have a preference for making a bid (the positive constant Bid). However, when a player wants to bid on a request, this effect is almost entirely abolished due to the negative effect of the parameter; number of requests (BNR). Because evidence is found that the number of requests (within a feasible bundle) negatively affects the likeliness of making a bid. Players presumably find it difficult to deal with the complexity of combining a bundle and feasible route when more requests need to be considered. This attribute of complexity has relatively the most substantial influence on the systematic bidding behaviour found by estimating the DCM. The other attribute of which evidence is found that it influences player bidding behaviour is penalty cost. The higher the penalty cost a player should pay when bidding on the corresponding request bundle, the less likely he/she will bid on it. However, this influence is quite logical and only really affects the bidding behaviour with hefty penalties. Although, even then this effect is relatively small compared to the previously mentioned complexity effect.

So it can be stated that the main factor influencing the bidding behaviour for carriers in this PI inspired transportation market environment (that could become a reality in the future) is the complexity of having to deal with combining a bundle and feasible routes. Other than in the game, carriers in real life could, however, have other incentives than only making a profit as well. They may also care about the region in which they conduct their transport or the length of the route. These extra requirements could make it even more complex for carriers to find their optimal bids. This complexity, as a result of bounded rationality, creates a sub-optimal market performance as bids are not made on the most efficient alternatives. Additionally, it generates a weak position for the independent carrier, as he/she is not able to compose the most attractive bid based on his/her requirements.

6.3. Phase 3; Create a game and choice based simulation to test a policy

6.3.1. Policy that could optimise the system's performance

Using the DCM results, practical knowledge of playing the game and correspondence with researchers, and the theoretical knowledge of the literature review, a policy that could optimise the performance of players and the system, will be defined in this section.

Based on the DCM conclusions drawn in the previous chapter, it can be stated that the players have difficulties with the complexity of combining requests with a feasible route in order to make a bid. This becomes more difficult when a player wants to create a bundle with multiple requests. So bundles with only one request are more likely to be bid on than bundles with multiple requests. This is bad for the efficiency of the market as bundles of combined requests create economies of scale effects. Based on the experience of playing the game and by talking to researchers of the game, it is considered plausible that players have difficulties with the complexity of creating a feasible bid. It looks like players are not able to consider all their bidding options to make a fully rational bidding decision. There are too many possibilities which makes it highly unlikely that players are able to create a full overview of their options and make a rational decision to bid or not bid on a bundle. Let alone a player is able to strategically incorporate the option of reallocation within his bidding process as this possibility creates even more bidding options. Game data shows that sometimes players have the possibility to bid on more than a thousand unique possible combinations of request bundle and routes. On the other hand, sometimes a player could even be glad to have found an option to bid on, as the restrictions of previously won bids and their corresponding routing obligations limit the possibilities a lot. So the options could be too many to find and oversee them all, or too little to be able to catch them. As is already described in section 5.1.1, this phenomenon of bounded rationality of carriers could decrease the effectiveness and efficiency of the transport market.

A solution can be found in the concept of a decision support system, which is also mentioned in the literature review. All the information regarding routing, load size, start and end time, reallocation, and so on, can logically not be processed by a human. Therefore a system that helps carriers to process all that information to improve their decision making, without them losing control, could make the transport market more efficient and effective. As has been mentioned in the literature review (section 3.6.), these kinds of decision support systems are used a lot in the world of transport and logistics for all kinds of challenges. However, to the best of the authors' knowledge, it has not yet been tested what the effect of such a system could be on the PI inspired decentralised market place with reallocation possibilities. Therefore a policy that helps with the processing of information in order to support the decision making of individual player/carrier will be investigated using a simulation of the "Freight Transportation Game".

In the PI inspired decentralised transportation market, two aspects are essential for an optimised transport system. At first, carriers want to bid on bundles with the lowest cost; in this way, they can set competitive prices. If all carriers receive information about feasible bundles and corresponding routes that have the lowest cost for them, it will lead to more transparency and a better market situation (if they bid on these proposed bundles). Because the transportation costs decrease and the competitive bids increase, which creates better competition and less global costs. Secondly, carriers want to utilise the reallocation more as it provides them with a win-win situation (see section 5.1.2.). This causes more efficiency and increases (less global costs) and better social conditions for carriers.

To capture the two aspects in one policy, a decision support tool for carriers is proposed that processes all the transportation information for each individual carrier and calculates their optimal bids. The optimal bids consist of request bundles that have the lowest total cost and pass by the reallocation point. By this way, carriers can set more competitive prices and utilise the reallocation opportunity of the PI concept more.

6.3.2. Experiment to test the policy

The to be tested policy hypothesis is: By providing carriers with support about feasible request bundles, that have the lowest cost and have a route that passes by the reallocation point, more transparency for players, more competitive bids are made per player per round and reallocation will occur more often. This will cause more competition, less global costs and more efficient transport.

To test the policy hypothesis in an experiment, a simulation based on the game will be used. Because DCM makes it possible to implement human behaviour into the simulation, the human bidding behaviour can be imitated in a simulation. Conducting a simulation experiment gives the opportunity to test the policy much faster than testing the policy in the game itself. Additionally, simulating makes it possible to make a strict ceteris paribus comparison between the current and the policy situation, and more game rounds (the game has only ten rounds) and gameplays can be simulated.

The experiment will work as follows, a game and choice based simulation will be created using the structure of the game and the estimated DCM. This simulation represents the current PI inspired transportation market behaviour. Additionally, two other simulation settings will be used as well. One simulation setting with implemented policy and one simulation setting representing a centralised market situation. This last setting portrays the transportation market with a centralised authority allocating loads to carriers in the most cost-efficient way, and the carriers will perform the plans exactly as proposed (Lafkihi, Pan & Ballot, 2019). Because this market type performs well in terms of efficiency and effectiveness, it will be used as a benchmark situation. So eventually, the three different simulation settings will be run ceteris paribus and the results will be compared using the following effectiveness and efficiency KPIs: number of unallocated requests, number of total delays, the total price of all allocated requests, the price per allocated request, the mean filling rate, the total number of reallocations. This will indicate whether the policy produces the desired effect and in what aspects it performs better or worse in comparison to the current situation and a central market situation. A visual representation of the experiment can be seen in figure 13.

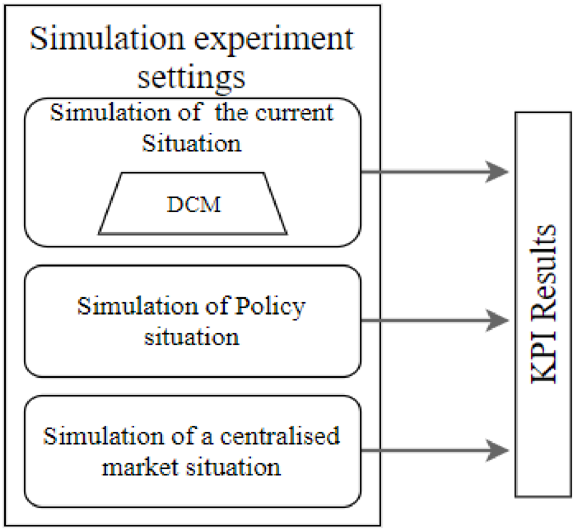


Figure 13, Simulation experiment settings

6.3.3. Creating the simulation

In this section, the simulations needed for the experiment will be described and elaborated on. The simulations will be based on mathematical simulation of the game as described in section 6.1.1. and coded using the software environment of MatLab.

<u>Creating a GCBS of the current PI inspired transportation market behaviour</u>

For the simulation that represents the current PI inspired transportation market behaviour, it is the aim to imitate the current situation as good as possible. For this simulation, the mathematical simulation of the game as described in section 6.1.1. will be used; however, the bidding procedure will be adjusted. In the mathematical simulation, carriers bid on all their feasible request bundles. To let this bidding process match better with the human bidding behaviour where bids are only made on a few of the feasible bundles, the estimated discrete choice model will be used. The DCM will imitate the behaviour of bidding or not bidding on a combination of request bundle and route.

The bidding process will be simulated as follows. Firstly, in each round, for each individual, all unique feasible request bundles and corresponding routes are calculated. This set is narrowed down to the generated considered choice sets in the same way as discussed in section 6.2.2. So of identical bundles (containing the exact same requests) only the ones with the shortest route will be considered further. If two or more have the same shortest route length;

the one with the lowest total cost is considered. Hereafter, the total utility per request bundle will be calculated. If the total utility to bid is higher than the total utility to not bid, a price will be set on the request bundle (based on the existing price functions) if the utility to bid is lower than the utility to not bid, no bid will be placed on the request bundle.

The observed utility derived from a request bundle is calculated using the utility functions and parameters of model 4 (section 6.2.3.). So the utility of a bundle will be calculated based on the penalty costs (PC) of the bundle and the total number of requests that are in the bundle (BNR). Additionally, the constant for "bidding" (ASC_Bid) is added.

The utility functions are previously (Model 4, section 6.2.3.) composed as follows :

$U_{Bid} = \beta_{PC} * PC + \beta_{BNR} * BNR + ASC\_Bid + \varepsilon$

$U_{NotBid} = 0 + \varepsilon$

The betas and constant are estimated as follows:

- β_{PC} = -0,0242
- β_{BNR} = -1,22
- ASC_Bid = 1,37

The ε represents the (general independent) unobserved utility. It is distributed i.i.d. Extreme Value type I, var = $\pi^2/6$. Therefore it will be drawn from a Standard Gumbel (μ = 0 and β = 1) distribution each time separately for every utility.

Eventually when $U_{Bid} > U_{NotBid}$ a bid is placed according to the consisting price functions, when $U_{Bid} < U_{NotBid}$ no bid is placed.

An example of a simulation of the bidding process for one player in one round is given in figure 14.

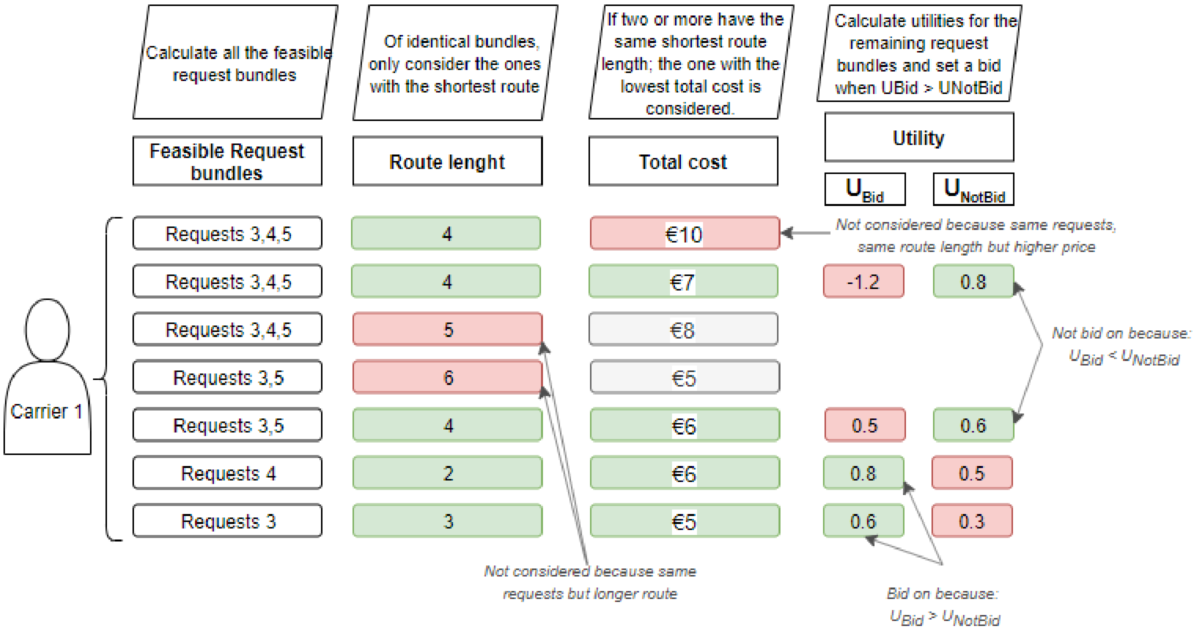


Figure 14, Example of the simulation of the current situation (for a carrier in one bidding round)

<u>Creating a simulation of future policy situation</u>

In the simulation of the future policy situation, the policy as is argued for in section 6.3.1. will be implemented in the simulation. This will imitate the working of the decision support tool for carriers in the PI inspired transportation market. Just as in the simulation of the current situation, the basis of this simulation remains the same; the mathematical simulation of the game as described in section 6.1.1. However, carriers now bid based on the provided information about feasible request bundles, that have the lowest cost and have a route that passes by the reallocation point. For this simulation, it is assumed that individuals will always bid on these proposed bids as that would be rational behaviour. Additionally, no bids will be made on other requests in the simulation, partly because this would be irrational behaviour but also because the pure effect of the decision support policy can be measured then.

So firstly, in each round, for each carrier, all unique feasible request bundles and corresponding routes are calculated. Hereafter a subset of bundles with the lowest cost will be selected of the feasible bundles. Finally, from this set, the bids that have a route that passes by node 9 (the reallocation point) will be selected and bid on by the carriers. An example of the simulation of the future situation with policy implementation is given in Figure 15.

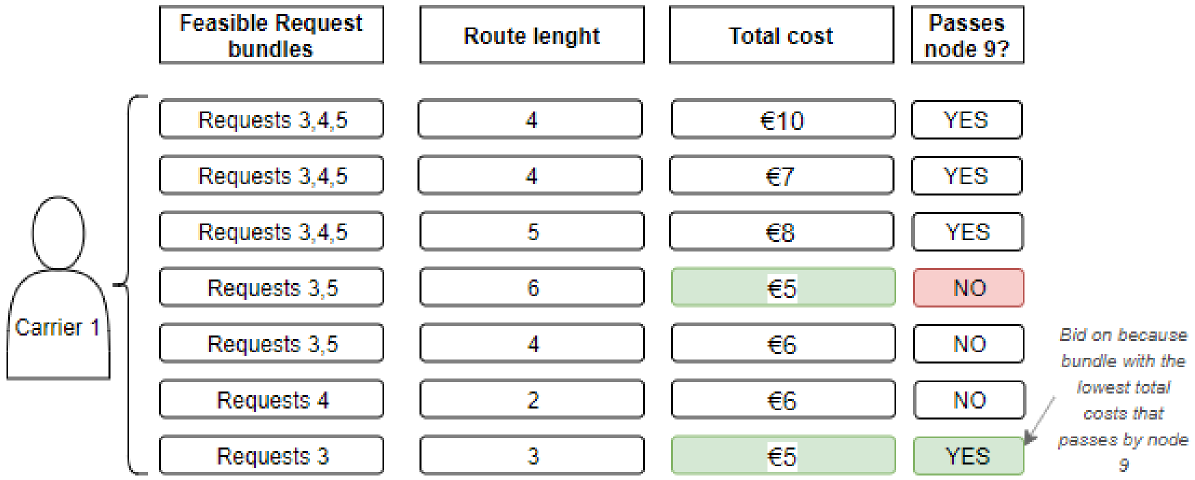


Figure 15, Example of the simulation of the future situation with policy (for a carrier in one bidding round)

6.3.4. Conducting the simulation experiment

<u>Experiment settings</u>

The experiment is conducted using the following settings. To create a strict comparison between the three simulation settings (current, future and centralised situation), the requests generated in each round, are the same in every simulation setting. The current and future simulations also use the same pricing functions for the carriers. So within one setting (current or future situation), carriers set different margins, representing the decentralised market, but these pricing functions are the same for the current and future simulations. The simulation of the centralised market situation uses price functions that set the same margin for each carrier. In one session the three simulations run for 33 bidding rounds which is more than three times as long as normal gameplay (ten rounds). This session is repeated nine times to obtain robust results. The experiment settings are summarised in Table 12.

Simulation settings per experiment	Current situation - Future situation - Centralised situation
Price function per setting	● Current & Future situation: use the same pricing functions that set different margins per carrier ● Centralised situation: uses a different pricing function that sets the same margin for each carrier
Generated requests by simulation within one experiment session	The same for each round for each simulation setting
Length of an experiment session	33 bidding rounds
Number of experiment sessions	9

Table 12, Experiment settings

Experiment results

The results of the experiment are presented in Table 13. They show the mean and the standard deviation value of the nine conducted sessions. At first sight, it seems remarkable that the total price of the transported request is the lowest for the simulation of the current situation, however on average about 35 requests are not allocated in this situation (versus an average of 1 and 0,56 unallocated requests in respectively the future and centralised market situation). So the price per allocated request is €1,09 higher than the situation with policy implementation. The filling rate of the future situation is way better than the current situation (53% versus 10%) and about equal to the centralised situation. Also, the number of conducted reallocations is more for the future situation (four versus zero), and even a bit better than the centralised situation, although it varies quite a lot in the future situation (standard deviation 2,79). Remarkably, none of the simulations shows any delayed request, presumably because of the corresponding penalty costs causing a low chance of bidding on these requests (in both the current as in the future situation).

KPI		Simulation of the current Situation		Simulation of the future situation with policy implementation		Simulation of a centralised market situation	
		Mean	Std	Mean	Std	Mean	Std
Effectiveness	Unallocated requests	35,22	1,55	1,00	0,94	0,56	0,68
	Total delays	0	0	0	0	0	0
Efficiency	Total price	€ 287,43	€ 10,49	€ 335,57	€ 53,04	€ 317,35*	€ 39,34*
	Price/allocated request	€ 4,51	€ 0,21	€ 3,42	€ 0,53	€ 3,23*	€ 0,42*
	Mean filling rate	10,15 %	0,89 %p	53,06 %	3,64 %p	50,89 %	2,71 %p
	Number of reallocations	0,00	0,00	4,00	2,79	3,11	1,52

** because other price functions are used for the simulation of a centralised market situation, the monetary values of this simulation setting can not be directly compared to the results of the other two situations.*

Table 13, Experiment results

6.3.5. Interpretation of the experiment results

The results show that the filling rate of trucks in the simulation of the current situation is low. This is presumably because carriers likely do not bid on bundles with multiple requests (because it becomes too complicated). The proposed policy is partly aimed at solving this complex issue for carriers. The simulations show that the policy works in this respect, as the filling rate is much higher and even about as high as in the centralised market situation. The other aim of the policy was to create more reallocations, which it did well. So the policy creates a much more efficient market situation. Additionally, almost all requests are allocated in the future situation, which is definitely not the case in the current situation. Therefore, the policy also creates a more effective market. In general, it can be stated that the policy of providing the player with decision-support about their most “attractive” potential bids causes as much more efficient and effective game performance, which is close to the situation of a central market situation.

It would be interesting to test the policy of implementing this decision support tool in the actual gameplay as well. Unfortunately for this thesis research, not enough resources were available to do this. It could give some other results as players may not always follow the suggested optimal bids (which would, however, be in their best interest) and players have other pricing strategies as in the simulation. However, even if the suggested bids are only partly actually bid on by players, it presumably would still improve the gameplay performance.

As mentioned before, other than in the game, carriers in real life could have other incentives than only making a profit. They may also care about the region in which they conduct their transport or the length of the route. In this case, the decision support system should be adjustable to a variety of carrier’s preferences. For example, it should advise the carrier with the optimal bids based on his preference for low cost, service region, route length etc. Herewith, the carrier is in control, and the inefficient and ineffective effects of the complex market are taken away. So, a decision support tool for carriers in the complex PI inspired decentralised transportation market seems to be an essential tool to reach an optimal market performance with a firm and “in control” position of the independent carrier.

7. The final methodological GCBS framework

In this chapter, the final methodological GCBS framework will be designed and created. Herefore, the first framework design of chapter 4 will be evaluated and improved using the insights of the conducted modelling study. Eventually, the final design needs to meet the design requirements as defined in section 2.2.1.

7.1. Evaluation of the first framework design and insight of the modelling study

The framework designed in chapter 4 contains an explanation of the opportunities of the GCBS methodology and structured guidance on how to conduct it.

The opportunities as designed and created in section 4.2 (visible in Figure 7) proved to help motivate why the research case of the "Freight Transportation Game" suited the GCBS methodology. Eventually, the opportunities stated in the framework turned out to be a good match with the modelling study. In addition, these options appeared to not only be theoretically promising, but have also proved to be valuable in practice. This is because the GCBS methodology helped to create valid and reliable insight into people's behaviour within a future setting, and the data was gathered time efficiently and accurate enough to be able to create a valid DCM. Also, the possibility to create a game and choice based simulation was useful, as a successful experiment was conducted using it. Therefore, the designed sub-framework for the opportunities of the GCBS methodology of section 4.1 is considered to meet requirement 1; provide insight into the opportunities of the methodology.

Phase 1 of the sub-framework for conducting the GCBS methodology as designed and created in section 4.2 (visible in Figure 8) is considered to be an essential phase. This phase is crucial for the rest of the phases as creating a thorough understanding of the game provides the basis for the rest of the modelling phases. Additionally, creating a clear definition of the choice situation and alternatives of that situation is considered useful and essential. In conclusion, this phase created enough guidance to be able to perform the rest of the methodology.

Phase 2 of the first designed sub-framework (Figure 8) did not prove to be sufficient enough to conduct the methodology without doing further methodological research. However, this was expected, as some methodological challenges needed to be handled during the modelling study.

The first question that needed to be answered by conducting the modelling study was: How can a choice situation be defined in order to be able to capture it using a DCM? It turned out that, in addition to the choice definition created in phase one, it is important that the choice together with its alternatives (the choice set) needs to be collectively exhaustive, mutually exclusive, and the sets should contain a finite number of alternatives. Otherwise, it is not possible to create a DCM with it.

The second, to be answered question, was: how can the choice sets be created? It was found that, just as with RP data, it is hard (or impossible) for a researcher to know the considered choice sets of players when using a Player Preference data collection method. Therefore, based on theoretical insights of Fiorenzo-Catalano (2007), the following guideline to be able to generate considered choice sets: include all relevant and chosen alternatives. It is up to the users of the GCBS methodology to define what the "relevant" alternatives of a particular choice situation are. Because these generated considered choice sets were still not representative for the real considered choice sets it was chosen to select two categories of attributes; attributes that could explain the creation of the considered choices and attributes that could explain the consideration players make when choosing an alternative.

This leads to the final question that needed to be clarified: how can attributes that influence the choice be selected? Because no literature or experience about the specific choice situation of modelling case was available, more general literature and experience with the gameplay was used to define multiple attributes that could influence the choices behaviour. Eventually, by iteratively estimating multiple models with different compositions of utility functions and attributes a final model was chosen. This selection process was based on: the Rho Squared value of the models, the significance of estimated parameters, the purpose of the model and the explicability of the model. Eventually, this innovate created methodology of capturing a given choice situation into a DCM appeared to be successful as the validation of the final model turned out to be satisfactory. Additionally, the final DCM provided insight into the behaviour of players.

Phase 3 of the sub-framework (Figure 8) was sufficient enough for guiding the creation of the game and choice based simulation. It turned out to be straight forward as the structure of the game, unravelled in phase one, already provides a structure for the simulation, and the DCM is already created in Phase two. However, for creating the simulation based on the game and for implementing the DCM to imitate the selected choice behaviour correctly, still modelling skills and own insight of the user of the GCBS methodology are needed. The same applies to the process of defining an experiment and conducting it using the GCBS. Eventually, this phase helped to create a realistic simulation based on the gameplay, including human behaviour.

7.2. The improved methodological GCBS framework design

7.2.1. Final design of the sub-framework; opportunities of the GCBS methodology

As mentioned in the previous section, the designed sub-framework showing the opportunities of the GCBS methodology is considered to be helpful, sufficient and in line with the design requirement 1. Therefore it is decided that no improvements need to be made to this part of the framework, and its final design is shown in Figure 13.

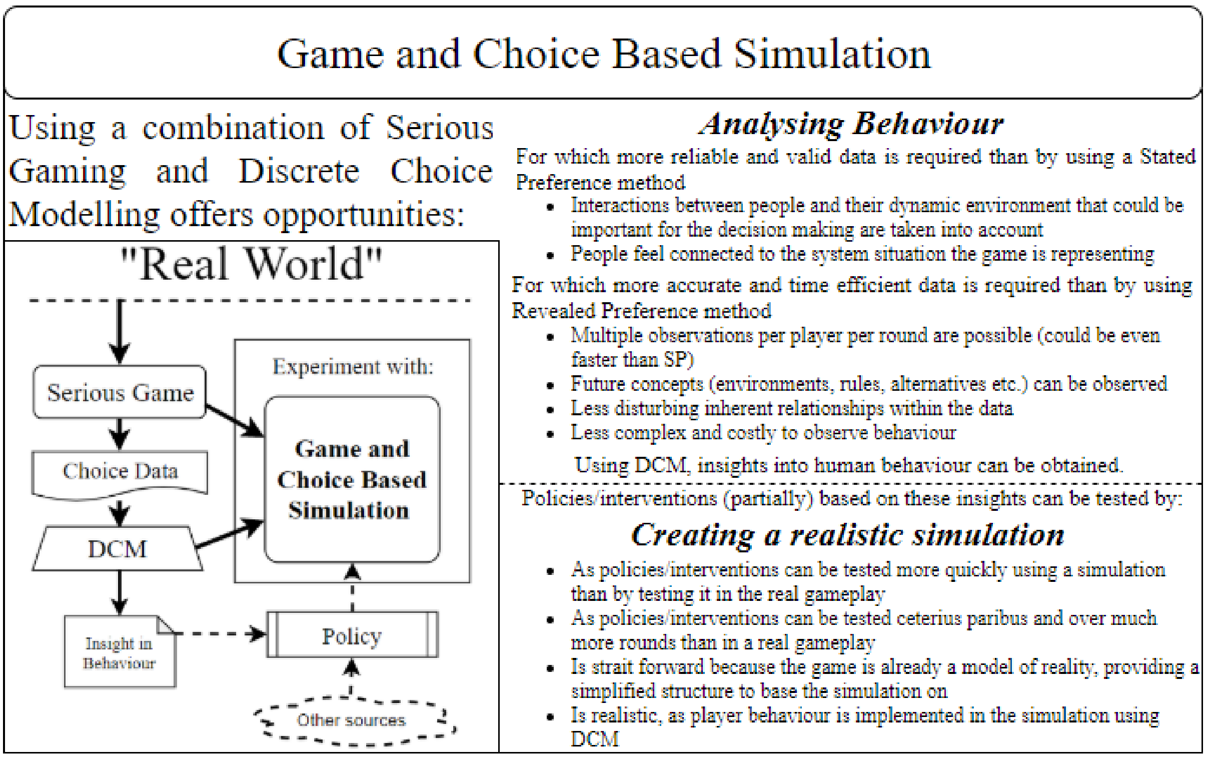


Figure 13, Final sub-framework showing the opportunities of the GCBS methodology

7.2.2. Final design of the sub-framework; how to conduct the GCBS methodology

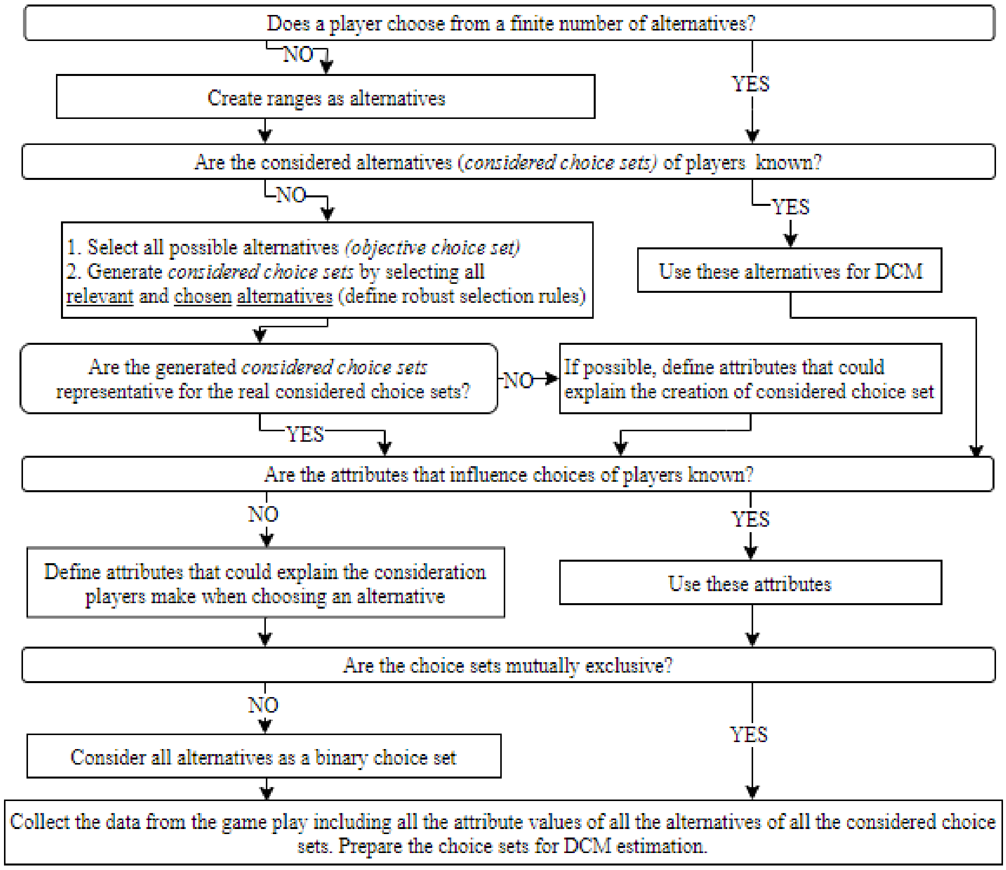
Because Phase 1 created enough guidance to be able to perform the rest of the methodology, it is decided that it will not be adjusted. However, in order to create better-structured guidance of

Phase 2, it is chosen to split it into a data collection/preparation phase and a DCM estimation phase. In the data collection phase a flowchart is created, telling the user what to do in order to generate considered choice sets, when and how to select what kind of attributes and how to deal with choice sets that do not contain a finite number of alternatives, and how to deal with the collectively exhaustive and mutually exclusive requirements. After following this flowchart thoroughly, the user is able to collect the right data and proceed to the next phase of the GCBS methodology. In the next phase, the user is presented with information about how to iteratively create and select a discrete choice model and validate it. The final phase, of creating a game and choice based simulation to test policies or interventions, stayed the same as in the first design as it met the design requirement 5 of helping to create a realistic simulation based on the gameplay, including human behaviour. The final sub-framework of conducting the GCBS methodology is shown in figure 14.

Conducting the methodology	
Phase 1	**Create understanding of the structure of the game** • Game steps • Game dynamics • Select important choice situation(s) that are interesting to gain insight in and/or are important for the gameplay dynamics • Create a clear definition of the choice situation and alternatives of that situation

Phase 2

Prepare and collect the Serious Gaming data for the modelling of a choice situation



Phase 3

Estimate a Discrete Choice Model using the collected and prepared Serious Gaming data

If the choice model is not unambiguously clear; iteratively estimate models with different:

- Attributes
- Utility functions
- Random variables (to capture nesting effects, taste heterogeneity, panel effects)
- Models (MNL, ML)

Select the model based on:

- Rho Squared value
- Significance of parameter value
- Purpose of the model (insight in behaviour, simulating choices, predicting choices, VOT estimation, etc.)
- A well explainable composition of the utility function

Validate the model e.g. using out-of-sample hit-rate computation

Interpreted the final estimated model and use the explained choice behaviour to gain insights

Phase 4	**Create a Game and Choice Based Simulation to test policies/interventions** Create a simulation experiment to test the policy/intervention Define KPIs to measure the results of the simulation performance Create a simulation of the gameplay 1. Simulate the game steps using mathematical rules (e.g. if, then, else), based on Phase 1 2. Simulate the (important) player behaviour using DCM For each choice situation let the simulation: • Create the considered choice set using the defined selection rules of Phase 2 (if needed) • Calculate the total utility for each alternative in the choice set based on the specifications of the selected model of Phase 3. Define choices between alternatives based on their utilities (inc. random utility). Create other simulations needed for the experiment (simulation with intervention or implemented policy) Conduct the experiment and interpreted the results

Figure 14, Final sub-framework showing how to conduct the GCBS methodology

7.3. Validation of the final framework design

In order to determine whether the final framework design is successful, a qualitative validation on the basis of the design requirements is shown in table 14. This shows how the requirements are met using the deliverables of the designed methodological GCBS framework.

Design requirement	**Corresponding deliverable**
1. Provide insight into the opportunities of the methodology	Sub-framework showing the opportunities of the GCBS methodology
2. Help to provide insight into the behaviour of players.	Phase 1 + Phase 2 + Phase 3
3. Provide structured guidance on how to conduct the methodology.	Sub-framework showing how to conduct the GCBS methodology
4. Contribute to the creation of a valid game based discrete choice model.	Phase 1 + Phase 2 + Phase 3
5. Help to create a realistic simulation based on the gameplay, including human behaviour.	Phase 4
6. Use a combination of Serious Gaming, DCM and simulation	In order to conduct the GCBS methodology a combination of Serious Gaming, DCM and simulation is needed

Table 14. Design requirements and corresponding deliverables

So eventually, using two design cycles of investigating, creating, designing and evaluating, a final design of the methodological GCBS framework is fulfilled. During the design cycle, the methodology and the framework proved its potential for the case of application of this research, as they helped to gain insight into the behaviour and test a policy using the created game and choice-based simulation. However, it is not possible to know how useful, reliable and robust the framework is when it is applied to other research projects that fit with the GCBS methodology.

8. Conclusion

This chapter presents the conclusion of this research. First, section 8.1. includes the main findings of this research. Section 8.2. discusses the remarks to be made to this research and section 8.3. provides recommendations for further research. Finally, the scientific and societal contribution of this research is elaborated on in section 8.4.

8.1. Main findings

The performed Master Thesis research was two-fold. At first, the research endeavoured to design a framework for conducting an innovative Game and Choice Based Simulation (GCBS) methodology for understanding behaviour and creating a realistic simulation. Secondly, the research aimed to analyse the behaviour of players in the PI inspired “Freight transportation game”, and create and test a policy that could optimise the system’s and people’s performance, by using the innovative GCBS methodology. Both parts have proven to synergise each other as the modelling study helped to evaluate and create insights in the methodology, and the methodological framework design cycle helped to analyse behaviour and create a realistic simulation. It is found that the strength of using GCBS as a research methodology lays in the promising Player Preference data collection method, the explanatory and predictive power of DCM and the available modelled structure of the serious game. The methodology proved to provide insight into the behaviour of players performing in a futuristic environment. Additionally, the methodology succeeded in helping to define and testing a decision support tool for carriers which showed to improve the performance of the PI inspired transportation market. The designed methodological framework practically explains when and how a GCBS methodology can be conducted. More specific conclusions with respect to the methodology and the application case; PI inspired “Freight Transportation Game”, are drawn in the next two sections.

8.1.1. Methodology

In this research, the methodology of using GCBS to analyse the behaviour and create a realistic simulation is conducted and tested. The GCBS methodology holds a few innovative characteristics; it uses a promising data collection method, combining this with DCM offers the opportunity to analyse player's behaviour, and by implementing this DCM in a simulation based on the gameplay a realistic simulation is created which is suitable for conducting time-efficient simulation experiments. It is found that this methodology is mainly of added value if behaviour needs to be analysed of future concepts or situations where interactions between people and their dynamic environment are important. Additionally, the methodology on itself provides an experimental environment, which is less complex and costly to analyse. Especially using a digital game, choice data can be observed in a very time-efficient manner. To estimate a DCM based on Serious Gaming data correctly and in a valid way, it is found that a thorough understanding of the game structure and dynamics are needed because the choice situations and gameplay dynamics are given and not in control of the researcher. A challenge could occur when the considered choice sets of players are unknown. Therefore theoretical based guidelines to generate these choice sets are created, and the use of extra attributes that could explain the creation of the real considered choice sets proved to be successful. Additionally, a way to deal with the situation where attributes that influence the behaviour of players are unknown is provided by this research. Based on the case of application, the methodology showed to contribute to the creation of a valid game-based discrete choice model, which helped to provide insight into the player's behaviour and helped to create a realistic simulation, including human behaviour.

Research question:

How can the methodology of Game and Choice Based Simulation, be used to create insight into players' behaviour and establish a realistic simulation that can be experimented with?

Answer:

By applying the designed methodological GCBS framework, which provides insight into the opportunities of the methodology and guidelines to systematically conduct it.

8.1.2. PI inspired "Freight Transportation Game"

The methodology of using a combination of Serious Gaming and discrete choice modelling suited the case of the PI inspired "Freight Transportation Game" well. Mainly because it is about a future concept in which interaction between players is important. Additionally, the facts that players behave sub-optimal and the potential of the market can be utilised better, gave need to investigate the behaviour and define and test possibilities to improve the system. By analysing the gameplay and creating a DCM about the bidding behaviour of players, it was found out that players have difficulties with the complexity of creating bundles and routes with multiple requests. Therefore a decision support tool that provides players with information about their most attractive bids, based on cost and reallocation possibilities, is created. By conducting a simulation experiment that uses a created game and choice based simulation, it was found that the tool causes a much more efficient and effective game performance, which is close to the situation of a central market situation. Due to the tool, the filling rate increased, the price per allocated request decreased, more reallocations occurred, and almost no request remained unallocated. So it can be stated that the complexity of the market design has a big impact on the bidding behaviour and system performance. However, in the real world, carriers could have other objectives besides making a profit (game objective) as well. Therefore, if implemented in the real world, the tool should be adjustable to a wider variety of carrier preferences. Nevertheless, a decision support tool for carriers in the complex PI inspired decentralised transportation market seems to be essential to reach an optimal market performance with a firm and "in control" position of the independent carrier.

Research question:

How can the system performance of the PI inspired "Freight transportation game" be improved using the Game and Choice Based Simulation methodology?

Answer:

Based on the DCM and simulation results, it can be stated that the complexity of the market design has a big impact on the bidding behaviour. A decision support tool showed the potential to optimise this behaviour of carriers and the system, creating a better market performance and a better position for the independent carriers.

8.2. Remarks

To structure the discussion on the research, this part is divided into a methodology and an application case part.

8.2.1. Methodology

At first, when using the GCBS methodology at which Serious Gaming and discrete choice modelling are combined to create a realistic simulation, a risk occurs in the fact that a model (game) is used to create other models (simulation and DCM). Herewith, it could be that a design flaw in one model affects the quality of the other model. The external validity of a (to be) tested policy/intervention is strongly dependent on the validity and design of the models it is tested with. Therefore it is crucial for this methodology that all models should be designed in a way that it uses and creates validly and reliably data; otherwise, the game and choice based simulation results are worth little. This challenge is kept in mind throughout the conducted research and framework design, however, it remains a point of attention for this methodology. A remark on the designed framework in this research is that it is mainly based on the insights of conducting the methodology on one game. Therefore the framework could be a bit less extensive on parts that did not cause a challenge in this research (e.g. creating ranges as alternatives when alternatives are not finite).

8.2.2. PI inspired “Freight Transportation Game”

The data gathered to estimate the parameters for the modelling of the bidding behaviour is obtained from one gameplay. Although these where already 480 choice observations the behaviour of players could differ between gameplays. So it is not known how robust the DCM and simulation results are when more gameplays are used to specify the DCM. Another remark that is already mentioned in the “Interpretation of the experiment results” (section 6.3.5.) is that the policy is not tested in the game itself, this is due to limited resources of time and money. However, therefore, it is chosen to interpret the simulation results not too literally but view it as evidence that the complexity of the game has a big impact on the bidding behaviour of players and on the PI inspired transportation market performance.

8.3. Recommendations for further research

To structure the recommendations for further research, this part is divided into a methodology and an application case part.

8.3.1. Methodology

At first, it would be good and interesting to apply the methodological framework on other serious games. This could provide new insights or additions to the framework and makes it more robust. Secondly, it would be interesting to create a serious game with the objective of applying the GCBS methodology with it. Currently, the methodological framework is designed for ex-post creation of the DCM, based on an existing game. If a game is created for a GCBS purpose, the choice situations of players in the game could be designed with a DCM perspective. Herewith the game could, for example, be designed in a way that considered choice sets of player are traceable, a limited correlation of attributes occurs, and the game has multiple goals so that trade-offs (e.g. time vs money) can be measured.

8.3.2. PI inspired "Freight Transportation Game"

In this research, only a DCM is created to capture the bidding behaviour of a player in a model. However, players also set a price in the game. Estimating a DCM on the price-setting behaviour could make the game and choice based simulation even more realistic. Secondly, it would be interesting to validate the policy in some way. This research shows the problem of complexity within the game and market and a tool that has the potential to improve the system's performance. However, it would be interesting to see if such a tool, which provides live decision support to carriers, is technically feasible and viable in the real world.

8.4. Scientific and societal contribution

8.4.1. Scientific contribution

This research contains a number of scientific contributions. At first, an innovative Player Preference data collection method for DCM is defined. It is considered to be a valuable alternative for the conventional RP and SP methods, and opportunities of this Player Preference method proved to be promising. Additionally, an innovative methodology of creating a game and choice based simulation is defined and tested. This methodology proved to be successful in gaining insight into the behaviour of people and creating a realistic simulation. To facilitate future research that suits this methodology, a methodological framework is designed. This provides insight into the opportunities of the methodology and guidelines to systematically conduct it. Finally, additions to the scientific knowledge of the Physical Internet concept is made by creating insight into the behaviour of carriers when performing in a PI inspired transportation market and by providing a policy that could improve the performance of this market.

8.4.2. Societal contribution

This research contains some societal contributions that can be valuable for policymakers, industries and other stakeholders involved with the transportation sector. At first, this research gained insight into the behaviour of carriers in a decentralised transportation market with reallocation opportunities. It showed that this market type has great potential to increase the efficiency and effectiveness of the market. However, it also showed that independent carriers need to be supported by processing all the market information as it is too complex for carriers to create optimal bids given all the possibilities. Therefore, this research proposes a decision support tool for the carriers that not only creates an efficient and effective market performance (comparable to the performance of a centralised market) but also creates a more firm and "in control" position of the independent carrier.

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Appendix A – Scientific Paper

The scientific paper that is written as a partial requirement for this Master thesis graduation research is shown on the next page.

Game and Choice Based Simulation

The design of a methodological framework using the case of the Physical Internet inspired "Freight Transportation Game"

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Abstract

Serious games have the potential to be used as an innovative data collection method. Combining this with Discrete Choice Modelling (DCM) could create a methodology that provides insight into the player's behaviour and allows for creating a realistic simulation. This innovative Game and Choice Based Simulation (GCBS) methodology has been conducted and evaluated using the case of the Physical Internet inspired "Freight Transportation Game". The bidding behaviour of players is analysed using DCM. Using the insights obtained from the estimated choice model, a decision support tool for carriers is defined as a policy to optimise the system's performance. Hereafter, the DCM is implemented into a simulation based on the gameplay, creating a realistic simulation of the PI inspired transportation market. By conducting a simulation experiment with this innovative simulation, the policy could be successfully evaluated. Considering this case of application, the GCBS methodology proved its potential. Using insights obtained during the research, a framework for GCBS has been designed explaining when and how to conduct the methodology. More research needs to be done to test the (external) validity of the decision support tool and to test and extend the methodological framework in order to increase its robustness.

Keywords: Serious Gaming, Discrete Choice Modelling, Simulation, Collecting Choice Data, Physical Internet, Freight Transportation Market, Decision support tool

1. Introduction

When designing in socio-technical systems, developing products and services, or creating policies, a profound understanding of user behaviour, user demand, and the user response is desirable. What are the best business models for upcoming new technologies as bike-sharing and electric vehicles? Buy, rent or lease? Do people prefer price over range or travel time over comfort? And what is the effect of tax breaks, free services and other regulations on the purchasing behaviour of people? All these types of questions are relevant in the numerous sectors. From transportation and logistics to energy and environment, from marketing to business administration, and from health to political science. To cope with these questions, quantitative, statistically rigorous answers, beyond psychology are needed (Chorus, 2018). Herefore, choice models are used to understand and be able to forecast (new) systems and predict the effects of policies. In the western world, choice models form a crucial pillar on which transport models and policies are built (Chorus, 2018).

Conventionally the choice data by which the choice models are estimated is collected using two methods (Krabbe, 2016). At first, the data is often gathered by observing choices in real life, so-called Revealed Preference (RP). Secondly, choice data is often retrieved by conducting advanced surveys; the so-called Stated Preference (SP) method. RP data portrays the world as it is, with all its complex and human interaction, and therefore usually results in reliable and valid choice data. However, because of these interactions, inherent relationships between attributes occur in the RP data. Additionally, the effect of non-existent or future alternatives can not be observed using RP and often only one observation per respondent is possible, making it a time-consuming method (Louviere, Hensher, & Swait, 2000). On the other hand, using

SP surveys, the effect of nonexistent alternatives can be studied, relationships between attributes can be controlled by the design of the survey and multiple observations per respondent is possible Louviere et al. (2000). However, because the recorded choices are only based on (perfect) information provided by the survey, complex interactions between individuals and their environment are neglected, and consequences of (nonexistent) alternatives are not felt. Therefore, respondents may show other behaviours than they would show if the choices were made in real life.

A solution to the drawbacks the RP and SP data collection methods could be found by using an innovative data collection method: Serious Gaming. In Serious Games, a simplified representation of a complex (future) reality can be created (Duke, 1975) in which the human factor and dynamic relationships are addressed (Bradley, Hax, & Magnanti, 1977). Herewith choices are made in a real-life inspired experimental setting with interacting players and changing in-game environments. Additionally, nonexistent alternatives can be included, and multiple observations per individual are possible. This way of collecting data, therefore, has the potential to form a more valid and reliable method than SP and a more accurate and time-efficient method than RP.

By estimating a discrete choice model (DCM) based on this collected game data, insight into the behaviour of players can be obtained. Additionally, the estimated choice model could be implemented into a simulation model that is based on the game. Herewith a simulation with modelled human decisions is conceived, creating a realistic simulation that incorporates the human dynamics of the system it represents. So, herewith a gaming model of the real world is used to estimate a discrete choice model, which is then implemented into a simulation model to create a realistic simulation of that same world. Eventually, the simulation model offers new possibilities for conducting experiments in a time-efficient and isolated way.

However, little is known about this methodology of combining serious gaming and DCM. To the best of the author's knowledge, only Karampelas (2018) ones used DCM to create a simulation based on a serious game. However, his work focussed more on the multi-model approach (gaming, simulation and optimisation). Although his insights are used, the conducted research described in this paper focussed more on the methodological combination of serious gaming and DCM, which will be further referred to as Game and Choice Based Simulation (GCBS). To create more knowledge, experience and to evaluate this innovative GCBS methodology, a methodological framework for GCBS is designed using a combination of qualitative research, and a performed modelling study that uses the GCBS methodology. This paper will present the main findings and insights of this research. Eventually, this paper can act as structured guidance and example for further research using GCBS methodology.

The game that is used to apply the GCBS methodology on is the Physical Internet (PI) inspired “Freight Transportation Game”. The current world of transport and logistics is inefficient and unsustainable (Montreuil, 2011). The innovative future concept of a decentralised, PI inspired, transportation market has the potential to increase efficiency and sustainability within the transport and logistics sector (Ballot, Montreuil, & Meller, 2014). To research the dynamics and performance of this non-existing market, the “Freight Transportation Game” is developed at MINES ParisTech - PSL (Lafkihi, Pan & Ballot, 2019). Experiences with game sessions show that the players behave sub-optimal, and the potential of the market can be utilised better. A DCM based on the game data is created to gain insight into the behaviour of players. Using these insights, a policy to optimise the behaviour is defined and tested in an experiment. The experiment is conducted using a simulation that is based on the structure of the gameplay, at which players’ behaviour is imitated through the DCM. One could argue that experiments could have also be conducted by playing the game. However, for this research, it was chosen to use a game and choice-based simulation, because the aim was to create more knowledge about the innovative GCBS methodology. Additionally, DCM provides more insight into the attributes that affect people’s decision making, which helps to find and endorse a policy that can improve this behaviour. By creating a simulation based on the game, a clean (ceteris paribus) comparison in performance between different settings of the simulation can be made as well. Finally, more game rounds can be simulated than in a typical game session, and multiple games can be simulated in far less time than by playing the game in real life.

This paper will have the following structure. In chapter 2, the conducted research approach is explained. Hereafter, in chapter 3, a brief overview of background literature is presented. In chapter 4, the first design of the methodological GCBS framework is described. This contains the opportunities of the methodology and a structure for conducting it. In chapter 5, the context and motive of the game are elaborated on. Additionally, the fit between the GCBS methodology and the application case is motivated. In chapter 6, the conduction of the GCBS methodology on the "Freight Transportation Game" is described. Based on the insights of chapter 6, the methodological GCBS framework of chapter 4 is evaluated and adjusted in chapter 7. Finally, in chapter 8, the conclusion and recommendations of the research are given.

2. Research Approach

In order to create the design of a methodological GCBS framework, design requirements are defined based on general methodological characteristics, as stated in the work of Ishak, & Alias (2005). The design requirements are determined as follows; the methodological GCBS framework should:

1. Provide insight into the opportunities of the methodology.
2. Help to provide insight into the behaviour of players.
3. Provide structured guidance on how to conduct the methodology.
4. Contribute to the creation of a valid game based discrete choice model.
5. Help to create a realistic simulation based on the gameplay, including human behaviour.
6. Use a combination of serious gaming, DCM and simulation.

Using these design requirements and based the argumentation of the introduction and a literature review on, a first design of the methodological framework is created. Hereafter a modelling study that uses the GCBS methodology is performed. Using insights obtained from this modelling study and by evaluating the first framework, eventually, an improved, final framework is created.

So, the final design of the methodological GCBS framework is to a significant extent based on insights obtained from applying the GCBS methodology on the case of the “Freight Transportation Game”. For this modelling study game data and discrete choice, modelling is used to analyse the behaviour of players. Together with practical and theoretical knowledge, this formed the basis of a new policy that could optimise the system’s and the player’s performance. Hereafter, the policy is tested in a simulation experiment. Therefore, a simulation based on the gameplay is created (GCBS), at which DCM is used to include the current behaviour of players. Eventually, the generated results of the simulation experiment show to what extent the policy is a success.

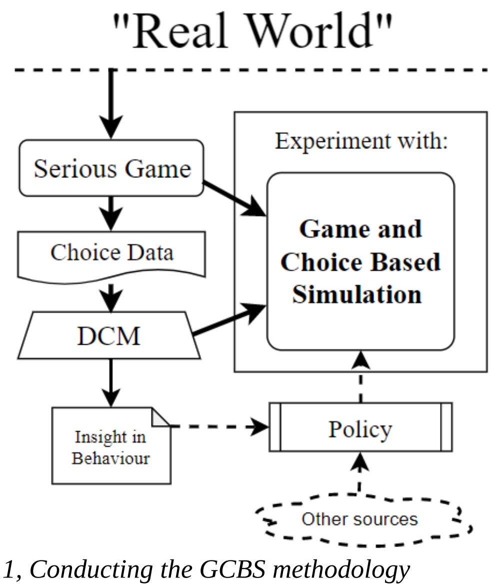

Figure 1, Conducting the GCBS methodology

3. Background literature

3.1 Data collection methods for DCM

Discrete choice modelling is focused on explaining choice behaviour. By using the modelling technique, the relative merit of a phenomenon can be computed as it makes it possible to estimate the relative importance of these attributes and even to estimate overall value for different combinations of attribute levels (Krabbe, 2016). DCM is applicable when individuals can choose between two or more distinct (“discrete”) alternatives. Because this conceptual requirement is common in our daily life (everyone makes choices between distinct alternatives every day) and because of its explanatory and predicting power DCM is a popular method used in all kinds of sectors. As mentioned in the introduction, conventionally the choice data by which the choice models are estimated is collected using two methods; RP and SP (Krabbe, 2016).

Using RP, choices are observed in a real-world context, herewith complex interactions between individuals and their environment are taken into account. This usually results in reliable and valid data. However, these interactions also cause a lot of inherent relationships between attributes making it hard to predict uncorrelated parameters. Using the carefully designed experimental surveys that usually form the basis of SP data, the correlations between attributes can be controlled by design, making it easier to estimate values for independent attributes. Additionally, SP is normally a much less time-consuming data collection method as taking a survey is easier than observing the behaviour and multiple choices can be observed per respondents. As has been argued in the introduction, using serious gaming data for discrete choice modelling could be an elegant method to combine the advantages of both RP and SP. By being a more valid method than SP and a more accurate and time-efficient method than RP.

The use of serious games or simulation games is a rather new but commonly used method in the field of transport and logistics (Kourounioti, Kurapati, Lukosch, Tavasszy, & Verbraeck, 2018). Within these games, players have the objective to win the game by managing their limited resources within the boundaries of certain rules (Greenblat, 1975). Simulation games are valuable as they provide the opportunity to effectively study complex systems that are future-oriented (Duke, 1975). Compared to experimenting in reality, gaming is a relatively easy and cheap way to study and experiment with a problem. Additionally, it makes a particular phenomenon more visible for observation and allows for the design of controlled experiments in a safe environment (Kurapati, Kourounioti, Lukosch, Tavasszy, & Verbraeck, 2018). An advantage compared to simulation model and an analytical model is that games take into account part of (important) human interactions that exist in the real world (Bradley et al., 1977). A digital game could be a potential source of loads of quantitative data (Lukosch, H. K., Bekebrede, Kurapati, & Lukosch, S. G., 2018). This data can be used to model the decisions of players as has been proposed by Kourounioti et al., (2018).

So, herewith serious games can obtain a new valuable function as a data collection instrument for discrete choice modelling, helping to analyse and simulate behaviour. The characteristics of this new Player Preference (a notion created for this research) data collection method in comparison to the RP and SP methods are summarised and compared in Appendix A.

3.2 Models

As mentioned before, using and creating models is central to the conducted research. A Discrete Choice Model is used to gain insight into players' behaviour and makes it possible to create a realistic simulation model, including human behaviour. The basis of this all is a serious game that in itself is also a model. The resulting innovative Game and Choice-Based Simulation is visualised in terms of modelling types in Figure 2, based on the modelling typology of Bradley et al., (1977). Using the GCBS methodology a game is used, based on the (future) real world (1), hereafter a DCM is created based on choice data of the game (2), then a simulation based on the structure of the gameplay is made (3) at which the DCM is used to imitate the behaviour of players (4). In this way, the human decision-maker is part of the simulation (in contrast to a conventional simulation) creating a modelling method with an increased degree of realism. So, a game and choice-based simulation can be seen as more realistic simulation type which retains its time efficiency quality.

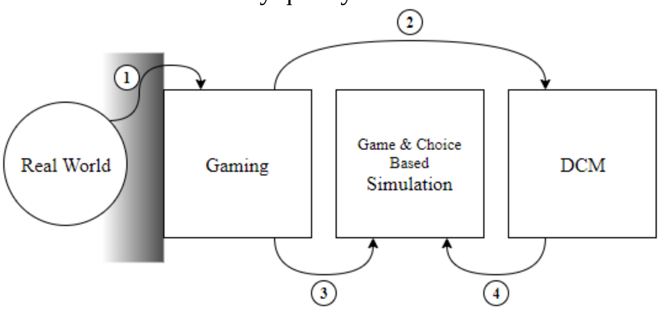

Figure 2, GCBS in terms of modelling types

4. First methodological GCBS framework design

Based on the argumentation of the introduction and the information of the background literature, a first version of the methodological GCBS framework is created. This design is focussed on requirements 1 and 3 of Table 1. So, it contains an elaboration on the opportunities if the GCBS methodology and a structure for conducting it.

4.1 Opportunities of the GCBS methodology

Gaming makes it possible to collect data with a so-called Players Preference method, which forms an alternative to the conventional RP and SP methods. The player preference method yields advantageous characteristics of both other methods. At first serious gaming makes it possible to gather data about human behaviour validly and reliably as players, to a certain extent, feel connected to the system situation the game is representing. Additionally, a serious game takes into account interactions between people and their (game) environment. Especially when these interactions are important for the decision-making process of people, it should be included in the data collection method. Secondly, using the player preference method accurate data can be gathered in a time-efficient way. Because a serious game makes it possible to control the environment in which choices are made, a more experimental setting than real life is created. This makes it less likely that disturbing inherent relationships in the data occur, resulting in accurate data collection. A controlled setting also means a possibility to observe and analyse the behaviour in future environments, or real-life behaviour that is hard to observe in an efficient way (costly and complex). Using serious games, especially a digital one, multiple choices per player per round can potentially be collected and transformed into usable data, making it much more efficient than RP and when using digital games maybe even faster than SP.

By estimating a DCM based on a player preference data collection method, quantitative and statistically rigorous insight into the choice behaviour of these players can be obtained. This will help to obtain a thorough understanding of the system being analysed. Additionally, the insights could form a basis for a policy or intervention that could optimise the performance of human behaviour and the system.

Finally using the estimated DCM a realistic simulation based on the gameplay, including human behaviour, can be made. The ability of DCM to predict choices can be used to simulate human choice behaviour. Because a game is already a model of reality, a simplified structure of the system is given already. This makes it relatively easier to construct a simulation. Eventually, based on the structure of the game and the estimated DCM, a realistic simulation of the (future) real world can be created. This simulation then makes it possible to quickly test and evaluate interventions or policies in a simulation experiment. With this experiment, a clean (ceteris paribus) comparison in performance between different settings of the simulation can be made over much more rounds than in real gameplay.

4.2 Structure for conducting the GCBS methodology

In order to guide the conduction of the GCBS methodology on the application case (modelling study), structured guidance for conducting the methodology is defined. This guidance consists of phases that are considered essential for performing the methodology. As it is impossible to know how certain specific challenges can be handled before the methodology is conducted, some challenges have been left to be solved during the modelling study.

Before the methodology is conducted, it should be argued for why the research case fits with the GCBS methodology.

So, a convincing motivation for a case, where GCBS can help to analyse behaviour and evaluate a policy/intervention using the simulation, should be performed. The opportunities described in the previous section can help with this.

In the first phase of conducting the GCBS methodology, a profound understanding of the structure of the game needs to be obtained. The game steps and game dynamics need to be researched to create a comprehensive understanding and to be able to select important choice situations in the game. Eventually, a choice situation that is interesting to gain insight in and important for the system dynamics needs to be chosen. A clear definition of this choice situation and its alternatives needs to be created because a DCM is only applicable when a choice situation is considered at which a choice is made between two or more distinct alternatives.

In the second phase, a valid DCM should be created that captures the selected choice behaviour and produces quantitative and statistically rigorous insight into this behaviour. Conventionally, a researcher defines a certain choice or trade-off situation and attributes that could influence it before it is analysed using DCM. However, now a choice situation is given by the game design and a DCM should be created to capture this situation in a model. This reverse way of modelling brings some challenges with it; the choice situation needs to be captured in a way that it is possible to be analysed using DCM, the choice sets of players need to be defined and attributes that influence these choices need to be selected. Together this should lead to a valid DCM that imitates the choice situation as well as possible. So, the following questions needed to be answered by means of the modelling study:

- How can a choice situation be defined in order to be able to capture it using a DCM?
- How can the choice sets of players be created?
- How can attributes that influence the choice be selected?

Eventually, the required data needs to be collected, and DCM should be estimated. The DCM should be checked to verify if the choice situation is modelled in a valid way. A conventional method to assess the validity, especially when the aim is to predict choices, is an out-of-sample hit rate calculation (Boughanmi, Kohli, & Jedidi, 2016). If the DCM appears to be valid, conclusions about the behaviour of players can be drawn based on the estimated parameters of the choice model.

In the third phase, a realistic simulation that is based on the gameplay and uses the DCM to imitate human behaviour should be created. To create this game and choice-based simulation, the game steps should be simulated using mathematical rules (e.g. if, then, else) at which the earlier obtained structural insights of the game can be used. The player's behaviour can be simulated using the estimated DCM. So, for each choice situation, the simulation should generate the corresponding choice set and calculate the utilities per alternative based on the estimated parameters and the utility function. Eventually, for each choice situation, the alternative with the highest total utility is chosen. When the GCBS is completed, experiments can be conducted with it to test policies or interventions. Using defined KPIs, the simulation results of the experiment can be interpreted.

5. Application case: the PI inspired Freight Transportation Game

5.1 Context and motive of the game

As mentioned in the introduction, the innovative future concept of a decentralised, Physical Internet inspired, transportation market has the potential to increase efficiency and sustainability within the transport and logistics sector (Ballot, Montreuil, & Meller, 2014). To investigate this future PI inspired market in real practice the "Freight Transportation Game" is developed at MINES ParisTech - PSL. It is a digital simulation game that allows analysing player decisions, behaviour and barriers to the best strategies (Lafkihi, Pan & Ballot, 2019).

The transportation market within the PI is decentralised, with independent carriers bidding for transportation requests. It roughly consists of hubs, carriers and a marketplace. The marketplace combines shipments to create the best composite offers, based on specific requirements, e.g. lead time, delivery date and costs. The offers are allocated by the marketplace, using an auction mechanism (Ballot, 2019). After auctioning the request is assigned to the carrier offering the lowest price and best service.

The game contains some crucial elements that relate to the Physical Internet transportation market. It has an open spot marked where players offer their own prices for requests. There is a central transit node and reallocation of requests is possible on that node.

The game has been played multiple times with characteristics of the current market and of the PI market. From a conversation with developers and researchers of the game (E. Ballot, M, Lafkihi, April 2019) and as described in the working paper (Lafkihi, in press) it is known that the scenario with the PI setting outperforms the scenario of the current market. However, players still do not use the full potential of reallocation and are not able to reach the market performance of a centralised market. Therefore, it is important to gain insight into the behaviour of carriers and investigate possibilities to utilise the potential of a PI inspired decentralised transportation market better

5.2 Fit between GCBS methodology and the application case

Using the "Freight Transportation Game" dynamics of the future transportation market are investigated. However, it provides little quantitative and statistically rigorous insight into why players behave in a certain way. Played game sessions show that the current behaviour of players is not optimal, so there is a need to get more insight into that behaviour. DCM provides a way to analyse the behaviour by estimating parameters for attributes that influence choices people make. Estimating a DCM based on choice data of "Freight Transportation Game" (Player Preference data collection method) is a valid, reliable and efficient method in this case. This is because real-life observation using an RP method is not possible due to the future (not yet existing) concept of the PI inspired transport market. Additionally, the interaction between players (competing market) and interaction with their changing environment (reallocation of request to other players) likely influences the behaviour of players. So, using a "flat" survey SP method is unsuitable for this case as crucial information about the dynamic behaviour may be missed. Finally, the game provides an experimental setting, so choices are less likely to be influenced by all kinds of disturbing factors. The game model also provides a simplified structure of the system its representing, making it relatively straightforward to create a simulation based on the game. With implemented discrete choice modelling to simulate the player's behaviour, this simulation can be used to test and evaluate policies in a realistic way and in addition more time-efficiently than testing the policy in the game. Playing a game session takes about two hours and simulating a game session is a matter of seconds or minutes.

The methodological choice to use the gaming data to analyse and simulate players behaviour is also motivated by recommendations given by researchers of the game, Lafkihi, Pan and Ballot (2019): "the developed game provides an efficient way to gather data for the future research work, for example, to test hypotheses in collaborative mechanism or to gather data to study carriers' behaviour empirically".

6. Conducting the GCBS methodology

Using the defined phases of section 4.2, the GCBS methodology is applied to the case of the PI inspired "Freight Transportation Game".

6.1 Phase 1; create an understanding of the structure of the game

In the game, each round starts with a pool of requests. This pool consists of the three randomly generated request per round and the reallocation requests. A request has an origin, destination, volume and lead time, telling from where to where the request with a volume of one or two units should be delivered and in how many rounds this should be completed. Players try to find a feasible combination of request or request bundle and a route. The possibility of combining a request bundle and route is bounded by the capacity of four units and already set routing obligations of previously won bundles. The transportation cost and penalty cost of the bundle and route are calculated using a cost function. Eventually, the player can choose to bid on a composed feasible bundle by setting a price. At the end of a round when players have made their bids, the requests are allocated automatically to the winners, by minimising the total cost of transport.

For this modelling study, it is decided to focus on the bidding process of players, as this part requires a lot of information processing for players. They need to find feasible request bundles by combining a request (bundle) with a route that fulfils the requirements of that bundle and of the requests already being transported. It is interesting to get more insight into this complex "bidding behaviour". Additionally, it has significant potential to be improved by a policy.

In the game, the bidding behaviour consists of two choices: selecting a bundle of one or more requests and selecting a route to transport these requests. Because a DCM is only applicable when a choice situation is considered at which a choice is made between two or more distinct alternatives, this bidding behaviour and its choices need to be redefined. Therefore, it is chosen to combine these choices and their alternatives. So, the alternatives used for capturing the bidding behaviour are considered as: all the unique possible combinations of requests and routes a player has in a certain round. For example, if a player in a certain round can select request "B" and transport this using six different routes (keeping in mind the requirements of the current load of the player), these are considered as six feasible alternatives. Because a player often can select multiple requests and combine them, the list of feasible alternatives per player (choice set) could be large.

6.2 Phase 2; create a DCM of the selected choice situation

6.2.1 Creating choice sets from the game data

To create a discrete choice model, a choice set should be collectively exhaustive, mutually exclusive, and the sets should contain a finite number of alternatives. At first, for this research, it is possible to collect all possible alternatives players have (collectively exhaustive), because the required information for this is digitally stored during game sessions. Secondly, players can choose multiple alternatives which does not meet the mutually exclusive requirement. However, by considering each alternative as a binary choice set, this requirement can still be met. Finally, the number of alternatives players can choose from is large but finite.

Because it is unknown which alternatives players considered while making a choice to bid or not, the considered choice sets had to be generated. Based on the insights of

Fiorenzo-Catalano (2007), it is defined that all relevant and chosen alternatives of all the possible alternatives should be selected to generate a considered choice set. So of all the feasible alternatives players have in a certain round, all unique ones (in terms of the combination of requests) with the shortest route are selected, together with all the chosen alternatives.

6.2.2 Attribute selection for DCM

Because this generated considered choice set is still quite large and players do not really consider all these alternatives during the gameplay, extra attributes that could explain the creation of the considered choice set (in this case the complexity to find a feasible alternative) are defined. Together with attributes that could explain the consideration players make when choosing an alternative, these form the selected attributes for the DCM estimation.

Based on literature and experience of playing the game, the attributes to capture the "complexity to find a feasible alternative" behaviour, have been selected. At first, "Game Round" is selected, as it is possible that players learn to play the game while playing it (Ryu, 2013) making it less complex to find feasible bundles as the game progresses. Additionally, "Total/Bundle of Request" and "Route Length" are selected as the more requests need to be considered and connected, the longer the feasible route is and the more difficult it is to find that bundle. Attributes to capture "choice to bid or not bid for a feasible bundle" behaviour have been selected as follows. The effect of the possibility to set competitive prices, make a profit and the profit already won as described by Van Duin, Tavasszy and Taniguchi (2007) are taken into account by selecting a constant for "Bidding" (the effect of potentially making profit), "Total/Penalty Costs" (the extent to which a competitive price can be set), "Current load" (the effect of profit already won) and "Player Ranking" (the relative effect of profit already won).

A visual presentation of the theoretical framework for imitating choice behaviour is shown in Appendix B.

6.2.3 DCM estimation

Based on a data-set of 485 observations, several possible MNL models are estimated to check whether evidence can be found if the attributes really do have their effect on the bidding behaviour. Herewith the: rho squared value of the model, significance of parameter value, the purpose of the model and the interpretability of the utility function composition, have been used as criteria for selecting the attributes and model.

Therefrom, the following attributes remained: Bundle Number of Requests, Penalty Costs and the constant for Bidding. More sophisticated ML models for capturing panel effects, nesting effects and beta heterogeneity have been tested as well. Eventually, a model is chosen with the following utility function:

$$U_{bid} = \beta_{BNR} * BNR + \beta_{PC} * PC + ASC_{Bid} + \varepsilon$$
$$U_{NotBid} = 0 + \varepsilon$$

This MNL model is chosen because it performs equally as good as the ML models (in terms of Rho-square value), it is well explainable and relatively straight forward to simulate. The estimated parameters are presented in Table 1.

Attribute	**Notation**	**Value**	**Std err.**	**p-value**
Beta Bundle Number of Requests	β_{BNR}	- 1,22	0,196	0,00
Beta Penalty Costs	β_{PC}	- 0,0242	0,0118	0,04
Constant for Bidding	ASC_{Bid}	1,37	0,313	0,00

Table 1, Estimated parameter values

The Rho squared value of the model is 0,256

6.2.4 Validation of the DCM

To check how reliable this model is considering its ability to predict the right choices, a validation of the model is carried out. Herewith, it is calculated what percentage of choices is predicted right by the model (hit rate). This validation consists of calculating the hit rate using out-of-sample testing. For this, the data-set of 485 observations is split into two parts. The first ⅔ of the observations is selected randomly to estimate the model on. Then this model is applied to the remaining ⅓ of the observations. The percentage of correctly predicted choices is the hit rate. To reach robust results, the hit rate is calculated ten times, each time with another randomly selected estimation- /data-set.

The hit-rate of the model was found to be quite stable over the ten validations, and on average, 73%. This is considered to be a good validation-score for the model. As herewith, the bidding behaviour can be realistically imitated.

6.2.5 Conclusions about players' behaviour based on the DCM

Based on the estimated parameters of the final chosen model, some careful conclusions could be drawn about the bidding behaviour of players. It can be stated that players prefer making a bid (the positive constant Bid). However, when a player wants to bid on a request, this effect is almost entirely abolished due to the negative effect of the parameter; number of requests (BNR). Because evidence is found that the number of requests (within a feasible bundle) negatively affects the likeliness of making a bid. Players presumably find it difficult to deal with the complexity of combining a bundle and feasible route when more requests need to be considered. This attribute of complexity has relatively the most substantial influence on the systematic bidding behaviour found by estimating the DCM. The other attribute of which evidence is found that it influences player bidding behaviour is penalty cost. The higher the penalty cost a player should pay when bidding on the corresponding request bundle, the less likely he/she will bid on it. However, this influence is logical, and it only really affects the bidding behaviour with hefty penalties. Although, even then this effect is relatively small compared to the previously mentioned complexity effect.

So, it can be stated that the main factor influencing the bidding behaviour for carriers in this PI inspired transportation market environment (that could become a reality in the future) is the complexity of having to deal with combining a bundle and feasible routes. Other than in the game, carriers in real life could, however, have other incentives than only making a profit as well. They may also care about the region in which they conduct their transport or the length of the route. These extra requirements could make it even more complex for carriers to find their optimal bids. This complexity, as a result of bounded rationality, creates a sub-optimal market performance as bids are not made on the most efficient alternatives. Additionally, it generates a weak position for the independent carrier, as he/she is not able to compose the most attractive bid based on his/her requirements.

6.3 Phase 3; create a game and choice-based simulation to test a policy

6.3.1 Create the game and choice-based simulation

To create a simulation based on the gameplay, all game steps of one game round, as described in section 6.1, are simulated in MatLab using mathematical rules. The bidding behaviour of players is imitated using the estimated DCM. Therefore, first, the considered choice set is selected by the simulation using the selection rules of 6.2.1. Hereafter the systematic utilities per alternative are calculated using the utility formula and estimated parameters of section 6.2.3. Eventually, a random parameter ε is added to represent the (general independent) unobserved utility. It is distributed i.i.d. Extreme Value type I, var = $\pi 2/6$. Therefore, it is drawn from a Standard Gumbel ($\mu = 0$ and $\beta = 1$) distribution each time separately for each utility calculation. Eventually, when the total utility to Bid on an alternative is bigger than the total utility Not Bid on that alternative, a bid is placed and vice versa. The prices are set using pricing functions based on costs. Herewith, a game round (or bidding round) is imitated, and as many rounds as needed can be simulated.

6.3.2 Policy definition

Based on the DCM conclusions drawn in section 6.2.5, it can be stated that the players have difficulties with the complexity of combining requests with a feasible route in order to make a bid. Additionally, game data shows that it could be plausible that players experience too many options to find and oversee them all, or too little options to be able to catch them. This phenomenon of bounded rationality of carriers could decrease the effectiveness and efficiency of the transport market and weakens the position of an independent carrier. A solution can be found in the concept of a decision support system. All the information regarding routing, load size, start and end time, reallocation, and so on, can logically not be processed by a human. Therefore a system that helps carriers to process all that information to improve their decision making, without them losing control, could make the transport market more efficient and effective. Decision support systems are used a lot in the world of transport and logistics for all kinds of challenges. However, to the best of the authors' knowledge, it has not been tested what the effect of such a system could be on the PI inspired decentralised market place with reallocation possibilities.

In the PI inspired decentralised transportation market, two aspects are essential for an optimised transport system. At first, carriers want to bid on bundles with the lowest cost; in this way, they can set competitive prices. Additionally, carriers want to utilise the reallocation more as it provides them with a win-win situation. To capture the two aspects in one policy, a decision support tool for carriers is proposed that processes all the transportation information for each individual carrier and calculates their optimal bid compositions. These optimal bids per carrier consist of request bundles that have the lowest total cost and pass by the reallocation point. By this way, carriers can set more competitive prices and utilise the reallocation opportunity of the PI concept more.

6.3.3 Experiment to test the policy

To test the effect of the policy, the created game and choice-based simulation is used. This simulation represents the current PI inspired transportation market behaviour. Additionally, two other simulation settings are used. One simulation setting with implemented policy, where carriers bid on bundles that have the lowest total cost and pass by the reallocation point, and one simulation setting representing a centralised market situation. Because this market type performs well in terms of efficiency and effectiveness, it is used as a benchmark situation. So eventually, the three different simulation settings have been run ceteris paribus and the results are compared using the following effectiveness and efficiency KPIs: number of unallocated requests, number of total delays, the total price of all allocated requests, the price per allocated request, the mean filling rate and the total number of reallocations. This indicates whether the policy produces the desired effect and in what aspects it performs better or worse in comparison to the current situation and a central market situation.

The experiment settings are summarised in Table 2.

Simulation settings per experiment	Current situation - Future situation - Centralised situation
Price function per setting	Current & Future situation: use the same pricing functions that set different margins per carrier Centralised situation: uses a different pricing function that sets the same margin for each carrier
Generated requests by simulation within one experiment session	The same for each round for each simulation setting
Length of an experiment session	33 bidding rounds
Number of experiment sessions	9

Table 2, Simulation settings

6.3.4 Experiment results

A table with the results of the conducted experiment is presented in Appendix C. It shows the mean and the standard deviation value of the nine conducted sessions.

The results show that the filling rate of trucks in the simulation of the current situation is low. This is presumably because carriers likely do not bid on bundles with multiple requests (because it becomes too complicated). The proposed policy was partly aimed at solving this complex issue for carriers. The simulations show that the policy works in this respect, as the filling rate is much higher and even about as high as in the centralised market situation. The other aim of the policy was to create more reallocations, which it did well. So, the policy creates a much more efficient market situation. Additionally, almost all requests are allocated in the future situation, which is definitely not the case in the current situation. Therefore, the policy also creates a more effective market. In general, it can be stated that the policy of providing the player with decision-support about their most "attractive" potential bids, causes as much more efficient and effective game performance, which is close to the results of a central market situation.

As mentioned before, other than in the game, carriers in real life could have other incentives than only making a profit. In this case, the decision support system should be adjustable to a variety of carrier's preferences. For example, it should advise the carrier with the optimal bids based on his preference for low cost, service region, route length etc. Herewith, the carrier is in control, and the inefficient and ineffective effects of the complex market and bounded rationality are taken away. So, a decision support tool for carriers in the complex PI inspired decentralised transportation market seems to be an essential tool to reach an optimal market performance with a firm and "in control" position of the independent carrier.

7. Final Methodological GCBS framework

The final methodological GCBS framework is designed by evaluating and improving the first design of chapter 3, using the insights of the conducted modelling study.

7.1 Evaluation of the first framework design and insight from the modelling study

The opportunities, as described in section 3.1, proved to help motivate why the research case of the "Freight Transportation Game" suited the GCBS methodology. Eventually, the opportunities stated in the framework turned out to be a good match with the modelling study. In addition, these options appeared to not only be theoretically promising, but have also proved to be valuable in practice. Therefore, the designed framework for the opportunities of the GCBS methodology of section 4.1 is considered to meet requirement 1; provide insight into the opportunities of the methodology.

Phase 1 of conducting the GCBS methodology is considered to be an essential phase. This phase is crucial for the rest of the phases as creating a thorough understanding of the game provides the basis for the rest of the modelling phases. Additionally, creating a clear definition of the choice situation and alternatives of that situation is considered useful and essential. In conclusion, this phase created enough guidance to be able to perform the rest of the methodology.

Phase 2 did not prove to be sufficient enough to conduct the methodology. However, this was expected, as some methodological challenges needed to be handled during the modelling study. The first question that needed to be answered by conducting the modelling study was: How can a choice situation be defined in order to be able to capture it using a DCM? It turned out that, in addition to the choice definition created in phase one, it is important that the choice together with its alternatives (the choice set) needs to be collectively exhaustive, mutually exclusive, and the sets should contain a finite number of alternatives. Otherwise, it is not possible to create a DCM with it. The second, to be answered question, was: how can the choice sets be created? It was found that, just as with RP data, it is hard (or impossible) for a researcher to know the considered choice sets of players when using a "player preference" data collection method. Therefore, based on theoretical insights of Fiorenzo-Catalano (2007), the following guideline to be able to generate considered choice sets are formulated: include all relevant and chosen alternatives. It is up to the users of the GCBS methodology to define what the "relevant" alternatives of a particular choice situation are. Because these generated considered choice sets were still not representative for the real considered choice sets it was chosen to select two categories of attributes; attributes that could explain the creation of the considered choices and attributes that could explain the consideration players make when choosing an alternative. This leads to the final question that needed to be clarified: how can attributes that influence the choice be selected? Because no literature or experience about the specific choice situation of modelling case was available, more general literature and experience with the gameplay was used to define multiple attributes that could influence the choices behaviour. Eventually, by iteratively estimating multiple models with different compositions of the utility function and attributes a final model was chosen. This selection process was based on: the Rho Squared value of the models, the significance of estimated parameters, the purpose of the model and the explicability of the model. Eventually, this innovate created methodology of capturing a given choice situation into a DCM appeared to be successful as the validation of the final model turned out to be satisfaction. Additionally, the final DCM provided insight into the behaviour of players.

Phase 3 was sufficient enough for guiding the creation of the game and choice-based simulation. It turned out to be straight forward as the structure of the game, unravelled in phase one, already provides a structure for the simulation, and the DCM is already created in Phase two. However, for creating the simulation based on the game and for implementing the DCM to imitate the selected choice behaviour correctly, still modelling skills and own insight of the user of the GCBS methodology are needed. The same applies to the process of defining an experiment and conducting it using the GCBS. Eventually, this phase helped to create a realistic simulation based on the gameplay, including human behaviour.

7.2 The improved methodological GCBS framework design

As mentioned in the previous section, the opportunities of the GCBS methodology are considered to be helpful, sufficient and in line with the design requirement 1. Therefore, it is decided that no adjustments need to be made to this part.

Because Phase 1 created enough guidance to be able to perform the rest of the methodology, it is decided that it needed no adjustment as well.

In order to create better-structured guidance of Phase 2, it is chosen to split this phase into a data collection/preparation phase and a DCM estimation phase. In the data collection phase, a flowchart is created, telling the user what to do in order to generate considered choice sets, when and how to select what kind of attributes and how to deal with choice sets that do not contain a finite number of alternatives, and how to deal with the collectively exhaustive and mutually exclusive requirements. After following this flowchart thoroughly, the user is able to collect the right data and proceed to the next phase of the GCBS methodology. In the next phase, the user is presented with information about how to iteratively create and select a discrete choice model and validate it.

The final phase, of creating a game and choice-based simulation to test policies or interventions, is not adjusted as it met the design requirement 5 of helping to create a realistic simulation based on the gameplay, including human behaviour. The final designed framework applying the GCBS methodology is shown in Appendix D.

7.3 Validation of the final framework design

In order to determine whether the final methodological GCBS framework design is successful, a qualitative validation on the basis of the design requirements is shown in table 3. This shows how the requirements are met using the deliverables of the designed methodological GCBS framework.

Design requirement	**Corresponding deliverable**
1. Provide insight into the opportunities of the methodology	Sub-framework showing the opportunities of the GCBS methodology
2. Help to provide insight into the behaviour of players.	Phase 1 + Phase 2 + Phase 3
3. Provide structured guidance on how to conduct the methodology.	Sub-framework showing how to conduct the GCBS methodology
4. Contribute to the creation of a valid game based discrete choice model.	Phase 1 + Phase 2 + Phase 3
5. Help to create a realistic simulation based on the gameplay, including human behaviour.	Phase 4
6. Use a combination of serious gaming, DCM and simulation	For conducting the GCBS serious gaming, DCM and simulation are needed

Table 3, Design requirements and corresponding deliverables

The methodology and the framework proved its potential for the case of application of this research, as they helped to gain insight into the behaviour and test a policy using the created game and choice-based simulation. However, it is not possible to know how useful, reliable and robust the framework is when it is applied to other research projects that fit with the GCBS methodology.

8. Conclusion and Recommendations

The conducted research, described in this paper, has provided some valuable insights and contributions to the existing literature. At first, an innovative Player Preference data collection method for DCM is been explored and defined. This method proved to be a valuable alternative for the conventional RP and SP methods, and opportunities of this Player Preference method proved to be promising.

Additionally, an innovative methodology of creating a game and choice-based simulation is been defined and tested. This methodology proved to be successful in gaining quantitative and statistically rigorous insight into the behaviour of people and creating a realistic simulation. By applying the methodology on the case of the PI inspired "Freight transportation game" it has been discovered that the bidding behaviour of players is affected mainly by the complexity of having to deal with combining a bundle and feasible routes. Additionally, using the GCBS methodology, it has been found out that a decision support tool for independent carriers in the PI inspired freight transportation market creates not only an efficient and effective market performance (comparable to the performance of a centralised market) but also creates a more firm and "in control" position of the independent carrier.

To facilitate future research that suits the GCBS methodology, a methodological framework has been designed. This provides insight into the opportunities of the methodology and guidelines to systematically conduct it.

Eventually, more research needs to be done to test the (external) validity of the decision support tool as it would be interesting to see if such a tool is technically feasible and viable in the real world. Additionally, it would be valuable to test and extend the designed methodological GCBS framework in order to increase its robustness. Finally, it would be interesting to create a serious game with the objective of applying the GCBS methodology with it. Currently, the methodological framework is designed for ex-post creation of the DCM, based on an existing game. If a game is created for a GCBS purpose, the choice situations of players in the game could be designed with a DCM perspective. Herewith the game could, for example, be designed in a way that considered choice sets of player are traceable, a limited correlation of attributes occurs, and a game with multiple goals so that trade-offs (e.g. time vs money) can be measured.

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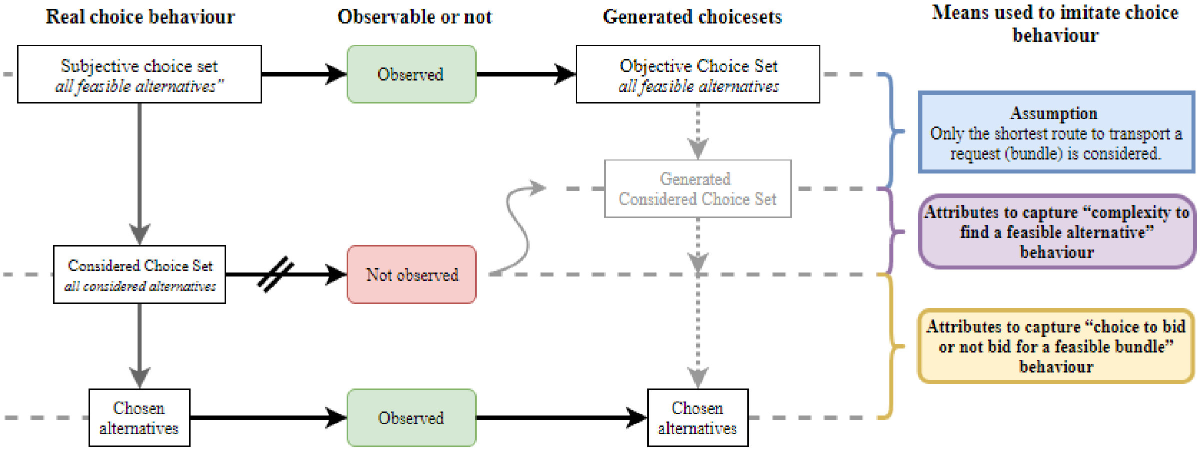
Appendix A

Compared data collection methods, based on Louviere et al. (2000)

Revealed Preference	Player Preference	Stated Preference
Portrays the world as it is	Portrays decision within the boundaries of the gameplay	Described hypothetical and virtual decisions context
Consist of inherent relationship between attributes	Consist of relationships between attributes	Control relationships between attributes
Only existing alternatives as observables	Including existing and/or proposed and/or generic alternatives	Including existing and/or proposed and/or generic alternatives
Represent market & personal limitations on decision-maker	Represent in-game market & player limitations	Does not represent changes in market & personal limitations effectively
High reliability & face validity	Assumed to be reliable when game is well designed, players understand the game and feel committed to the gameplay	Appears reliable when respondents understand, commit to and respond to tasks
Yield one observation per respondent	Yield multiple observations per respondent	Yield multiple observations per respondent
Valid & Reliable		**Accurate & Efficient**

Appendix B

The theoretical framework for imitating choice behaviour



Appendix C

Simulation Results

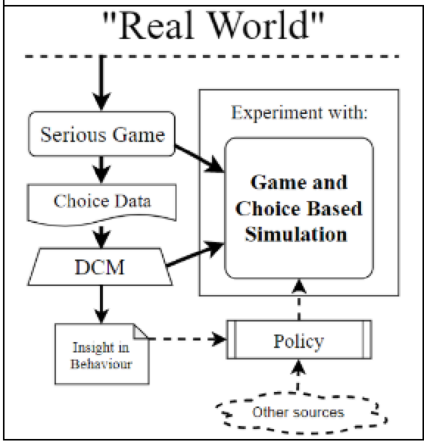
KPI		Simulation of the current Situation		Simulation with Policy		Simulation of a Centralised Market Situation	
		Mean	Std	Mean	Std	Mean	Std
Effectiveness	Unallocated requests	35,22	1,55	1,00	0,94	0,56	0,68
	Total delays	0	0	0	0	0	0
Efficiency	Total price	€ 287,43	€ 10,49	€ 335,57	€ 53,04	€ 317,35*	€ 39,34*
	Price/allocated request	€ 4,51	€ 0,21	€ 3,42	€ 0,53	€ 3,23*	€ 0,42*
	Mean filling rate	10,15 %	0,89 %p	53,06 %	3,64 %p	50,89 %	2,71 %p
	Number of reallocations	0,00	0,00	4,00	2,79	3,11	1,52

Appendix D

Game and Choice Based Simulation (GCBS) Methodological Framework

Game and Choice Based Simulation

Using a combination of Serious Gaming and Discrete Choice Modelling offers opportunities:



Analysing Behaviour

For which more reliable and valid data is required than by using a Stated Preference method

- Interactions between people and their dynamic environment that could be important for the decision making are taken into account
- People feel connected to the system situation the game is representing

For which more accurate and time efficient data is required than by using Revealed Preference method

- Multiple observations per player per round are possible (could be even faster than SP)
- Future concepts (environments, rules, alternatives etc.) can be observed
- Less disturbing inherent relationships within the data
- Less complex and costly to observe behaviour

Using DCM, insights into human behaviour can be obtained.

Policies/interventions (partially) based on these insights can be tested by:

Creating a realistic simulation

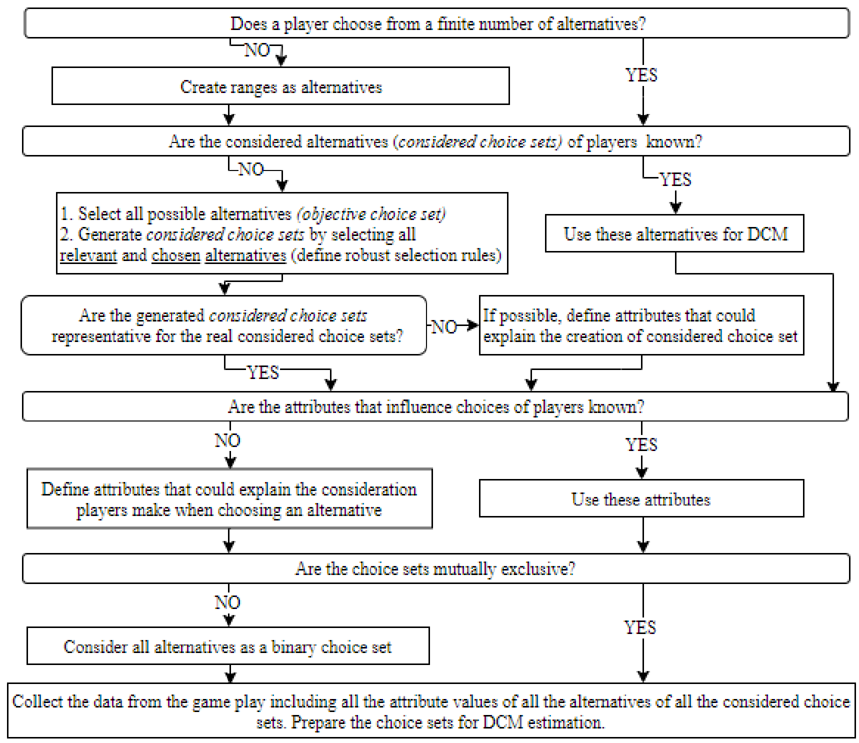
- As policies/interventions can be tested more quickly using a simulation than by testing it in the real gameplay
- As policies/interventions can be tested ceteris paribus and over much more rounds than in a real gameplay
- Is strait forward because the game is already a model of reality, providing a simplified structure to base the simulation on
- Is realistic, as player behaviour is implemented in the simulation using DCM

Conducting the methodology

Phase 1	**Create understanding of the structure of the game** • Game steps • Game dynamics • Select important choice situation(s) that are interesting to gain insight in and/or are important for the gameplay dynamics • Create a clear definition of the choice situation and alternatives of that situation

Phase 2

Prepare and collect the Serious Gaming data for the modelling of a choice situation



Phase 3	**Estimate a Discrete Choice Model using the collected and prepared Serious Gaming data** If the choice model is not unambiguously clear; iteratively estimate models with different: • Attributes • Utility functions • Random variables (to capture nesting effects, taste heterogeneity, panel effects) • Models (MNL, ML) Select the model based on: • Rho Squared value • Significance of parameter value • Purpose of the model (insight in behaviour, simulating choices, predicting choices, VOT estimation, etc.) • A well explainable composition of the utility function Validate the model e.g. using out-of-sample hit-rate computation Interpreted the final estimated model and use the explained choice behaviour to gain insights

Phase 4	**Create a Game and Choice Based Simulation to test policies/interventions** Create a simulation experiment to test the policy/intervention Define KPIs to measure the results of the simulation performance Create a simulation of the gameplay 1. Simulate the game steps using mathematical rules (e.g. if, then, else), based on Phase 1 2. Simulate the (important) player behaviour using DCM For each choice situation let the simulation: • Create the considered choice set using the defined selection rules of Phase 2 (if needed) • Calculate the total utility for each alternative in the choice set based on the specifications of the selected model of Phase 3. Define choices between alternatives based on their utilities (inc. random utility). Create other simulations needed for the experiment (simulation with intervention or implemented policy) Conduct the experiment and interpreted the results