Pollution in manufacturing: An unavoidable incidence?

A simulation study into cross-contamination effects in a multi-product factory

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Challenge the future

Pollution in manufacturing: An unavoidable incidence?

A simulation study into cross-contamination effects in a multi-product factory

by

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Preface

This report concludes my thesis project of the Master in Management of Technology as well as my education at Delft University of Technology in the Netherlands. It has been fun and challenging time abroad, and during these just over two years I have evolved considerably. It is high time now to part ways with the academia and set out to the 'real world' taking all the learned lessons with me. This thesis is the prime example of the abilities I obtained.

I would like to thank all those who contributed to the final version of this thesis in its current form. I am grateful to have had the opportunity of working closely with not just one, but three companies, solving a real-world problem, and based on that writing a thesis to graduate at a university. Despite many frustrations coming from various conflicts of interests among the involved parties as well as my own affinities, I am glad for the experience that will definitely shape my future. Now, with a relief that is it all over, I would like to express my gratitude towards those, who especially assisted in making it happen.

Eventually, I conclude this foreword with a remark on the process. In theory, writing a thesis should start with a research question, and all needs and requirements ought to naturally follow from there and create a complementary whole. Although this is hardly ever done so, just as in my case, there is little room left to enjoy the writing itself and the freedom of expression that comes with it. Yet, I did my best to rather follow the approach of one of my favourite novelists:

> *I chart a little first-list of names, rough synopsis of chapters, and so on. But one daren't overplan; so many things are generated by the sheer act of writing.*
>
> — Anthony Burgess

In the end, this sizeable text is a verbalisation of my understanding of the significance of the performed work as well as the storytelling skills that I have. I only wish I could make it more like a work of fiction to ease the read but apparently this would disqualify me in the field of engineering where everything must follow a clear path, and where sudden twists in the plot are certainly not appreciated. Perhaps some other time...

Paweł Tomasz Kołodziejczyk
Delft, October 2015

SUMMARY

Companies can lose a substantial portion of their revenues due to deterioration in value of their products as a result of processing impediments, which might occur in the entire supply chain. Sometimes, the reasons for a decline in product quality are not fully understood, and thus there are no appropriate measures taken to prevent it. Yet, it is vital to comprehend what is actually happening during production and material handling so that proper, well-informed decisions can be made. This project deals with one of the unexplored problems – quality loss due to product cross-contamination, which is a common occurrence in material handling, multi-product plants. It is a process of mixing product going through multi-purpose equipment and piping with leftover residue that is currently there, which takes place when there is no intermediate cleaning in between two consecutive products, though the precise character of it is usually not known. Omitting cleaning runs to save production time and money is a common practice in the industry.

This research introduces a novel simulation method to quantify and predict the extent of cross-contamination as well as to assess its effects. Many models for material handling in multi-product plant have been made in the past but very few relate to the issue of cross-contamination, which is of extreme importance in quality assurance and informed decision-making. As no similar models have been developed previously, or other research done based on a real industrial setting, it is a truly innovative study, intended to establish foundation for further research, and to raise awareness of the issue by starting to fill a gap of knowledge about what can happen during material processing.

Initially, a thorough literature research is done, dealing with issues of trade-offs in manufacturing, cross-contamination in production, as well as how to combine scheduling methodologies with a powder mixing model in a discrete event simulation (DES). Then modelling boundaries and assumptions are established together with a conceptual model. Based on that, a general DES building blocks – class models for a bagging machine, conveyor, mixer, silo as well as product batches and orders are created.

Specific analysis is performed in Sloten, a young animal feed plant in Deventer, the Netherlands, in order to find a more precise character of cross-contamination over time, as well as to test the model application in a realistic setting. Contamination measurements using tracer–collector method over material flow with multiple intermediate sampling points help, together with relevant theoretical models, build mathematical representation of chaotic changes occurring within material flow. Obtained curves fitted with a sum of two exponentially decreasing curves correspond well to the measurements but do not explain everything that happens during the process. Nevertheless they are used to model the cross-contamination phenomenon.

Two unique cross-contamination models suitable for implementation in DES are developed, basing on principles of segmentation, quantity conservation, product similarity and proportionality, and are fundamentally models of mixing between material flow and residue in the crossed container. More general one, called partial mass exchange model, allows to customize fraction of material mixed, characteristic to a given piece of equipment, while the other, mixing model, assumes homogeneous resulting composition.

Finally, a case-specific simulation model, joining material handling system with cross-contamination calculations as well as customizable layout configuration and settable scheduling methodologies, is established. Experimental setup with four-stage production process consisting of ingredient feeder, a single mixer, limited intermediate storage buffers and multiple system exits, mostly bagging machines, connected by conveying equipment, is discussed. All of the machines involved are multi-purpose, flexible but with some limitations, together with the interconnections and logic among them, basing on a genuine example.

Analysis shows considerable impact of system layout and scheduling rules on product contamination. In order to limit cross-contamination appropriate product sequencing, minimising the differences between consecutive products in all stages of the process in needed, while that might impede throughput because of resulting constraints. There is thus a trade-off relation among various aspects of production efficiency, as well as amidst that efficiency and flexibility, when number of storage buffers and their capacity is changed.

In the end, research first benefits from measuring the extent of cross-contamination, then succeeding in giving an original example of how to build a cross-contamination model, and how to combine it with a stochastic DES, capable of suiting different designs and scheduling methodologies. Performed experiments show, that cross-contamination effects can be reasonably well simulated with a DES model. It also describes possible effects of certain interventions on various performance indicators, and demonstrates possible risks of increasing flexibility in the system. Additional, more thorough trials are needed in the future to improve the model and generalise it further. Yet, the very important first step to understand the issue has been taken, which will aid in application to other types of systems as well as help in mitigating product contamination.

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Abbreviations and Definitions

In the document the following abbreviations are used:

APS	Advanced planning and scheduling
CRN	Common random numbers
CSLSP	Capacitated Stochastic Lot-Sizing Problem
DEM	Discrete element method
DES	Discrete event simulation
ERP	Enterprise Resource Planning
EU	European Union
FIFO	First in first out (queuing principle)
FMS	Flexible manufacturing system
GMO	Genetically Modified Organism
KPI	Key performance indicator
MAS	Multi-agent systems
MO	Manufacturing orders
MHS	Material handling system
MTBF	Mean time between failures
OR	Operations Research
SN	Scenario Navigator (software)
TTR	Time to repair
WIP	Work in progress

And the following most important definitions are distinguished:

Carry-over
a separation of portions of mixture from the production batch, left in the manufacturing line or its parts as a remainder

Cross-contamination
unwanted release of the carry-over by mixing it into a subsequent product

Nutrient
any distinguishable substance that provides nourishment essential for the maintenance of life and for growth

Product Contamination
amount of foreign, other than specified material in a product, comprised of picked up residue

Release curve
also called “cross-contamination curve”, a graphical representation of ratio of contamination as a function of material flow for a given container

Residue
stationary amount of carry-over in a distinguished processing or transportation segment, comprised of products priorly occupying it

Tardiness
also “lateness”, the quality or condition of occurring after scheduled time.

1

INTRODUCTION

This chapter establishes the problem to be investigated, and gives a description about the work context. It is followed by a research objectives and questions formulation, together with the utilised methodology and planned deliverables. Finally, the supporting company, that delivers vital data and allows to place the issue is more precise context, is briefly introduced.

1.1. RESEARCH PROBLEM

In 2004 four edible products were recalled from shelves in New Zealand due to exceedingly high levels of lead. Investigation quickly traced the source to a particular batch of corn imported from China, then milled into flour. However, detailed analysis could not identify the exact point of entry to either maize supplier, milling or further processing, and the origin of the pollution remained unknown for a long time. Eventually, after extensive and costly search, the source of the contamination was determined to come from a bulk shipment of corn, where an unclean cargo container was used, and the previous product residue was carried over.[1]

The above is one of many examples of product cross-contamination, which can occur throughout the entire supply-chain, being very difficult to pinpoint, and often resulting in commodity quality deterioration. That is why companies need to put more effort to recognising and dealing with risks of such pollution, if they want to assure long-term stability in the value of their output. Especially, that their good reputation is at stake, as the eventual company on a product label is considered responsible by the customers or the public opinion.

1.1.1. BACKGROUND

Production processes in factories are often optimised for high capacity, where a lot of high technology solutions are used to increase productivity (Mieghem, 2003). With more added automation comes more complexity, that makes it difficult to understand the production process, especially when allowing for high manufacturing flexibility and a large product base. In such cases the technology making it possible is also the source of hidden problems, that manifest themselves in deteriorated finished product quality, but are otherwise very difficult to locate. Managing not fully understood problems has then little chance of success. It is alarming that the knowledge of what happens during product processing is so limited, and that so many managers only prioritise performance.

Nevertheless, a lot of companies spend plenty of their resources on quality assurance of their finished goods, but fail to understand what really happens or what could happen during processing necessary to deliver that particular product. Misguided actions can measure the exact quality of selected finished commodities, but do not specify reasons for it being at a determined level, providing purely factual data on the end state, which cannot be used for a proper investigation. Moreover, there is a limit to expenditure on quality assurance, as the enterprises must believe in acquiring profits while these measures have a direct impact of the prices of goods (Mapes et al., 1997). That is why, more focus needs to be put to understanding why a specific output is achieved and what causes it, as otherwise it is not possible to take steps to improve the process. Better recognition of quality deterioration risks can not only help in avoiding them, but also reduce costs associated with quality assurance.

[1] Source: http://www.foodsafety.govt.nz/elibrary/industry/Source_Lead-Nzfsa_Confident.htm

This research deals with a possible decline in product quality caused by cross-contamination, which often occurs in multi-product manufacturing lines. Term “cross-contamination” refers to unwanted additions to a product as a result of picking up residue from the preceding product, left in utilised equipment, which has not been cleaned (or properly cleaned) in between (Strauch, 2003). It is a very common but hardly well-understood issue, which might result in a significant decline in quality of some goods. Specialists with considerable industry experience can name plenty of factors that they think have influence over the process,[2] ranging from equipment properties, through product specifications to production scheduling. Cross-contamination is acknowledged as probably the greatest source of quality related issues and the need to improve on that is generally expressed. However, there is no knowledge about the precise nature of the phenomenon or its largest contributors, and this is the named reason why measures taken to mitigate the problem are not comprehensive.

1.1.2. PROBLEM STATEMENT

A lot of factories use versatile and flexible multi-product lines to manufacture various goods, employing the same machinery with a whole network of interconnections. Such solution allows for being agile, producing smaller batches, quickly responding to customer demands, and keeping warehousing to minimum. With more advanced and multi-purpose automated equipment, it has become possible to produce miscellaneous products easily, utilising the devices as much as possible (Erenguc et al., 1999). Because of that, separate lines for each product are no longer required, allowing to save money on equipment and personnel, especially when potential production capacity is much higher than the market demand. The common practice is now to increase the product base considerably, suiting more precisely to various needs of the identified customer segments. More narrow client groups, limited product shelf life and required manufacturing agility lead to small batches and numerous production changeovers.

With production line versatility also come certain complex problems. Flexibility allows companies to have multiple connections, and use various machines for the same job, combining the sets almost freely, depending on the organisational structure. However, the complexity of scheduling and managing production rises along with flexibility, leading to situations where it is very difficult to find the best solution for manufacturing planned goods. Moreover, companies tend to prioritise machine utilisation as a measure of production performance, which in general needs to be high to create more finished products (Smith, 2003). But high equipment utilisation leads to time pressure, and might result in poor preparation for the following product, in terms of e.g. improper cleaning, lack of supplies or rushed setup. Determining, what is the relation between production efficiency (the aspects of which are e.g. throughput, quality, tardiness, etc.) and process flexibility in relation to cross-contamination could help gain better insight on choices to be made, especially if there are any trade-off characteristics.

Every time a manufacturing line has to be converted to suit a different good, there is a risk of cross-contamination. Equipment that has previously handled certain product is very likely to be polluted with a carry-over from it, which might transfer into the subsequent one. When a cleaning run in between them is omitted or one performed does not remove all residue, there is a chance of mixing it with contents of the following commodity. Naturally, the amount of pollution in the beginning is on average higher and decreases with every processed unit. However, due to sticking to surfaces or deposition in pockets some of the material can be released in a chaotic, seemingly random way, that is very difficult to predict. If the transferred material is unwanted, it might lead to a significant decline in quality, and result in an inferior product, considered by the manufacturer as out of specification, where certain measurable properties are outside established limits. Moreover, in cases like food processing or for pharmaceutical use, such occurrence might even be harmful for the user. But not all cross-contamination is adverse to product quality. Sometimes, large amounts of very similar in composition additive might not be as unwelcome as small inclusion of another, sensitive material.

Surprisingly, little research has been done to measure and quantify the extent of cross-contamination. Companies are very reluctant to admit their quality assurance problems or do not realise them fully[3]. Moreover, the cross-contamination phenomenon exists along the entire production line and is very specific to equipment characteristics, handled material properties and cleaning procedures, having many difficult, if not impossible to predict, aspects. Determining cross-contamination features for one product does not necessarily lead to increasing knowledge about another.

The accurate knowledge on how residue from one product is transferred into the subsequent one is normally missing. Because of that and a considerable difficulty in procuring it, investigation into cross-

[2] Based on 5 separate interviews with employees of Sloten B.V.

[3] See footnote 2

contamination is normally absent in production models or scheduling solutions. At best, based on the historical issues, companies include such scrutiny for operations as a final ‘nuisance’ to be accounted for. In such cases cross-contamination is treated as a black-box to which ‘clean’ ingredients enter to be processed, and exit as finished goods with some pollution. Thus, understanding the phenomenon, and ability to predict its extent as a multi-stage process, dependent on different variables, would be very beneficial to final quality assurance.

There are three potential sources of quality norms: internal standards, regulations in law and customer expectation. Normally companies follow the legal requirements but also specify their own internal limits on contents or significant aspects of their products, or comply with quality standards of private systems, either compulsory or voluntary (Trienekens & Zuurbier, 2008). However, clients often do not have resources to measure the quality of products or prove their inferiority, and the producer reputation serves then as assurance. Because of that, customers are possibly more prone to react to scandals publicized by the media. Sometimes to comply to regulations or mitigate risks the companies reluctantly admit that there are some possible trace amount of additives present, which are not included in their recipe. An example for that is presence of trace amounts of peanuts in many products in the food industry, only because the same line is used to produce commodities including them. Following products, which have no specified peanut content, despite a thorough cleaning, are still at risk of cross-contamination (Taylor & Baumert, 2010). Due to a large number of people allergic to peanuts it is safer for companies to admit possible (but not certain) contamination, than to face potential lawsuits.

Prediction of the extent of cross-contamination has a direct relation to manufacturing costs and risks, and can be used for devising interventions. First of all, measures different than cleaning can be taken to reduce cross-contamination hazard. If certain, known portion of the goods in front could be reworked or discarded, it might prove less costly than to perform cleaning and losing production time. Moreover, more informed production scheduling can be done to mitigate risks associated with cross-contamination. All in all, understanding and predicting the extent of quality loss due to cross-contamination is the first step to devising procedures aiming to limit it.

Nonetheless, there is a perceived trade-off relation between production performance, product quality as well as system flexibility. The latter, viewed often as having more options to choose from when allocating resources, is an essential source of the cross-contamination problem, as well as its inherent solution. In principle, multi-product manufacturing requires easily adaptable connections among various pieces of machinery and storage, which is enabled by technology. Was that not possible, the cross-contamination problem would no longer be a major issue as the production lines would be fixed and product-specific (or product family specific). When that is not the case, broad flexibility poses a greater risk of cross-contamination, when multiple connections can be contaminated to various degrees, and the ability to predict the outcome decreases.

Finally, investigation into possible effects of cross-contamination is not specific to factory operations but could come much earlier, in the design stage, to evaluate different layout possibilities and choose one best suited. Normally, detailed analysis in this matter is not done, and the knowledge about the issue is gathered from operational experience, when it is too late or too costly to introduce any major changes to the line. Moreover, such analysis can result in alternative strategic choices, like limiting the number of handled products or specific sensitive ingredients, striving for better monitoring, reducing system flexibility to reduce risks, or other.

1.2. RESEARCH OBJECTIVES

The following section lists several intermediate steps to be taken during the study. It is divided into two groups, the first dealing with the main research itself and the other with testing and experimentation based on a case study. At first, in the theoretical part, an initial analysis is done and conceptual model derived with general definitions of possible interventions. Then, in a case study, cross-contamination measurements lead to a complete formulation of a specific experimental setup, fully defined simulation model, that is later investigated. Then, data gathered is analysed and conclusions are made. Thus, the intermediate goals are:

- Analysis of factors related to cross-contamination in a multi-product plant, based on interviews;
- Literature study on cross-contamination issues,
- Construction of a conceptual model,
- Derivation of generalised cross-contamination models,
- Definition of possible dispatching and sequencing rules to be investigated,

- Case study experimentation:
  - Cross-contamination measurements preparation, conduct and analysis,
  - Simulation model build, comprising production and cross-contamination models with user input of various scheduling rules, using Simio software,
  - Verification and validation of the simulation model,
  - Experimentation with various system layouts and scheduling methodologies,
  - Analysis of the experiments results.
- Set of general conclusions arising from the case study,
- Proposal of possible future additions and improvements to the model and research.

The most important research step is to draw general conclusions from the case study and experiments within, that could be applicable to a wider group of problems.

1.3. Research Questions

The following section formulates questions to be answered during research. The central issue of the analysis is cross-contamination phenomenon and its impact on production performance. The main study inquiry is specified to be:

What are the effects of cross-contamination on the amount of out of specification goods in a multi-product plant with varying buffer capacity and scheduling rules?

Thus, the research is to contribute in quantifying the consequences of cross-contamination process for finished products in factories, with multiple production changeovers, where there are two main areas of interventions: intermediate buffer number and capacity as well as production scheduling. With the main research question come a few ancillary ones, formulated to specify the study focus:

1. *What is cross-contamination, and why is it important for multi-product factories?*
2. *What are the relationships between factors influencing cross-contamination?*
3. *What are the effects of cross-contamination, and how are they relevant?*
4. *When is a product considered out of specification?*
5. *How to express product-residue mixing in a mathematical way so that it can be used as a general approach for expressing product contamination?*
6. *Can cross-contamination phenomenon be modelled in a discrete event simulation paradigm?*
7. *What are the effects of additional buffer capacity in manufacturing on cross-contamination and production capacity?*
8. *Which scheduling rules are beneficial for reducing the extent of cross-contamination, and what is their impact on production capacity?*

Provided questions are to structure research objectives to in the end provide insight into considered problem, and assist in answering the main question. They indicate that the research is of quantitative, experimental nature but often basing on more abstract issues like risk and importance perceptions, quality assurance.

1.4. Methodology

Several different methodologies are used to tackle various problems of the project. Firstly, some imposed constraints and requirements are mentioned, and a general approach to supply chain as well as production planning is presented. Then, a simulation approach, describing the requirements and limitations of DES is given, followed by a more guided scheduling scheme, especially utilising dispatching rules. The research can be thus divided into 5 main phases: problem formulation, specification, model build & testing, experimentation and analysis with conclusions. At first, knowledge base is built and the problem to investigate defined. Requirements for further investigation as well as theoretical foundations are prepared in the second stage. Then, these are translated into a simulation model for a specific case and tested. Consequently, a set of experiments exploring the impact of independent variables on dependent ones (KPIs) is performed, and the results are analysed in the last part. Finally, conclusions and recommendations are made.

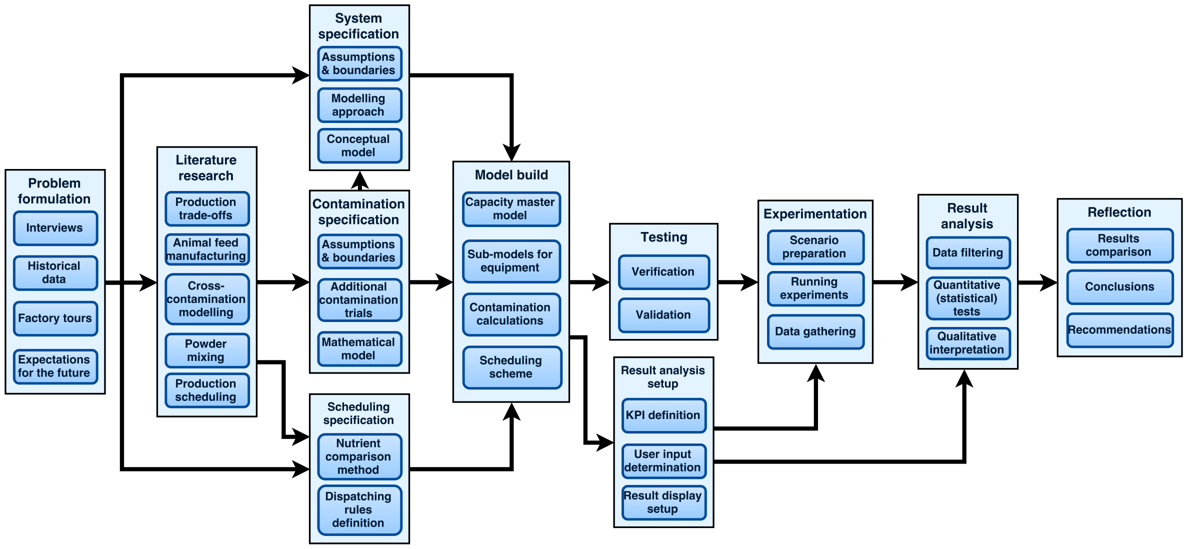

Figure 1.1: A schematic overview of the research steps

1.5. DELIVERABLES

The following deliverables are to be submitted as a result of the project:

1. Conceptual model on how to include cross-contamination effects in a multi-product, powder-handling plant,
2. Discrete event simulation model based on the case of Sloten constructed in Simio® software,
3. Scenario Navigator® tool allowing for scenario setup and simulation result visualisation,
4. Recommendations for limiting the possible effects of cross-contamination regarding system layout and scheduling methodology.

As it is not the intent of this research to deliver a tool to assist with experimentation and result assessment, the created SN software is to be of demonstrative nature, handling data and automatically preparing visualisations.

1.6. CASE COMPANY

The experimental setup bases on the case of a major young animal feed producer Sloten, a subsidiary of Nutreco corporation. Its facility in Deventer, the Netherlands, is chosen as an example to provide a real-world data, and to test the performance as well as validity in a realistic setting.

Because of the handled material structure - a sticky powder, and lower safety standards in the industry, comparing to human food production, animal feed manufacturing is a prime example of a relatively high cross-contamination issue, where a lot can be gained if the process is understood and taken advantage of. Strauch (2003) bringing the result of a survey from the German Research Institute of Feed Technology shows, that cross-contamination is present in all examined plants and it is increasing, because of constantly introduced new feed formulations, produced on the same line. Moreover, there seems to be a consensus, that contamination-free manufacturing is not possible, due to scale effects, in comparison to especially pharmaceutical industry, where it is an absolute must. Despite that, and also in consequence of limited knowledge on the effects contamination has on animals and further on humans, regulatory bodies strive for a "zero tolerance" restrictions on any carry-over. Being pushed by the authorities, their customers as well as trying to provide high quality products, companies are forced to research and mitigate the effects of cross-contamination in their facilities.

Cleaning the processing equipment, to reduce the impact of cross-contamination between one product and the following one, is normally possible. It is based on releasing another material in place of the product, and sending it through the same line to gather the residue. But for handling low-moisture powder, as in the feed industry, no liquid or any watery substance can be used, because it would affect product quality. Thus, normally a regular sales item is used to perform the cleaning, which is then disposed of, sold as inferior quality product or reworked. All of these are costly to the manufacturer. When asked about possible impact of closer scrutiny of cross-contamination, specialists[4] list greater complexity of planning, more production time and product losses, and more constricting manufacturing procedures. As all of them are viewed as negative, the ignorance about the cross-contamination character is viewed as bliss, because no immediate action needs to be taken. Thus, organisational reluctance has its tow on possible investigation. All in all, if the extent of quality loss in unknown, then the potential gains of better quality assurance are even more uncertain.

Moreover, mixing powders, an intermediate step in feed production, is very difficult as usually the added ingredients have varying physical properties, like size, viscosity or density, which prevent from equal distribution of particles. What is more, a reverse process to mixing, called segregation, occurs strongly in the mixing of solids, and is not limited to stirring equipment but happens with every powder movement (Poux et al., 1991). Ramifications of this process for long transportation lines are vital if the material is to be divided into smaller parts (e.g. packaged), as some of them might contain ratios of certain components that is much lower or higher than intended. On top of that, measuring the homogeneity is not an easy task as it requires sampling, in which it is vital to determine location, size and number of taken samples as based on that, the quality of the entire structure is assessed. Reducing the uncertainty about the mixture contents would yield quantifiable benefits to the producers.

Cross-contamination has an impact not only on product quality, but also on feed safety issues, which might lead to human food safety concerns. One of the representative examples is adding copper to piglet feed, which has positive effect on their growth. If such additive gets mixed up with products targeted to lamb, the excess of copper might lead to the animal's poisoning and eventual death (Zervas et al., 1990). For impact on humans, it is sometimes desired to exclude e.g. medicated feed, especially antibiotics, because of public health issues, or genetically modified organisms[5] (GMOs). Naturally, to avoid lawsuits and damage to the brand name, companies would like to prevent such occurrences.

Finally, the project is also supported by Systems Navigator, a consultancy firm with a vast experience in supply-chain simulations. They offered their expertise as well as software tools necessary to handle the problem. Together with the Sloten's parent company Nutreco, a global animal nutrition and fish feed supplier, they are involved to provide counsel and know-how to help gain insight on the issue.

1.7. STRUCTURE

This report comprises of eight main chapters, complemented with an extensive appendix. The structure of the main part is overlaid on the methodology graph and presented in Figure 1.2. Following this introduc-

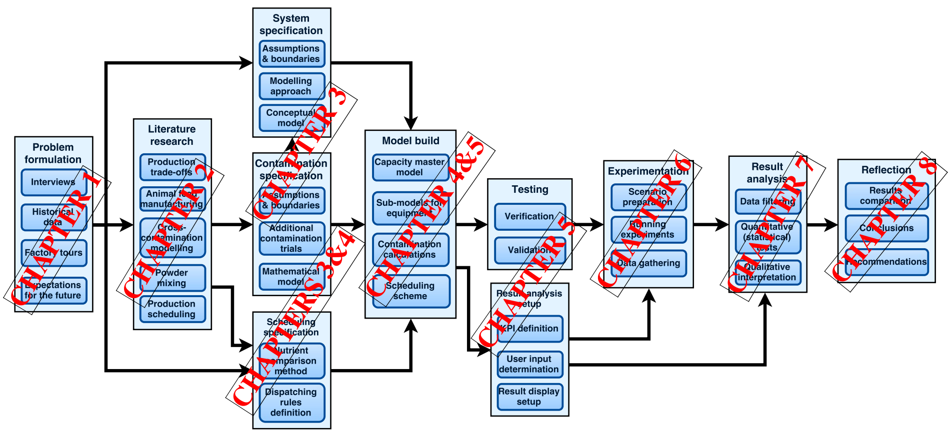

Figure 1.2: An overview of the document structure overlaid on the research steps

tory chapter is a thorough analysis of current state of knowledge about the topic (chapter 2). Specifications and requirements for modelling are included in the first part of chapter 3, along with boundaries, simulation approach and modelling choices made. Chapter 4 describes the production model - a base for capacity analysis and model components. It is followed by cross-contamination model derived in section 4.4, where

[4] Independent reaction of three employees of Sloten, working in operations.
[5] See: http://www.cdc.gov/narms/animals.html

the method and path to obtain both mixing and partial mass exchange models is depicted. This is followed by description of implemented scheduling methodology and dispatching rules, that concludes the design phase.

Experimental setup, based on the factory layout and organisation of Sloten, is defined in chapter 5, after which all derived models are verified and validated to the best extent of possessed data in section 5.7. Chapters 6 and 7 deal respectively with conducted experiments and their analysis, where the conclusions on the scientific relevance are made. These are followed by recommendations arisen from the results scrutiny. Conclusions about the work can be found in chapter 8 with a rumination on the project and the report is completed with a set of possible future expansion of the investigation.

2

Literature Analysis

In order to undertake any research, a solid theoretical foundations are essential beforehand. This chapter presents a review of fundamental and contemporary knowledge on the topic at hand.

As the main scope of the research is to determine the effects of cross-contamination in production, these need to be defined first before the simulation model exploring production scheduling with cross-contamination calculations is built and investigated. Then, answering how does the analysis fit in a landscape of Operations Research (OR) and in particular in production line manufacturing of similar endeavours. Especially, how to define production efficiency, versatility as well as flexibility and what are the trade-offs between them, if there are any. Furthermore, how to construct and validate a production line DES model and complement it with cross-contamination model as well as scheduling possibilities. Moreover, a short review on the animal feed manufacturing framework and an extensive production scheduling review is included, referring to topics like dispatching and sequencing.

2.1. Production Trade-offs

Production is an intermediate step in supply chain logistics. It deals with transforming raw materials into products, by giving them value that is recognized by customers (Min & Zhou, 2002). In this context, it is highly focused on a single production line, taken from the entire landscape of supply chain (mostly procurement and distribution), and dealt with on its own. Yet it is acknowledged, as Min & Zhou (2002) or Beamon (1998) emphasize, that the entire supply chain needs to be treated as an integrated system. Furthermore, uncertainties need to be incorporated into the system to achieve better results (Mula et al., 2006). However, Erenguc et al. (1999) recognises that some uncertainties, like poor coordination, discrimination against internal customers or linking problems between inbound and outbound logistics are not easily quantifiable, and thus often not included in such analysis.

There are four main categories of supply-chain goals, each looking at a different part of the business. First deals with customer service and distinguishes variables like product availability or response time. Second, monetary value, is characterized by cost behaviour, return on investment and asset utilisation. Furthermore, there could be a goal to gain information or knowledge by the company, and finally risk elements in terms of quality and imperfect information sharing (Min & Zhou, 2002). All of those are different aspects of production efficiency, and are typically interconnected with trade-off relations, where one has to choose which variable is more important to satisfy. This is of great importance to companies, having real economic significance. Gupta & Goyal (1992) give an example of a large product base that might reduce the plant's ability to produce large volumes. Yet Erenguc et al. (1999) claim that these should not be each other trade-offs but rather need to be simultaneously prioritised, looking from a strategic point of view. Thus products need to be delivered quickly and cheaply, keeping production agile, their quality impeccable and inventories low. Mapes et al. (1997) name six most common decision variables in these terms: quality consistency, quality specification, lead time, delivery reliability, cost, flexibility and innovativeness. Min & Zhou (2002) expand it and classify to determine three major group of restrictions on possible decisions managers can make and the feasibility of which, they need to asses. These are:

- capacity, including financial, production, supply, technical, workforce or IT adoption, among others,

- service compliance, for meeting customer requirements, or e.g. quality,
- the extent of demand, so that the capacity of supply is balanced with the extent of consumption.

Adler et al. (1999) define flexibility as the ability of a manufacturing system to cope with changing circumstances, and calls the trade of between it and efficiency one of the firmer grounded notions in the entire OR. The idea is that efficiency requires bureaucracy, standardisation, formalisation, specialisation as well as hierarchy, and these all impede adjustments and smoothness.

An interesting shift in understanding and dealing with production trade-offs can be found in literature. Gupta & Goyal (1992) and Mapes et al. (1997) understand trade-offs literally, as sacrificing one performance indicator for another, possibly finding a minimum impact point of their combination. Since then, Adler et al. (1999) change this view to postulate for parallel improvement of all, supported by an appropriate organisational approach. Also Silveira & Slack (2001) call trade-offs a 'myth', which holds back companies while other manage to outperform them in many areas simultaneously. As trade-offs are believed to exist, they create a significant bias on how managers approach process improvement.

For example Sandborn & Vertal (1998) perform inquiry into trade-offs in production due to different packaging options. They conclude that such analysis needs to be done for entire product families life-cycles, sometimes sacrificing individual performance for the entire portfolio. Mapes et al. (1997) notice that producing wide variety of products with different quality specifications increases process complexity that leads to errors in scheduling, unplanned delays and poorer quality in general. On the other hand, Silveira & Slack (2001) regard the trade-off concept as more problematic to academics than it is for practising managers.

2.1.1. PLANT LAYOUT DESIGN

System design is making decisions on long-term features of the system, such as layout, configurations and capacities. It is vital to commit proper resources to that, to assure the best possible structure, as it might not change for a long time. The analysis and adjustments can be much more easily done with support of simulation (Smith, 2003). In this case, a problem of production scheduling in multi-stage, multi-item capacitated systems is described. Moreover, analysis of production trade-offs needs to be incorporated with functional verification and layout design so that more optimum solution can be found (Sandborn & Vertal, 1998).

As companies are under constant pressure to offer a wider group of products, the complexity in managing that rises as well. Mapes et al. (1997) acknowledge that such impact might be limited by the organisational structure, but it is unlikely to be non-negative. That is why organisations tend to offer great variety of products but try to limit it within particular plants. Still, for a single facility there are numerous products, whose efficiency of production needs to be supported by the plant layout (Benjaafar et al., 2002, Djassemi, 2007). This is a serious problem as often factories are upgraded from their previous schemes, which was not built for multi-product purposes, and the changes are hardly ever composite, involving only a part of the process.

Typical design criteria for plant layouts also do not capture the relationship between layout flexibility (in terms of operational interconnections) and performance. Thus, analysis into trade-off relations of different design possibilities are vital for finding superior solution (Benjaafar et al., 2002). Most measures evaluating layout suitability deal with material handling efficiency (like throughputs) to evaluate candidate scenarios (Djassemi, 2007). However, these often fail to capture other characteristics like quality (or cross-contamination as in this research), punctuality or organisational structure. It is very important to expand such analysis to suit wider needs and increase prediction validity.

2.2. ANIMAL FEED PRODUCTION AND CONTAMINATION

Because animal agriculture has been rapidly growing for the past decades, there is an increasing interest in choosing the right feeds to allow for faster and more efficient growth of livestock. Young animals are especially susceptible to given nutrients, so the industry puts special effort to providing them with best suited and balanced diet. This often includes dried dairy products and derivatives (Crawshaw, 2012). Thus, the industry expanded and now every species has a specially developed for them feed or multiple feeds. But with variety comes also greater manufacturing cost and production process complexity. All that while striving for low production costs and retail price as well as increased manufacturing techniques and quality (Behnke, 1996). Growing number of products manufactured on a single line entails higher difficulty of keeping their critical components separate and larger risk of cross-contamination via their carry-over (Strauch, 2003).

According to Fink-Gremmels (2012) animal feed production industry is often disregarded and only mentioned when some emergency arises causing harm to people via livestock. Such occurrences might include pathogens (e.g. prions), dioxins or adverse substances like melamine in milk. But the importance of proper nutrition of animals, especially the young ones, should not be underestimated, as it becomes a highly innovative business with specialised targets, high quality resources and considerable socio-economic impact. Moreover, the number of regulation and contamination limitations increases steadily, especially in the EU, where since 2002 animal feed is recognised as a part of the human food chain (Crawshaw, 2012, Fink-Gremmels, 2012).

However, typical contamination considerations involve mostly potentially harmful additives, comprising only marginal portion of the feed, especially microbiological or chemical agents that can pollute the material not only during production, but also be a part of incoming raw materials or enter during storage or transportation (Fink-Gremmels, 2012). This report concentrates on cross-contamination, which is, according to Leloup et al. (2011), Strauch (2003), a process of mixing of carry-over of additives during material handling, which is a common issue for animal feed industry that can be extended to many powder-based industries. In consequence, sometimes finished products contain other than specified ingredients, which in general are unwanted but have no adverse effects on the animals. However, there also might be severe repercussions, for example when lamb product gets contaminated with high levels of copper (typical for piglet feed), which causes harsh poisoning to the animal (Zervas et al., 1990). To understand more about the issue Leloup et al. (2011) prepared a test-bench for material elevator using several different feeds, and a tracer with collector method. Although differences among feeds are noticeable (which is explained by different cohesiveness due to varying fat content), the behaviour for single powders is consistent with limited variability. Fitzpatrick et al. (2004) perform analysis on the flow characteristics of milk powders with different fat contents. They conclude that these differ significantly in terms of cohesiveness as well as friction angles thus varying considerably in flow properties, which demands distinguishing in modelling.

Moreover, Leloup et al. (2011) emphasise that trials during production are difficult to carry-out, especially because of lack of access points to equipment and freedom to watch the particle movements, while experimental setup differs from the real system, and is often simplified. Therefore careful trials on the actual equipment with intermediate steps are necessary to derive a model for cross-contamination. Toso et al. (2009) investigate a production scheduling problem for an animal feed plant, which can be a starting point for the research at hand. They claim that proper sequencing of products can take advantage of a ‘cleaning’ property of two consecutive products if the lots are big enough, which means that the previous residue is collected and no intermediate cleaning is required. But that usually works only with very similar products and other might pick up too much residue to fit quality norms.

Furthermore, manipulating product batches by means od lot-sizing (see Lee et al., 1997), can join or split orders and take advantage of the lower residue and changeover times that may not follow the triangular rule. That means that separate set-up change from first product A to B and then B to C might be in total shorter than straight change from A to C. Also, Toso et al. (2009) point out that while normally lot-sizing and sequencing is dealt with separately, combining those might lead to greater flexibility and overall performance, which is also confirmed by (e.g Drexl & Kimms, 1997). Finally, animal feed demand follows a seasonal pattern which impacts the scheduling greatly. Normally, companies deal with it by working overtime and making sure they have enough ingredients in stock to avoid a backlog (Toso et al., 2009, Behnke, 1996). Clark et al. (2014) propose a more general solution to scheduling with contamination and non-triangular sequence-dependent setup times. They point out that a capability to absorb contamination presents opportunity that cannot be ignored as it might result in reducing the number of intermediate cleaning runs as well as the processing time.

2.3. SIMULATION OVERVIEW

According to Min & Zhou (2002) supply chain models can be divided into four categories: deterministic, stochastic, IT-driven and hybrid. This analysis concentrates on the latter, as it includes simulation (especially DES), which combines all of these methods and can potentially result in superior outcomes. Also Mula et al. (2006) recognise that models which do not include uncertainty produce inferior results. By further dividing uncertainties into several categories they discover that simulation models, including Multi-agent systems (MAS), have been utilised in the past for each of distinguished categories (Mula et al., 2006, see Table 2, pp. 272). Terzi & Cavalieri (2004) claim that the use of simulation methods has been increasing more rapidly than a general use of IT, and in particular DES is considered a vital key-success factor for company survival. Also Jeong & Kim (1998), Gupta & Goyal (1992) claim that simulation can be effectively used in design, implementation and operations of FMS.

Negahban & Smith (2014) postulate that simulation is an appropriate method to evaluate design of manufacturing systems, and to attempt to improve it by exploring different layout alternatives. Most important part of the simulation is a material handling system (MHS), that is concerned with the use of raw materials and their transformation. Jeong & Kim (1998) present an extension approach to production called a flexible manufacturing system (FMS), which consists of a collection of numerically controlled machines, that are further regulated by an automatic MHS. Setup is then divided into four decision-making stages: design, planning, scheduling and control, that work closely together. For this case, it is vital to understand how planning and scheduling exchange information and cooperate.

In a discrete event simulation the state of the model can change only at discrete time points, called events. Between those events the time is continuous, and the system trajectories can be thus considered piecewise constant, i.e. the state variables remain fixed between events. There can be any number of state changes, called transitions during an event, for the being of which time does not progress. A simulation model specifies how the events are scheduled and what state transitions are caused. Then a given simulator tool handles the execution of the model (Schriber et al., 2012, Zeigler et al., 2000). Simio® is a popular DES commercial tool[1] that follows object-oriented world-view, in which all objects are derived from the same base object. Execution is based on Processes, that can be expanded and customized by users to create own objects (Schriber et al., 2012). Software includes stochasticity considerations, allows for experimentation and use of additional packages. For further details see Kelton et al. (2013).

Furthermore, it is crucial that any developed production simulation model could be used as a part of a larger supply-chain business simulation, as interconnectivity plays a major role and needs to be taken care of, by choosing appropriate techniques in the early stages of modelling (Terzi & Cavalieri, 2004). Support of distributed real-time platforms might be necessary for proper information exchange, and is definitely useful for possible future additions. As such, any model cannot be considered completely standalone, but should allow for coupling it with other models or systems. Simulation can play an important role as a support for decision making on design of system layouts. Providing the model is complete and transparent, built with full involvement of the analyst skills and process experts, it can be useful to both high-level alternative comparison as well as visual interactive communication means (van der Zee & van der Vorst, 2005). They also point out that the model control structure needs to be clear and centralised, in order to allow the decision makers to efficiently control the system, without arbitrary hard-coded parameters. Only with clearly and realistically defined model elements and relationships, adequately reflected model dynamics, separate user interface and easy setup of various scenarios, can the demands for suitable decision support tool be fulfilled. Consequently, combining different performance indicators with a means of comparing them directly is a vital part of a possible multi-criteria decision-making problem (Gupta & Goyal, 1992).

2.4. POWDER MIXING

Powder mixing is an important process in many industries. It is a mechanism of bringing together solid particles to produce a mixture of regular consistency, which occurs due to different velocities and directions of the agitated material (Sen & Ramachandran, 2013). Being able to mathematically express and predict the level of homogeneity in mixing is an important step in order to control that, and thus many models for that have been developed in the past. Obtaining homogeneity might be problematic due to mixed product diversity, expressed by parameters such as size, shape, moisture, surface nature as well as mixing apparatus differences. Moreover, mixtures also undergo a reverse process to mixing simultaneously, called segregation, which often prevents from achieving homogeneity (Poux et al., 1991, Sen & Ramachandran, 2013).

Sen & Ramachandran (2013) distinguish several modelling approaches to the problem: Monte-Carlo methods, continuum and constitutive models, data-driven statistical models, compartment models, residence time distribution methods, hybrid models and discrete element method (DEM) based models. Additionally, they create a population balance model which describes the development of separate entities, where particles can combine and break up over time. Portillo et al. (2006) compartmentalize investigated V-blender in order to decrease computational intensity and allow for a relatively large number of particles. At discrete time steps particles can randomly (and depending on the particle flux) enter or leave given compartment, that is assumed to be uniformly mixed, leading to a large-scale mixing process. Most accurate models for granular mixing are based on DEM, especially useful for processes requiring high accuracy e.g. pharmaceutical, where proper dosage in pills is of utmost importance. Bertrand et al. (2005) reviews several different approaches and solutions to this problem, also discussing limitations, especially in processing power. Al-

[1] Software website: http://www.simio.com/index.php

though this has improved significantly over the past years, it still remains one of the biggest drawbacks of this method (Sen & Ramachandran, 2013).

However, all aforementioned models describe processes of intentional mixing, where rotating equipment stirs the particles. Models for coincidental mixing or involving a mixer and adjacent particle transportation system are very limited in the literature, especially when including a whole production system and not just its part. This gap must be filled in order to suitably support the industry as these effect will occur whether recognised or not, and the only right way to limit them is by analysis first. Still, many investigated the possible mixing effect in silos. E.g. Wu et al. (2009), Cleary & Sawley (2002) perform detailed analysis on silo flows, and conclude that the incoming material to silo amasses roughly in a heap shape, while discharge forms a funnel, resulting in shifting of material. As such, if the inflow material has some changing characteristic (e.g. contamination level), its outflow behaviour will be altered in a way, that is very difficult to predict unless the material and silo properties are very well known. This makes it extremely difficult to make general predictions on material quality.

2.5. PRODUCTION SCHEDULING

Scheduling is the process of arranging, controlling and optimizing work and workloads in a production process. Scheduling is used to allocate plant and machinery resources, plan human resources, plan production processes and purchase materials. In this case, it is the determination of a production sequence, manufacturing runs and times, and the route to be followed. At the same time, scheduling takes into account the constraints on production activities and resources in such a way that the goals, e.g. no deadline violation, are realized (Drexl & Kimms, 1997, Herrmann, 2006). Supply-chain logistics is characterized by a large number of interdependent variables. For its transformation network models Erenguc et al. (1999) list: products, stages, minimum and desired stocks, time periods as the most important ones at this stage, given the predecessor relationships among all supply-chain stages. Proper scheduling has real economic significance for all manufacturers, and they are extremely interested in taking advantage of it to suit their needs.

Given problem can be described as Capacitated Stochastic Lot-Sizing Problem (CSLSP) with intermediate storage, that deals with scheduling for a stochastic production system with multiple items, for which set-up times and setup costs occur when a production is switched from one product to another (Kämpf & Köchel, 2006, Drexl & Kimms, 1997). The issue is to find a sequencing and lot-sizing rules to maximise performance (in terms for e.g. maximizing profit). The solving of CSLSP usually leads to mixed integer programming formulations, which can only be solved efficiently by the means of heuristics, i.e. either there is no analytical solution or it is too expensive and does not handle stochasticity well. According to Mula et al. (2006) scheduling problems in production are optimisation problems and are very complex, requiring new approaches to manage uncertainty. There are a few criteria that drive the choice of production scheduling, depending on the level of aggregation. In this case Min & Zhou (2002) names six decision variables. These are: allocation of resources, number of stages, service sequence, volume, inventory level, workforce and extent of outsourcing. On the other hand, Erenguc et al. (1999) reduces all this variables to monetary value beforehand and optimises costs as a whole. This approach reduces complexity for optimisation itself but increases uncertainty of transitions to single dimension.

Scheduling can be also incorporated with an enterprise resource planning (ERP) system, as an attempt, as stated before, to integrate various branches of the supply chain. Such an attempt is made by Józefowska & Zimniak (2008). They first point out that it is important to take into account the aspects of capacity constraints, backlogging, set-up costs, sequence dependence, number of production stages and possible number of products. Only then one can endeavour to solve the problems, which depending on above parameters are called differently, and the approach to tackle them should change. Developing heuristics to find near-optimum results fast is suggested, to help solve multi-objective combinatorial optimisation problem at hand. Despite not incorporating stochasticity Genetic Algorithms approach is used, mostly because the model has a much broader spectrum and includes not only production but also costs, in and out stocks as well as multiple products and machines (Józefowska & Zimniak, 2008).

Another approach, that does not require optimisation and fits well with simulation, is scheduling via dispatching rules. When lot-sizes are fixed, and there is no desire for costly optimisation, in many cases dispatching rules can be a good enough substitution (Jeong & Kim, 1998, Pinedo, 2008). Blackstone et al. (1982) describe dispatching rules as logic, according to which the next job is chosen from a set of jobs awaiting service. While this logic can be simple or complex the drawback is that these rules are applied independently among workstations and only within the logic prescribed to them. For complex systems, introducing highly sophisticated dispatching rules, taking into account the state of other, relevant stations might not be feasible. Moreover, as Blackstone et al. (1982) mentions, no single rule can be identified as best in all circumstances, and lists a comprehensive set of dispatching rules for job shop operations in the paper. Interestingly, these rules can be also intentionally violated, using dispatching heuristics, to e.g. insert idle time to a station to await for a high-priority job. Another example of such application is pre-emption, i.e. interrupting a task if a more suitable situation can be achieved.

Job selection can be also solved via job sequencing, which is ordering all awaiting jobs in a queue, while dispatching rules only choose a single next job. Job sequencing is useful especially when the set of awaiting jobs is fixed, without new arrivals, which are then processed by a single server (Blackstone et al., 1982). Lee et al. (1997) distinguish two methodologies for that: constructive heuristics, which builds up a non-reversible queue of jobs, and improvement heuristics, that tries to optimize the set either via local search or guided search of the sampling space. The constructive heuristic is thus similar to dispatching rules for a fixed set of jobs. Selection of dispatching rules might be in the end left to an experienced planner, who knows the system and uses such scheduling tool for support (Herrmann, 2006).

2.6. Literature Relevance

Desk research done in this chapter, together with performed interviews, allows to conceptualise how to constrain and model the given problem, and elaborate more on the current state of knowledge about the issue. Clearly, there are a few gaps that need to be filled to fully understand the subject, especially involving the precise nature of cross-contamination and its impact, but also the effect facility layout can have on pollution. Then, understanding how material residue is released during processing is missing, and thus it is not yet possible to express it with a mathematical model. As no DES model for cross-contamination could be found, a question arises whether this method can be suitably well used for its representation. Moreover, it is unknown whether there are any trade-offs involved in the process because of cross-contamination, or what could they be exactly. In the end, literature is used to help develop the cross-contamination models in section 4.4 and to relate to the experimentation results in chapter 7.

3

Modelling Specifications and Requirements

This chapter describes the implications arising from the introduced research problem and choices made, in order to come up with tools to help answer the research questions. In the first part, modelling boundaries and constraints are listed, and then the theoretical model is constructed.

3.1. Investigation Boundaries

As the problem environment – multi-product manufacturing is put in general terms, there is a need to constrain it. Cross-contamination is an issue for all multi-functional production lines, but for some it is considerably greater, depending of multitude of factors like equipment properties: internal area, volume, line length, angle of inclination, internal shape, surface texture, processing speed and others. Moreover, it is highly dependent on the type of handled products, whether these are liquid, bulk particulates, discrete solid parts or assemblies, and on the technique of production - batch or continuous. Product properties like material type and quantity, particle size, shape and number, cohesiveness, friction angles, are also vital components. It is not possible to investigate all of them in a single research project, and thus a representative of the larger class of problems is chosen. Investigation into continuously handling loose, dry material in form of powder can serve as a good enough example for the group with relatively high pollution effects (Strauch, 2003). Then, cross-contamination happens not only in particular machines but without break along the entire route with varying intensity, especially including transportation and storage equipment. In addition, only short term repercussions of cross-contamination are studied, where material mixes in predictable way, excluding rare events of long-term residue release.

Production process might be quite complex with alternative routes and possible multiple, varying number of stages per product. Additionally, there could be repeated processing on the same machine, rework, exclusions and other aspects, making it a very compound problem from scheduling perspective, and blurring the insight into cross-contamination in between (Mapes et al., 1997). Therefore, in order to understand the complexity of cross-contamination, the process should be relatively simple but allowing for scheduling and layout interventions. Figure 3.1 depicts the chosen example of process to investigate further. It starts with material dosing, where automatic equipment applies several ingredients from storage, that is not within the scope of the inquiry, into a single, main mixer. Mixing machine distributes the components evenly and creates a homogeneous powder, which is then sent to an intermediate storage buffer – a silo. There is a limited number of the silos with varying capacity and connections and the mixed product can be sent to more than one. Subsequently, there are several bagging machines that package the ready products, to which they are transported with a network of automated conveying equipment. Carry-over occurs then in every interval of the process and so can cross-contamination, depending on the route chosen for a given product and previous occupants of this path.

Additional constraints, specific to equipment, products or job organisation can be applied to increase the realism of the process. Moreover, pollution gathered before the mixing can be incorporated into the analysis and accounted for. The resulting production scheme can be described as scheduling and sequencing problem with limited intermediate storage (silos) in which all the products go through the main mixer to be

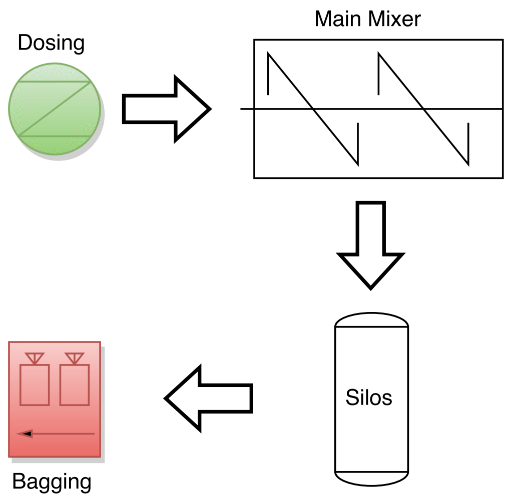

Figure 3.1: A diagram of a representative process for the chosen problem

dispatched to one of the silos and then await the capacity for bagging (or bulk loading).

Every multi-product manufacturing process comprises of orders or jobs that need to be scheduled and then handled (Herrmann, 2006). This highest level list contains information of the product (normally there is only a single type of product per order), its quantity, identifier and due date. Every job has to have at least one product assigned to it, and usually more that physically moves through the system. For bulk processing items can be discretized into small batches and processed as individual units of homogeneous composition, small enough to withstand that assumption for large processing amounts. Furthermore, every product has a recipe, or unique specified component composition, that can identify counterparts that are packaged into different size of bag (or released as bulk), or possibly have different contamination rules. These are based on nutrients and sensitive components where every product for every nutrient has particularised specification level as well as lower and upper acceptable thresholds. The number of such rules can differ per system, and they can be easily compared to their equivalents in another products.

Normally, production planning is done on three levels: strategic, tactical and operational (Erenguc et al., 1999). This investigation concentrates mostly on the tactical one with some considerations about the strategy, and names possible operational uses with further development. In order to constrain the investigation and focus on the most important aspects of the problem several boundaries are set:

- Model begins at the end of the feeding system to the mixer,
- There are four types of equipment involved: mixer, bagging machine, silo and conveyor;
- Dynamic object classes include orders, product batches and bags;
- Possible contamination before the mixer (e.g. in the elevator) is not taken into account directly, but is included together with one occurring in the mixer;
- Raw materials (ingredients) are always available and the finished products are removed and stored independently,
- Total amount of residue in the system is roughly constant so the contamination is an equal exchange of the manufactured product with the equipment residue,
- Cross-contamination is independent of the type of transported material. It varies with equipment/pipe type and contents of materials participating in the exchange,
- Products with different recipes cannot be in the same place,
- Backlogs or rush orders are not taken into account,
- The model does not investigate any further than the bagging lines and bulk stations.

These model boundaries are set to concentrate on investigating the research problem, and to exclude non-vital system parts from scrutiny. Based on them, modelling assumptions are made that are used for model implementation.

3.2. MODELLING CHOICES

Several modelling choices are made to describe the system in more detail and prepare for implementation. First of all, it is vital to split mixing and bagging to allow for taking advantage of the system's flexibility. Since due dates only apply to the product leaving the system and shelf life is not an issue, product can be mixed any time beforehand and be 'suspended' in silos until further processed. Then, orders can leave the system no earlier than the set due date from planning.

System can be therefore imagined as a push-pull construct. The main mixer prepares the recipes and tries to allocate them in a silo. Mixing process can only start when there is sufficient silo capacity available, and any time the mixing and storage capacity are available, there should be material 'pushed' to the silos. As such, the amount of work in progress (WIP) is of no concern, providing there is sufficient material available to be bagged. Once the material reaches the silo it can be 'pulled' by an appropriate system exit with available capacity, providing the transportation line is not blocked. If there is always material available in the storage, it is up to the exit points to decide which order to process next, that is to be included in the model logic and scheduling rules.

Another important choice is to assign every material batch to its order and move it through the system in a FIFO manner with no passing by, and cross-contamination is also to work in this way. It is to assure proper sequence of orders, though can be limiting, e.g. in case where there are two or more products of the same recipe in a silo, and only one in a middle could be processed at the moment, due to availability of equipment. On the other hand, it ensures that the first product collects most of the (possible) contamination, and is useful when splitting orders among multiple silos. Given a possible large number of entities in the system, all materials in containers i.e. mixer, silos and buffers are to be batched to a single entity but retain their references and contamination data. Calculation of cross-contamination is then done after each interval with only single possible route, distinguished in a model by separate objects (one object - one contamination calculation per product batch).

3.3. RECOGNISING EXCESSIVE CROSS-CONTAMINATION

Classifying whether given occurrence is cross-contamination, and determining if the outcome product is too largely affected by it, is a vital step to take measures in order to limit it. Assuming no cross-contamination

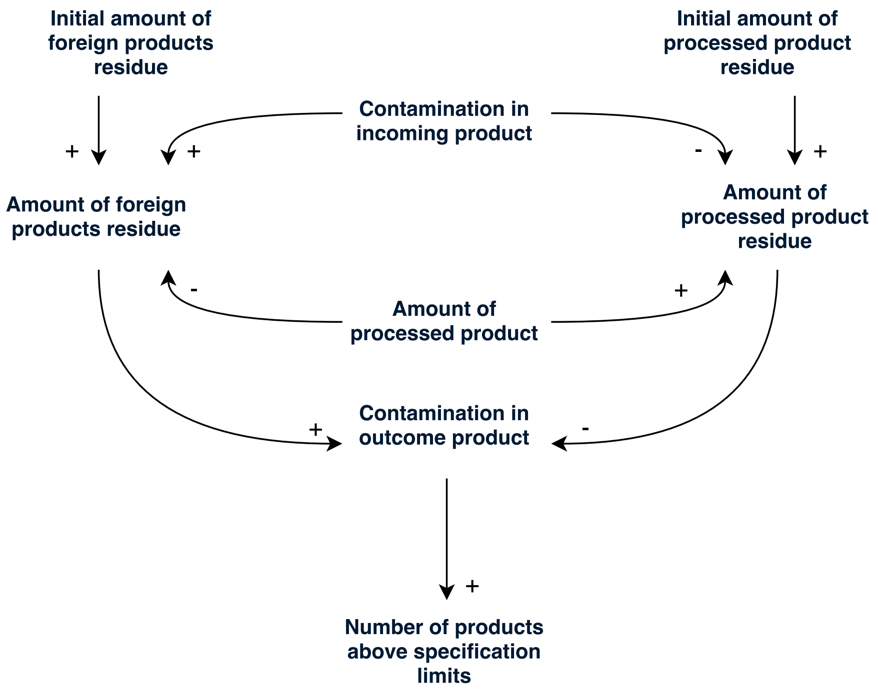

Figure 3.2: A causal diagram of cross-contamination process

is allowed should be treated as an unrealistic idealism, impossible to implement for larger quantities, even despite multiple cleaning treatments. Although pharmaceutical industry manages to limit cross-contamination, which is an absolute must for drug production, other industries, such as food processing, are not as thorough with cleanliness norms. For example trace amounts of peanuts can be found in other products, even after considerable following material flow, which can cause a serious threat to allergy sufferers (Taylor & Baumert, 2010).

Assuming all products are subjected to unintended mixing along the route, the outcome composition depends on what is being mixed and how. Most commonly, it is between different portions the same product, and then it does not matter how much product was involved and how it happened, as it has no consequence to the resulting structure. But when there is another product involved, the quantity and path are vital. Differentiating among neutral and significant processes for a model is difficult, though being able to do so could save a lot of processing power. Therefore, all calculations done for cross-contamination are performed regardless of material and residue structure. Moreover, the idealised situation of mixing just two products is hardly ever going to happen. Diluted residues of products remain in the system for a long time, until their amount in a given place can be considered so small, that can be omitted (Fink-Gremmels, 2012).

A causal diagram for cross-contamination is presented in Figure 3.2. There are two main factors, except for equipment properties, influencing the resulting product contamination in the outgoing products: initial material residue and contamination in incoming product. In general, it is expected that the more product is processed, the more of its residue remains in the system and the less of other products (Leloup et al., 2011).

When a finished product is contaminated, it does not necessarily mean it is out of specification, though there is a higher chance for that. It is the ingredients, especially the sensitive ones, that are vital to determine whether it is within requirements (Fink-Gremmels, 2012). The number of product ingredients is generally vast, and it is difficult to handle them all. Therefore the approach taken is to include necessary nutrients, combining them with relevant other, usually trace components, to which the product can be susceptible. By giving specification limits to all, and comparing with the actual content, final determination of quality in terms of cross-contamination can be made. This way, minor addition of some might result in rejection of a given item, while large intake of another, similar product might be neutral to the outcome.

3.4. MODEL STRUCTURE

A simplified Unified Modeling Language (UML) class diagram is presented in Figure 3.3. It contains the most important interactions and variables, based on the aforementioned boundaries and assumptions.

The most important relation in the system is one of product batch – place, that defines material handling logic and applies cross-contamination calculations. Every product batch has a parent object - its order, defining type of product, quantity and a due date. Product batch also has a recipe, limiting the maximum dosing speed and identified by its number, and several different items may have the same recipe. Furthermore, products should abide contamination rules, which specify the particularised nutrient level and its minimum and maximum values for the finished product. They can be also empty if such levels are not specified.

Product batch always occupies a certain place, one of four distinguished: a mixer, silo, bagging machine or conveyor. Every place has a certain capacity limiting the number of product batches occupying it and the total residue parameter used for cross-contamination calculations. Moreover, every place keeps information on the current product residues in it and their quantities. Clean product batches, with original recipe content of 100%, might become contaminated along their route by the residue in places they go through (by the process of residue-product mixing), keeping the information in the contamination table. As such product batches contaminate each other via an indirect interaction in a certain place. Material content from products of the same item number is not considered contamination, while any other additives are recognised as pollutants. Contamination is only considered extensive if the nutrient levels are breached for the sum of product batches in a bag leaving the system. Depending on the content of a place and a batch, the total contamination can either increase, stay the same or decrease.

Conveyors are places that connect places with each other (so a conveyor can connect two conveyors as well). They transport material in FIFO manner according to their fixed speed along fixed conveyor length. Conveyor types, screw or pneumatic, are distinguished to calculate their capacity and conveying speed. An air filtering station, placed at the end on pneumatic conveying system and before a bagging buffer, can be also viewed as a conveyor with zero length that only performs material exchange for cross-contamination.

A silo is an object that holds product batches for an indefinite amount of time, i.e. from the moment they enter until they can be processed further, which does not depend on the silo. Contingent upon product batch destination the discharge speed from a silo may vary. Discharge is a process of sending material form a silo to its destination, subjected to various model constraints. Another important function performed by a silo is checking whether material from a single order is split among multiple silo, and attempting to merge its discharge when the silo runs empty of a given order child objects.

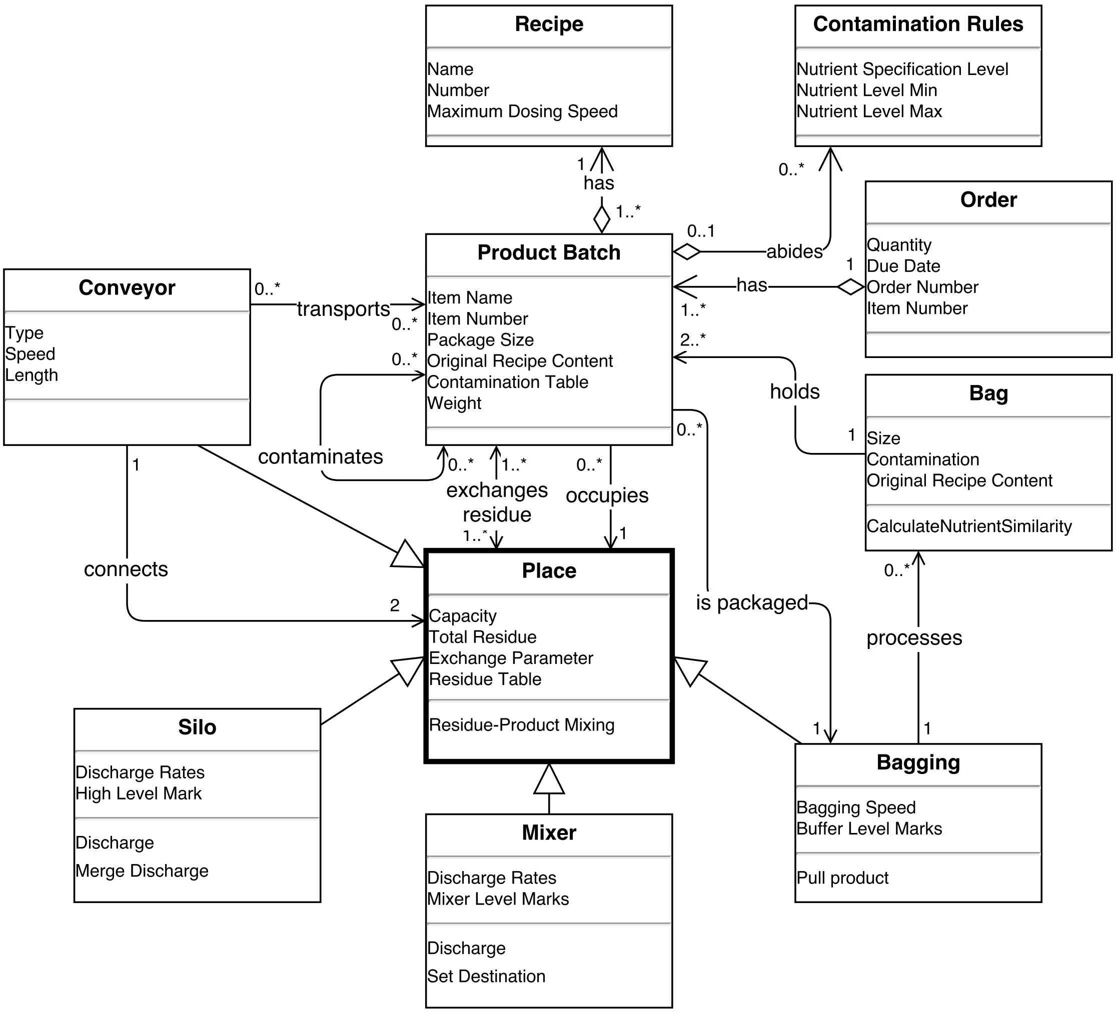

Figure 3.3: A simplified class diagram for the model

A mixer is a similar piece of equipment to a silo. It also holds multiple product batches and delays them before sending to their assigned destination (a silo). But the discharge logic is subjected to the chosen mixer output as well as material level monitors, that can hold off discharge if breached.

Finally, bagging is responsible for grouping product batches together, and putting them into bags, which can hold several of them. Product batches are stored in buffers, from where they are put together in accordance with the machine processing speed and product batch package size. In the end, whole contamination in a bag is added up, and recalculated into nutrients to be compared with the nutrient minimum and maximum levels to eventually determine whether the bag is within specified limits or not.

The class diagram from Figure 3.3 is thus a vital specification element to be used further in software implementation.

3.4.1. ANALYSIS CRITERIA

Cost analysis is not within the scope of investigation, therefore it is the line performance, mostly in terms of capacity, flow times and contamination, that is to be examined. All derived useful performance indicators are listed in section C.3. The following set of high level Key Performance Indicators (KPIs) is used to compare different scenarios with each other, often joining them to express in more general term (e.g. throughput):

Important equipment:	• average daily throughput	[bags]
	• average daily throughput	[kg]
Manufacturing orders:	◦ number completed	[-]
	◦ number completed on time	[-]
	◦ average contaminated order ratio above limit	[-]
	◦ ratio of material above limits to total processed	[-]

Thus, all comparisons among scenarios defined in chapter 6 are done using (some of) the above six parameters.

3.4.2. SIMULATION APPROACH

One of the most important issues to point out, is that the production in question can be best described as continuous, rather than batch, because of handled material properties and its flow through the system. This is so because the mixing process, after an initial setup, gives out a steady flow of mixed product. And that continuous process is to be represented by a discrete event simulation. According to Kelton et al. (2013) the modelling steps can be divided into seven parts:

- Problem formulation,
- System and simulation specification,
- Model formulation and construction,
- Verification and validation,
- Experimentation and analysis,
- Presenting and preserving the results,
- Reflection.

These are to be followed in search for a well-founded approach to model the problem and represent it in the Simio package. As the research problem is stated and methodology chosen in chapter 1, this chapter continues with system specification. At first, the specification of the modelling problem in more detail is made, followed by an identification of constraints and boundaries as foundations for the further steps. These are vital to represent the issue at the right level and only including relevant features, as in general such systems are too complex to be modelled fully, and unnecessary features only obscure its understanding. The following stages continue according to the list, where a model formulation is done in the next chapter. Then, the final simulation model is defined and validated, as the essential tool to discover possible consequences of certain interventions (chapter 5), and following experimentation is described in chapter 6, its analysis in 7, and is finally concluded in chapter 8. Detailed tables with experimentation results can be found in Appendix G.

4
Production Model

Production model is the basis of the project that provides the fundamental functionalities of the simulation. This chapter explores the translation of a real-world manufacturing plant problem into a discrete-event simulation model, as a necessary means to explore impact of selected specific interventions on production performance. In the following sections, the model is complemented with cross-contamination calculations and dispatching logic.

4.1. Purpose

In order to explore possible performance of different scheduling alternatives as well as to determine the extent of contamination in the products, the production system within investigation boundaries needs to be represented in a DES paradigm. For this purpose an object oriented simulation tool Simio® from Simio LLC is chosen as a powerful and commercially well-established program. Production model as such is meant here as an 'engine' that creates and directs the flow of material, and steers the execution logic in a manner similar to the real-world system. With parametrised properties and hierarchical structure, the final model is to consist of several parts that harmoniously perform necessary production steps, i.e. create product batches (entities) in specified intervals, and send them to their destinations with relevant delays for mixing, storage, waiting and transportation, to end up in one of the system exit points as according to entity properties, be handled there and leave the system as finished product. Eventually, the production model contains four sub-models:

Mixer model to represent mixing delay, control discharge logic and material destination,

Silo model to store material in a designated space and discharge it to a specified system exit when available,

Bagging machine model to combine material batches into bags according to particularized characteristics,

Conveyor model to act as transportation delay of specified capacity.

4.2. Assumptions

On top of the system boundaries and assumptions specified earlier in section 3.1, there are several additional assumptions made to help model the investigated problem at the chosen level, disregarding unwanted details. Thus the following assumptions are made:

- Dosing and mixing are always exact and according to specifications,
- Mixing is completely uniform, and fits exactly to the specifications (excluding contamination),
- Ingredient mixing is not to be modelled – products enter the system with specification contents to be only delayed in the mixer,
- All material flow considerations are expressed in terms of mass flow rather than volume,
- All material is represented in batches (entities) of equal size,
- Workforce availability is modelled as a schedule with possible overtime,
- Model is to have modular construction to allow for future expansions.

An important choice is not to include considerations on the uniformity of mixing, and thus not to model the mixing itself. Although it could be very interesting to look at the cross-contamination issue when products might deviate from their specification values, by either non-homogeneous mixing, imprecise ingredient dosing or segregation, at this stage of knowledge about the phenomenon, it could only blur the outcome. In the presented model any deviation from the norm is a result of cross-contamination and thus is easily recognised.

Moreover, to assure consistency and ease of the modelling of cross-contamination, all material flow is to be divided into batches of equal size (mass), in order for the discrete simulator engine to process them. Discretising entities is vital to record specific statistics as well as to allow for cross-contamination investigation. The size of an order to be mixed next is divided by the size of a single product batch to determine the number of active entities to insert into the system. They enter via a dosing feeder in intervals with restrictions of the automated system (recipe specific), and this way arrival of new products is solved.

Equipment involved, that needs to be manned in order to operate, is given a capacity schedule. Thus, without modelling the specific workers, the limitations of working day availability can be incorporated. Additionally, it is possible to set a working overtime to be used when not all orders for a given day are finished.

Finally, to support the generic nature of the structure, the model needs to be modular, also allowing for future expansions. Creating a full model of a system is then done by including chosen equipment, joining them with conveyors, and assigning specific parameters and references. Then, on the highest level, material flow logic between the main object instances needs to be incorporated.

4.3. MODEL CHARACTERISTICS

In the model two major parts can be distinguished: object definitions and flow logic description. Both are shortly described in the following sections. Additionally, characteristics of more specific model features are given next.

4.3.1. OBJECTS AND SUB-MODELS

The model is divided into several important object classes and components that execute the logic and steer the flow of material through the system as defined in Figure 3.3. Important object characteristics from the point of view of production capacity model are described below.

ENTITIES

There are three types of entities (dynamic objects) in the system: orders, product batches and batch entities. First represent the actual production orders, containing essential information about it and gathering important performance indicators. They appear in the system in groups of orders for a given day, are rearranged according to scheduling rules and wait their turn for mixing. Once that happens, child entities – product batches, are being created to express the flow of material through the system. As such, order entities are just logical objects, that have no physical real-life equivalent, performing function of handling and translating unordered data from table into schedule conforming to the set rules. They also perform an important role in distributing their child products through the system, as they hold information about designated system exit and according to that are assigned a list of possible intermediate storage silos. Product batches leave the system as soon as they are bagged, while the order entities only after the last child entity has been packaged. Batch entities are containers used to group products together (e.g. in bags or silos) and hold information on their total contents. A comprehensive flowchart of order entity logic can be found in Appendix, in Figure E.1 on page 102.

DOSING AND THE MAIN MIXER

Dosing is the source of product batches in the system for the main mixer. It creates them in intervals in accordance with specified dosing speeds that differ among recipes, and conforms to model logic imposed by the order entities and the main mixer. Dosing can be only started if there is sufficient intermediate storage space available for the entire order. Thus a situation that an order was started and there is no equipment to receive its product cannot occur. Product batches are directly getting to the main mixer that delays them accordingly controlled by the level switch logic. When leaving the mixer an entity is assigned its intermediate storage destination according to possible ones held by the parent order and the current fill level of the silos.

The main mixer can be thus viewed as a push system that sends out material to possible silos, trying to get rid of it and to be able to start the next order as soon as possible.

CONVEYORS

There are two types of conveyors in the system: screw and pneumatic, represented with a single sub-model based on a time-path construct, and a switching value is used to assign specific parameters and limit amount of repeated data. They transport motionless product to assigned destination in FIFO manner, without passing-by. Both are accumulating and have fixed, theoretical speed.

Screw conveyor uses rotational movement of an inner helical screw to transport material within a tube in a roughly linear trajectory, and is a typical mechanism used in transportation of bulk products, especially upwards. It is often used for high capacity lines, when large volumes need to be moved. Assuming there is no slip, the resulting material speed is a product of the rotational speed and the screw pitch, and the maximum volume of material inside is close to the volume of the conveyor. When the angle of inclination to the ground is bigger than zero the performance of such conveyor decreases, so in order to account for that different mechanism properties or higher rotational speed is normally chosen.

Pneumatic conveyor, on the other hand, takes advantage of compressed air for material propulsion. A separate inflow pushes in air that snatches powder, and quickly moves it to the destination where it is filtered before further processing. Particle, once it is accelerated, has a velocity similar to the air, but the piping has a typically much lower diameter than screw conveyors, and thus can hold less material. Also, the piping can hold much less material, as with excessive quantity it might become clogged. Moreover, too high air velocity can damage powder particles and thus cannot be used. Pneumatic conveyors end with an air filter to separate powder from the air, which cone be modelled also as one with zero length and a different contamination characteristic.

SILOS

Silos are storage units that hold entities, batching them together and always utilising the First In First Out (FIFO) principle. Having a fixed volume, they can always hold the same amount of uniform density product. Inflow to silos is unrestricted, providing there is enough space and the outflow rate depends on the destination. Outflow valve can be closed at any time if the amount of discharged material in the bagging buffers exceeds predefined limits. Additionally, silos hold information about the products that are currently in, and perform a very important function in the model logic, as they are involved in allocating material from the mixer as well as discharging it to system exit points. The logic preventing different products to occupy the same conveyors (links) is embedded within silo processes, so that a discharge will not commence while there is a parallel material flow. A flowchart with description of the silo logic can be found in Appendix in Figure E.6.

BAGGING

Bagging bases on a pull principle to choose next material to package, and it only accounts for the current system state to make such decision (no prediction). At the beginning of a shift, when there is a new inflow to a silo, and when a machine finished its changeover, model logic performs a search on which product to process further. It bases on system state and boundaries, product constraints and scheduling rules (described in section 5.5). A flowchart presenting how a given machine picks orders is shown in Figure E.12 on page 113.

A packaging machine takes material from a bagging buffer, located just before it, of a quantity that is corresponding to the package size. These entities (at least 2) are batched into a parent entity – a bag, specially created to hold them and move further as a single entity, after a processing delay. Bagging speed is modelled deterministically, which is a close enough representation of a numerically controlled machine without failures. To reduce this speed and provide a more realistic performance of the equipment short stops are introduced, that limit the speed indirectly by suspending some of the processed items for a short time.

Normal operation of a bagging machine during shift time involves processing an order (including short stops), then a changeover, and a following product. Sometimes in between products, after a changeover, there is a break in product supply, resulting in machine starving time. An example resource chart for bagging is shows in Figure 4.1.

4.3.2. MATERIAL FLOW LOGIC

Material flow, or specifically movements of differentiated substance batches, needs to follow a clear, customisable progress logic. In this case, material enters the system via a single source, and never returns to the place, that it has already been to before. Moreover, for a given product batch, it can only be placed in a silo once. Then, flow logic needs to assure that in a given place only product batches with the same recipes can reside.

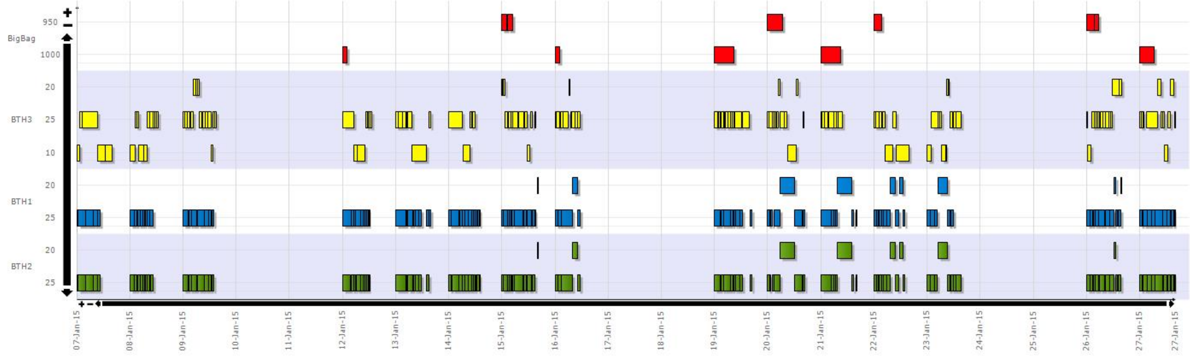

Figure 4.1: An example resource chart for bagging machines utilisation, grouped by package size

Negahban & Smith (2014) name DES as an appropriate tool to analyse and understand the dynamics of a modern manufacturing system, the vital part of which is often a material handling system (MHS). It is used to solve problems regarding movement, storage, control and protection of goods throughout the process. It can be thus understood as the principle logic steering the progression of material in the entire system, which in this case is mostly:

- Choosing when to start and dose a new order,
- Delaying the material appropriately in the mixer,
- Controlling discharge from the main mixer to a previously chosen silo,
- Keeping track of the material in the silos,
- Allocating the silo discharge to an appropriate, available system exit,
- Assigning product progression speed as a resultant of the product and equipment properties,
- Recording important data about the performance.

In the end, as described by Schriber et al. (2012), the execution of a DES model is characterised mostly by assigning entities into appropriate states, and handling the consecutive event list as well as delay lists. Thus, one can imagine material progress as a set of queues and delays on its way in between starting the simulation run and leaving the system.

However, having fully described product and system properties as well as established order set, does not complete the execution logic. In any manufacturing circumstance, orders need to be scheduled and appropriate resources allocated to allow them to progress. This can be done at random or any other way, but usually follows a certain approach, aimed to be beneficial in some aspect to the production process. This way has to be clearly defined, and preferably customisable to determine, whether (or how big) scheduling interventions have effect on production performance.

4.3.3. IMPORTANT FEATURES

Next to the main objects and flow logic there are a few more interesting and important characteristics of the built model that are defined below.

Work schedules

The most important equipment is given a customizable work schedule feature – an ability to define specific working hours separately. The standard operation assumes 5-day week with 16-hour shift and no breaks but it can be changed at will, for instance taking some machine off-line or reducing (extending) its shift. The intention is to mimic availability of the workforce while not specifically modelling workers. Thus, a work schedule is defined as a resource that has to be usable in order to proceed with work. Dosing and bagging machines are equipped with this feature, and it is assumed that supervision over the entire system is performed by the same workers as for the dosing. Logic used to make a decision on ending shift for an example bagging machine is presented in Figure E.13 on page 114.

Order possible destination search
Before mixing can start, the next order in line has to have guaranteed available space in the intermediate storage to fit the entire order. But the way which of the available intermediate storage silos are sent material to, should be efficient and subjected to user defined logic i.e. scheduling rules. More about these can be found in chapter 5.5. In practice, every order needs to undergo a process of checking this availability, picking the best silo(s) according to defined rules and then start dosing. A flow chart of the procedure is presented in Figure E.9 on page 110, and its core involves two logical queues - possible destination queue and arranged order allocation queue. First contains all silos that are present in current configuration of the system, excluding those that are switched off by user and those which were reserved for specific recipes (another user input feature is possibility to constrain material in chosen silo to particular recipe). From the possible destination queue in the chosen sequence by scheduling rules silos are moved to the order allocation queue, and once that is done there is another attempt to reorder this queue, if more appropriate arrangement can be found in case of split orders among multiple silos.

Splitting and merging material
In some cases material can be sent to multiple silos. This happens when an order is too big to fit to a single silo, or when it is preferred to join identical recipes and the remaining capacity of the silo is not sufficient. When silo high level mark is reached the material from the main mixer is sent to the next silo in the queue. After the second is full, the list is always searched from the beginning (in case some material was removed from the silo in the meantime), and the chosen destination follows the queue till the order is finished. Material that is then placed in multiple intermediate storages should be then bagged as a single order to avoid lengthy changeovers. Thus, a search function is executed any time an order finishes in one silo, but only when globally not all of the material has been processed. Then the flows are smoothly merged, unless the route is blocked or is not the first one in line. If it is impossible to merge the order, bagging machines does not wait but executes a changeover and proceeds with another order, to finish the split one later.

Data collection
An important feature of any simulation model is gathering suitable and comprehensive data about the performance, to be later processed and appropriately presented (van der Zee & van der Vorst, 2005). In order to allow for communication between Simio and SN text files are created to store the data. Then Simio inbuilt write to file step is used to save important parameters after significant events or periodically in accordance to timers. KPIs defined in section C.3 are thus obtained in a manner that is suitable for further data processing.

4.4. CROSS-CONTAMINATION INVESTIGATION

Product cross-contamination is a serious issue for quality when the same equipment is used for more than a single product. It happens when a given product enters a piece of equipment, sweeps some of a leftover residue released by the previous product, and drops some of its own behind. In the following sections an investigation into powder cross-contamination is performed, where a generalised mathematical model for such process is derived and discussed. The analysis and implementation is then conducted based on the case of Sloten in section 5.4.

4.4.1. MODELLING CROSS-CONTAMINATION

Every product leaves some of its contents behind, and picks up whatever is in the system. This means there is a considerable extent of accidental static mixing in the system, as the flow of material proceeds through the piping. Parts left by a product are called residue, and only become contamination once picked by the following one, and only if it is not a specified product content. It is assumed that the portfolio of products sent through the same network is rather similar. Known differences among products are considered negligible and any product is assumed to have exactly the same behaviour.

Investigated powder has a very fine grade, leading to enormous number of involved particles, the simulation of which is beyond the capabilities of modern computing. To assure efficiency but not hinder the quality of analysis, moving material is grouped into fixed-sized batches (segments), that are assumed to have homogeneous composition and always mix with the equipment residue, also divided into compartments, proportionally to their contents. The approach is thus similar to one proposed by Portillo et al. (2006). The material starts uncontaminated at the dosing machine, i.e. having only its original, intended composition, and exchanges some of its contents for different products via mixing with the residue of equipment it is passing through. The size of a batch remains constant but the composition, in terms of comprising products, changes along the path.

Once the product is bagged and ready to send to the customer, the analysis on its nutrient specifications and limits needs to be performed. Product batches making up the bag contents are grouped together and assumed homogeneously spread in the bag, so that sampling is not an issue. Because some of the products picked up by the batch are more similar than others, a means of comparison between them is necessary, in order to determine whether the cross-contamination is acceptable or not. As normally the number of relevant ingredients comprising products is considerable, expressing the final bag contents in terms of them might be counter-productive, leading to even greater complexity. Moreover, comparing similar ingredients (e.g. different concentrates of the same material) would still be impossible. Thus an approach to compare different products with each other is limited to nutrients with addition of relevant, recognised contaminants, collectively referred to as nutrients. This way, a list of important, company-specific elements can be identified and assigned to each product. By adding lower and upper limits for each of the nutrients, the desired levels of these can be checked and controlled. Then, after bagging the product batches, the model is to add up all nutrients from comprising contents and compare each of them with specified limits. The number of off-specification bags is counted and recorded, to allow comparison with other products but especially with another scenarios, having different scheduling rules.

In literature, product contamination is usually connected to trace elements such as microbiological or chemical agents, that can be potentially harmful after consumption. Some adverse cases of animal diseases, such as Bovine spongiform encephalopathy (mad cow disease), originate from such contamination, by prions in this case (Fink-Gremmels, 2012). These occurrences are not in question in this analysis as they should be a part of thorough risk analysis and laboratory trials, because they cannot be quantified and expressed as a regular part of the production process. However, unwanted pollution of one product by another (cross-contamination), as a result of production method, where the total amount of material introduced into the system is known, can be quantified in search for the answer of how long and how much specific residue remains in the system. In general there are three sources of norms that dictate what is considered as unwanted pollution: internal company norms, legislation and customer demands. These norms can be strict or conveyed as a preference, without major impact. In any case, all added nutrients are grouped together and expressed with their own units of measurement and only compared to each other. For various plants and industries different ingredients will be considered significant in such analysis. These are either main ingredients creating the nutritional value or trace amounts of other, sensitive because of aforementioned reasons. Small bits of other additives can be considered irrelevant and excluded from the analysis.

DEFINING CROSS-CONTAMINATION

Cross-contamination character is specific to the investigated system. Although detailed simulation analysis of particle movement using DEM, based on powder and equipment properties, could be possible, it would not be feasible to include it as a part other analysis (e.g. throughput, scheduling), mostly because of computational limitations (Bertrand et al., 2005). Thus, the powder behaviour is to be investigated based on field trials, its characteristic plotted and generalised for any situation. This section presents one of the methods of such research, well established in the industry, including two products with a tracer material.

A typical process consists of two consecutive stages: first polluting the system with sufficient amount of material, including high amounts of the tracer, then sending collector material (without the tracer particles) through the same route, and taking samples in multiple points over time, so that the amount of tracer material as a function of time can be expressed. Assuming the tracer to be homogeneously mixed in drawn samples, one can proportionally establish the amount of the initial material and thus the level of cross-contamination in the samples with reference to some base level. According to literature, the behaviour of contamination over time is exponentially decreasing (Leloup et al., 2011), and by integrating the established curve over time one can determine the total (initial) amount of residue material in the measured intervals. The change in this amount constitutes for how much is swept by incoming product with respect to the constant base level. However, expressing incrementally from point to point how contamination changes is not straightforward, as reference levels change continuously and the exponential character of the curves is lost. In such a case, it is expected that without additional mixing effects the level of contamination in respective samples can only increase for consecutive measurement points. To illustrate it, if contamination level measured after 100 kg flow is 5% at point A, then for point B being further along the route, the corresponding contamination after 100 kg flow should be no less than 5% and possibly more. However, due to trial conduct, additional (unaccounted for) mixing effects and method uncertainty, this amount could actually be lower. Therefore it is more convenient to express relation to the base level, even though the change in contamination and its calculations need to be incremental in a model. The description of the actual trials performed in Sloten, Deventer can be found in Appendix C.4.

The character of cross-contamination and resulting exponential curve can be explained as a random chance release curve. More specifically, it can be connected to axial dispersion curve in chemical reactions in fluids, defined as a dynamic but reproducible blending of sample area with a reagent and/or carrier, as a result of turbulent flow patterns, created by fluid going through a narrow-bore tubing[1]. Models for axial dispersion are common in chemical engineering, (see e.g. Liao & Shiau, 2000).

Another part of the analysis is extending the tracer-collector scrutiny to multiple products, that could be involved with cross-contamination. At this point, the requirement for homogeneity and proportionality of mixing is vital, especially that no trials with more than two products can be found in literature. Even though these assumptions are not exactly exact, they are certainly sensible. Multi-product contamination possibility is necessary because of some trace elements, which are important from the product safety perspective and which need to decrease by a large factor. Moreover, as the consecutive products are often allocated into different silos, taking alternative routes, the primary contaminants in various places differ, so the final batch composition must comprise of multiple products. Proportionality of mixing is maintained with regards to the current residue composition of a certain piece of equipment, and the contents of the product batch coming through it. This means that any amount that is mixed, which can be only partial, takes equal amounts of material from both, distributes homogeneously and attaches the mixture back to them, changing their composition and conserving the mass balance. As the products move in FIFO manner, the calculations can be discretized and performed when the batch leaves the equipment.

CONTAMINATION ASSUMPTIONS

Based on the analysis of the trials the following assumptions are made for contamination investigation and modelling:

- Material always moves on First In First Out (FIFO) basis,
- There is no loss of mass in the system,
- Material in equipment and product batches is always homogeneously mixed,
- Total amount of residue in equipment is constant,
- Cross-contamination is a process of equal exchange of residue between the equipment and the product batch coming through it,
- Contamination in a product batch is always expressed as a mass content of different than nominal product in it,
- Cross-contamination behaviour is independent of the type of transported material and only bases on equipment properties,
- Resultant material composition after cross-contamination mixing is proportional to the contents before the process,
- Depending on the residue in a container the level of contamination in a product batch can increase, remain the same or even decrease,
- After the product is packaged, contamination is calculated for bags as the average of its contents,
- Total bag nutritional elements are in the end compared with product admissible limits, determining its quality.

MODEL DERIVATION

In order for the measured curves to be useful for modelling, they need to be expressed with numerical equations. Because the shapes highly resemble exponential lines, which should also be the case based on the previous experience, only exponential curve fitting is considered. In general, single measurement points are too uncertain to be used directly, and an equation for a curve best fitting all values for a given measurement point needs to be found, to account for random errors and allow generating values in between measured intervals. For all curve fitting done for contamination trials, the minimisation of the sum of squared deviations method is used, employing MS Excel solver to find the minimum. Investigated functions are fully constrained

[1] Definition origin: http://www.globalfia.com/tutorials/lesson-4-dispersion

i.e. there are maximum and minimum values given for each parameter and the result in order to obtain values of contamination in between 0 and 1. Both non-linear and evolutionary solvers are used to find the best fit.

To achieve better fitting results a sum of two exponentially decreasing curves is utilised. Using two basic functions implies that there is more than a single mixing effect in the equipment. As cross-contamination is a process of partial mixing of the residue with product coming through, there might be more than one cumulative effect, which cannot be distinguished in the tracer–collector measurements. For such, a thorough statistical analysis needs to be conducted to find correlations between equipment characteristics and fitted curves. Such limited analysis is done further in this document. The general equation for the fitting curve is thus:

$$R(x) = a_1 \cdot e^{a_2 x} + a_3 \cdot e^{a_4 x} \tag{4.1}$$

Where x is the amount of material that has been put through and a_1 to a_4 are constants. The first exponential element in the equation relates thus to residue that is flushed quickly, and the second to a long-term pollution. As such, both the steep descent part of the curve as well as long tail in the end can be accounted for. Total picked up residue can be calculated for each of the obtained curves by integrating them with respect to weight:

$$TR = \int_0^\infty R(x)\mathrm{d}x \tag{4.2}$$

Then, by subtracting the consecutive total residues the amount of added carry-over can be determined for each of the measured intervals.
For the model construction the following designations are chosen:

$R_i[item, quantity]$	Equipment residue matrix containing item number and its quantity
$C_j[item, quantity]$	Product batch contamination containing item number and its quantity
$i, j \in N^+$	row indexes
M	Mass of a product batch
$C_0[original\,item, M]$	Initial, original content of the product batch
$EAP \in (0, M)$	Exchange amount parameter, specific for a segment
EA	Exchanged amount of material in a given transaction
TR	Total material residue in a given piece of equipment
σ	Random deviation parameter
P_i, L_j	Picked and left material, auxiliary variables
n	Number of product batches in a segment

Partial mass exchange model
The cross-contamination process is actually a mixing process, after which the amount of contamination in a product batch can either increase, remain the same or decrease, depending on the contents of the equipment R_i and the batch C_j beforehand. In order to retain conservation of mass the mixing has to be a proportional mass exchange between the batch and the equipment. This exchange can apply to the entire material involved or just a portion of it, but it has to be smaller to both batch size M and equipment residue TR. Therefore, assuming this amount to be equipment property, due to similarity of all products, and calling it EAP, a mathematical method for this exchange can be derived. For each transaction, involving a single product in an exchange, there are certain amounts of picked contamination P_i and left residue L_j. The equations can be thus formulated:

$$P_i = EA\frac{R_i[quantity]}{TR} \tag{4.3}$$

$$L_j = EA\frac{C_j[quantity]}{M} \tag{4.4}$$

The resulting exchange is:

$$R_i^{'}[quantity] = R_i[quantity] + P_i - L_j \tag{4.5}$$

$$C_j^{'}[quantity] = C_j[quantity] - P_i + L_j \tag{4.6}$$

Providing that $R_i[item] = C_j[item]$ and the calculations are done for all i, j where $R_i[item]! = $ NULL and $C_j[item]! = $ NULL. If one of the participants does not have given product, the corresponding transaction quantity is zero. Exchanged amount is normally equal to the exchange amount parameter ($EA = EAP$) but it can be varied by adding to it a random component, then:

$$EA = \min[\max(0, \text{random.normal}(EAP, \sigma \cdot EAP)), \min(TR, M)] \tag{4.7}$$

This way one can assign different exchange values from the distribution, trying to account for e.g. measurement error, while still being within set boundaries. Note that when $\sigma = 0$, the value of EA equals the parameter EAP. Also, the exchanged amount cannot be lower than zero or higher that the lower of equipment residue or batch mass, as it would result in negative values. Because of numerical errors when $EA = min(TR, M)$, and another method exploring full mixing, this amount is constrained to:

$$EA = \min[\max(0, \text{random.normal}(EAP, \sigma \cdot EAP)), 0.95 \cdot \min(TR, M)] \tag{4.8}$$

Also, as there is no possibility of having dynamic vectors in Simio the size of vectors R_i, C_j is set to 20. To show that for both equipment and product batch eventually exchange the amount EA, the following sums of individual transactions are made:

$$\sum_{i=1}^{\infty} P_i = EA \frac{\sum_{i=1}^{\infty} R_i[quantity]}{TR} = EA \frac{TR}{TR} = EA \tag{4.9}$$

$$\sum_{j=0}^{\infty} L_j = EA \frac{\sum_{j=0}^{\infty} Cj[quantity]}{M} = EA \frac{M}{M} = EA \tag{4.10}$$

Meaning that both participants always exchange the whole amount EA, but the difference between their previous state and one after exchange depends on the contents, and is usually lower because material of the same items is often present and the actual difference is between the absolute difference of P_i, L_j.

Also, the calculations are general for a piece of equipment and independent of time or material flow. In the implementation it is possible to set the random component $\sigma > 0$ until a certain quantity of product is through, and then assume $\sigma = 0$, in order to investigate resemblance to peaks and valleys from the contamination trials, shown in Figure 5.2.

Mixing model

Another, specific possibility of material exchange between a product batch and a piece of equipment is full mixing. It can be imagined as homogeneously mixing both first, and then detaching part of the material from the mixture, with the size of the batch, and sending it further. Following the nomenclature from the previous paragraph and adjusting to the methodology, the exchanged amount is:

$$EA = \frac{M}{M + TR} \tag{4.11}$$

While the whole material for given item $R_i[item] = C_j[item]$ is summed together for the exchange:

$$P_i = EA \cdot (R_i[quantity] + C_j[quantity]) \tag{4.12}$$

$$L_j = (1 - EA) \cdot (R_i[quantity] + C_j[quantity]) \tag{4.13}$$

Then, the final contents are not dependent on the previous state:

$$R_i^{'}[quantity] = P_i \tag{4.14}$$

$$C_j^{'}[quantity] = L_j \tag{4.15}$$

In this case, the cross-contamination process is quicker and has greater extent with steeper curves, but the total amount of contamination picked up by the flow of material is not bigger than TR.

Model comparison
The main differences between the proposed models is shown in Figure 4.2. In the partial mass exchange model a certain settable, equal portions of the equipment residue and product content are taken and mixed uniformly, to be later proportionally redistributed to the participants. By changing the size of the exchange, different outcome characteristics can be obtained. In the mixing model, on the other hand, all material contents are mixed together and then product batch is detached from this homogeneous blend and the rest remains in the equipment.

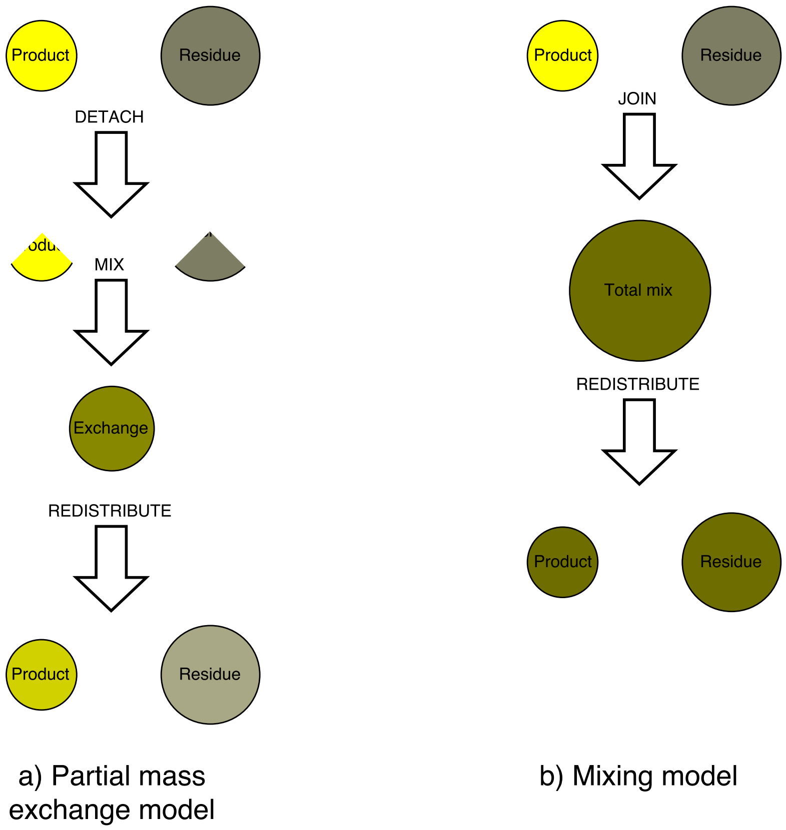

Figure 4.2: A comparison of derived cross-contamination models

It is expected, that in the mixing model the foreign residue is swept much quicker than in the partial mass exchange model, as all of the contents always participate in the exchange and the equipment residue is normally bigger that the product batch size.

Main mixer
Final special case of cross-contamination calculations is the main mixer, the only piece of equipment that purposely stirs the material within it to stimulate homogeneity. Thus, the material picked up by products before the mixer and the residue in it, are proportionally spread among everything that is in the mixer and not only with the first batch, as in case of the previous models. Then the product batches can be treated as ‘clean’ when entering the main mixer, meaning they contain only their original product:

$$C_0[original\,item, M] \tag{4.16}$$

$$\sum_{j=1}^{\infty} Cj[quantity] = 0 \tag{4.17}$$

These batches exchange their original contents with whatever is in the mixer, and the exchanged amount can be written as:

$$EA = \frac{M}{n*M+TR} \tag{4.18}$$

This way the final cross-contamination models were established and implemented in software. For detailed algorithm see Figures E.7 and E.8 on page 109 in the Appendix. The user has thus a choice which of the general cross-contamination models to include: partial mass exchange, mixing or none, and whether to include contamination occurring before and in the mixer. For the partial mass exchange model random component can be added to vary the swap of material in a chaotic way, which can be stopped for each new inflow after a certain amount of material has passed.

4.5. DETERMINED NEEDS

Having introduced the specifications in chapter 3, this stage describes the purpose, assumptions and derived features of the simulation model, including specific classes and steering logic. Especially, it concentrates on mathematical representation of cross-contamination process and how to implement it in a DES model.

In order to fully define the cross-contamination character in a model, the equipment properties TR and EAP, as well as product mass M, and possibly random deviation parameter σ are needed (as defined in section 4.4.1). Since there is no appropriate knowledge in literature, the best approach is to perform measurements in an actual factory. Then, not only an example data for determining the impact of certain interventions can be obtained, but also a means of validation of the model, which is vital to the generalisation of the possible findings.

Moreover, placing the research in a realistic setting, where an actual production data is used, is needed to test the developed methods. Access to specialist expertise, plant resources as well as statistics and knowledge base, obtained over an extended period of time, is useful not only for evaluation and validity assessment of the performed research, but also to determine the usability for the industry.

Then, a scheduling solution is required for the production environment to fully define manufacturing logic, and make room for an analysis of the impact of certain changes to the model execution logic. Full scheduling optimisation, by means of e.g. linear programming, looking for the best solution to maximise chosen KPIs, is not within the scope of the research. It would be beneficial though to derive a method for scheduling, where cross-contamination is involved in detail, and not just as a cost function for certain sequences as in Toso et al. (2009). However, control over the choices made by the simulation model in terms of scheduling, or at least a clear formalisation of the method, is necessary for a complete solution. One without a means to intervene would be, and rightfully so, rejected by the problem owner as insufficient. That is why, for the simulation model, scheduling using dispatching rules, incremental choices for a set of available jobs, is a good enough substitute for scheduling optimisation (Pinedo, 2008, pp. 377). Furthermore, it allows to approach scheduling as a set of consecutive choices, that can be altered in another experiment and not a pre-defined, fixed collection. These selection rules can be then defined based on a specific case, investigated thoroughly, and in the end be quite complex and close to the optimal solution. Finally, the issue of stochasticity is not as difficult to handle in dispatching rules, as it is for optimisation. The former is even more transparent, as various simulation runs (with different values of the stochastic variables) can be directly compared with each other.

The above three problems can be tackled as a whole, if a case study is used to combine them. This is done and presented in the following chapter (5). The company is thus used as a realistic case to procure data, perform measurements and test the developed approach in a genuine production environment. Moreover, such setting, and insiders knowledge of company specialists, are important aspects in judging the validity of the model.

5

Experimental Setup

This chapter introduces the experimental setup, based on the case company Sloten, to test the foundations of the model. At first, the production process is briefly described and system boundaries with assumptions given. Then, the DES production setting is fully defined and complemented with cross-contamination model, established on the performed measurements. Finally, scheduling solution for the case is presented, and the complete model is verified and validated, to the best extent of possessed data.

5.1. Production Process

Sloten's factory in Deventer is used to mix spray-dried milk fat concentrate with other raw ingredients, e.g. whey, soy or skimmed milk powders, minerals, vitamins. Then, most of the products are packaged into small bags, and then palletized. The rest is put either to big bags or moved as bulk material. As a result the final product, young animal feed, is prepared, and can be transported to a customer.

Production begins with raw ingredients that are shipped from another Sloten factory in Friesland province in the Netherlands or procured from third parties. These are then stored in designated raw component silos or storage containers when the usage is low. Sometimes before the main mixing, minor elements need to be premixed separately to assure uniformity in a mixture. They are then weighted and manually added to one of the available premix mixers. From then on, the process is controlled numerically. Weight feeding system is used to automatically draw material from ingredient silos and premix mixers and convey it via a single possible route to the main mixer.

From the main mixer, the product can be transported either directly to the bagging machines, or sent to an intermediate storage silo. Currently, most material is bagged immediately, causing a downtime interlink between engaged equipment, but in the future it is desired to solve this issue by using intermediate storage for all products. There are 7 big and 4 small silos that can be used for such purpose and, if need be, there can be a few additional medium-sized silos added. For details on their placement and product route constraints see Figure 5.1. For transportation either screw conveyors are used, mostly for high capacity connections between the main mixer and silos, or pneumatic conveying lines starting from existing intermediate silos. In accordance to the product type, material has to end in one of the five system exits and often can take many routes to get there, depending on the current system state and product properties.

There are three main product groups in Sloten. First and foremost, there are small bag products that are put into paper packaging of 10, 20 or 25 kilograms. Under normal operations these comprise over 90% of the entire production, and are considered most important. Then, there are big bag products packaged separately into large polyester bags of 950 to 1100 kilograms. These require considerable input of manual labour to fill and replace, while small bags are sent by conveyor belts for palletizing. Because there is a single shared palletizing machine for bagging machines BTH1 and BTH2, they are treated as a single line. The last way for product to leave the system is via bulk station, when discharged directly to a truck as a loose product. This option is used rarely, mostly for clients in the Netherlands with relatively high usage, and appropriate storage possibility.

With a large number of produced goods in Sloten, there is a considerable complexity in planning. Customer orders average around 13 tonnes, which results in roughly 11 different mixing orders per day after planning consolidation and usually more for the most-used bagging lines, leading to considerable changeover losses. The number of sales products is anticipated to steadily increase and so is the number of customer orders. Moreover, in the investigated period of January 2015 there were 226 mixing orders (and 352 bagging orders), totalling over 8000 tonnes for 21 working days, averaging 381 tonnes per day.

Preparing production schedule is a constant burden for planners who need to take into consideration several variables and make a decision. The operational planning in Sloten is a daily routine, for two days ahead. Every day, the planning department makes a list of the bagging and bulk loading orders that need to be dispatched and beforehand produced, on a specific date. Then the required mixing orders are defined and consolidated as much as possible. For more detailed information on planning and scheduling process see Figure C.2 on page 85.

5.1.1. PROPOSED OUTLINE

The initial planned production outline, designed by the company specialists is presented in Figure 5.1. It only includes in-scope parts, and thus starts with dosing (green), having 5 different system exits: bagging machines BTH1-3, big bag filling line and bulk stations (red).

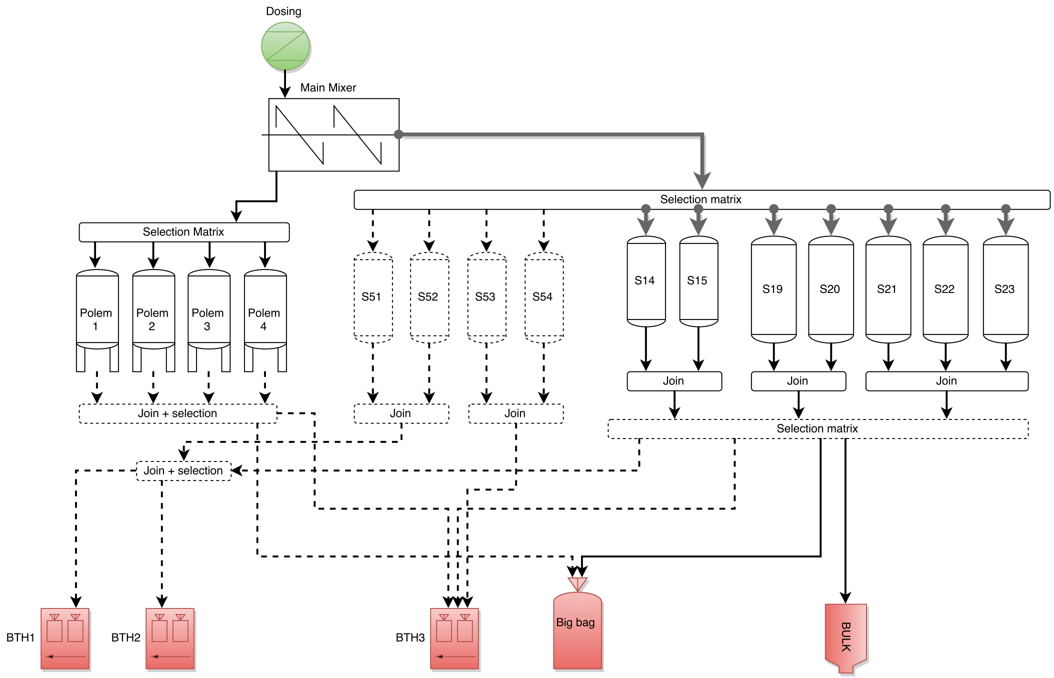

Figure 5.1: A schematic of the investigation boundaries

Silos with dashed line borders are proposed ones, that may but do not have to be included, and their desired number is to be determined using simulation. As it is a network system and different parts are contaminated by various products, a means of keeping track what pollution is in a given interval is necessary.

5.2. STRATEGIC OVERVIEW

Sloten as a subsidiary of Nutreco is slowly finding its place in organisational culture of the corporation. Being a specialised producer of feed for infant animals, the changes to adjust to the corporate strategy seem to have been limited. The apparent biggest aspiration is to increase quality control, and unify it with Nutreco standards, for which e.g. OEE system was introduced. As the project might be expanded in the future, it is important that the general approach to the problem is taken, and that the Sloten-specific circumstances are used to set the project in a realistic setting with a possibility to compare with the current structure.

As previously mentioned the number of products offered by Sloten is expected only to increase as well as the total amount of goods to produce. Therefore the company is very much interested in bigger production flexibility as well as higher overall capacity, both of which might be in conflict. Anticipating a certain trade-off between them, the company is willing to investigate the possible solutions to the problem. By establishing a good scheduling methodology one might take advantage of the lack of cleaning runs, while maintaining acceptable contamination. Although cleaning is done with a sales product of similar content to the next one in line, its quality is poorer and cost increase. A solution solving two problems at once, or at least limiting their extent, would be most advantageous.

Normally, regarding production efficiency, the most important factor for Sloten managers is definitely throughput, with rapidly increasing recognition of high quality standards, including especially cross-contamination. Planners are also keen on ensuring timely completion of products and their delivery. It has also been noted that the cost assessment should be the ultimate decision aspect, but the relations between its components are not trivial. Versatility is the ability to process different products by the same equipment, which is definitely the case for the main mixer. Also bagging lines can process multiple products with varying bag sizes, packaging options and material properties. But the flexibility is not complete, as only a single machine is equipped with possibility of bagging into 10 kg packages or dealing with coloured products. In this sense, BTH3 machine is the most versatile one in the system, capable of processing the biggest number of products. Thus, it is also the most flexible one, as it should be considered for handling them all. Production flexibility mostly arises from interconnections and their multi-purpose character. The main mixer blends all products and is connected to all intermediate storage silos, which are normally not reserved for certain recipes. Moreover, the silos can be used as buffers for indefinite period, allowing for flexibility in choosing the orders to be processed. Also when unforeseen circumstances occur, like machine breakage or rushed jobs, a flexible system is much more likely to handle them well. But with flexibility arises complexity, which, if not managed properly, might lead to inferior planning and lower production efficiency.

Currently, there is little mitigation of trade-offs between the production efficiency and flexibility, as the layout of the system differs from the investigated one. Bad experience with downtime interlinking, lack of freedom and low equipment utilisation, is the reason for exploring a possible performance of a system with intermediate storage buffers. There is a certain dose of planning flexibility, when contingencies are made if not all orders are completed for a given day (e.g. including overtime), but it affects the entire job floor, which is a big drawback. All in all, the level of flexibility needs to increase but so will the complexity and the company needs to be prepared for that.

Product Portfolio

There are around 600 sales products that could be produced by Sloten, based on around 230 recipes i.e. unique ingredient structures. Thus, often several sales products have the same recipe but differ in terms of bag size or packaging type (sealing, label language etc.), and might have different contamination rules.

The number of products and ingredients is only believed to grow[1] as more specialised feeds are created, to better suit specific animal breeds. Also more and more regulations arise, depending on the destination country, further specifications of quality standards, and increasing knowledge of their dietary impact. Detailed company specific description of contamination issues is included in section C.4 on page 88.

Due to limitations in transportation of materials from raw ingredient silos, each recipe has a maximum speed of delivery to the system, that is often smaller than the theoretical mixing speed, limiting it. Products and recipes are identified by their unique identification numbers, and a product can only have one recipe, while a single recipe can be assigned to multiple products.

Data and Features

Many parameter values used in the models are taken from the analysis of the Overall Equipment Effectiveness (OEE) measurement system data that is gathered in the facility. Most of all, the data is used to determine the distributions of random variables described in the next section but also to help with validation od the simulation results. Traditionally OEE systems are used as a process improvement tools to determine possible problems and thus help solving them. Only some of the performance indicators are utilised in the simulation model, as defined in Appendix C.3. Representing the same performance indicators is believed to be helpful to readers and useful for validation.

There are two sets of data available, one detailing stops in production, and interval query, measuring performance in given time periods. The latter divides the day into one hour intervals and adds extra periods once a product is changed. This way performance characteristics in relation to processed products are obtained for the mixer and all bagging machines separately. OEE data is used in chapter 5.7 to validate simulation results.

[1] View of Sloten employees responsible for product formulations

5.3. MODELLING IMPLICATIONS

There are several implications arising from the chosen case that need to be incorporated into the simulation model.

Product batches have fixed density of 500 kg/m^3 and mass of 5 kg, as the highest common divisor from the package sizes they need to fit in. Although that will result in a number of active entities in the system of magnitude of 30000–70000 (see Appendix A.3), and significantly reduce computing speed, it is a preferred solution for possible future expansions of the model as well as one more favoured by the client. Moreover, cross-contamination calculations described in section 4.4 can be generalised only for a uniform entity size.

5.3.1. SIMULATION MODEL ELEMENTS

Some of the used objects are special cases of the classes depicted in the conceptual model from Figure 3.3 on page 18. Below paragraphs shortly describe the specifics.

Bulk stations

Bulk dispensers are similar to silos but smaller, that imitate system exit points for loose product discharged to trucks. It is important that the product is mixed and transported before the due date and await for the truck. Currently, it is common practice to mix and discharge material via silo to bulk stations on the day before, as the number of bulk orders is low (typically one truck a week). The model explores a worse case scenario, when the product can be mixed to silo beforehand but is dispensed further on the same date, typically in the morning. This way for some time the transportation capacity is seized which, as in case of big bag station, can lower capacity of other components by delaying discharge.

BTH machines

Three small bagging machines called shortly BTH1-3 (common name originates from their producer) are the most utilised system exits, recognised as system bottlenecks in terms of capacity. Bagging consists of a buffer (small silo), batching into a bag and a fixed delay while the flow logic for buffer is based on threshold levels. BTH machines process small bags of sizes 10 kg (only BTH3), 20 kg and 25 kg with a fixed deterministic processing speed per bag. Random components are included for short stops, that effectively slow down the bagging process, and for changeovers. For more details about stochasticity see section 5.3.2

Big bag station

Big bags are just another type (size) of bags, utilising the same bagging sub-model, with a different buffer discharge logic to fill the bags. Because big bag filling station is not used as frequently as BTH machines, and because the rate of filling depends highly on the workers abilities, there is no randomisation included. Although the simulation results for big bags are not that interesting, this component performs an important role of using mixing capacity, blocking a silo and discharge line, and can in some cases limit the throughout of the other system exits.

Air filters

Air filters are a special case of conveyors, located at the end of pneumatic conveying line. The path inside them, that product batches traverse, is limited and assumed to be zero but the residue inside, due to the equipment properties, is much higher than the average conveyor. But in fact, they base on the same principle and can be considered zero-length conveyors. For the ease of representation in the interactive mode in Simio, as well as to avoid infinities in calculations, a node construct is used to suit the modelling needs.

5.3.2. STOCHASTICITY

The OEE system in Sloten also gathers and classifies information on stops in production. Upon filtering this data, knowledge on short stops and changeovers is obtained. Short stops for each equipment are fitted with a single distribution and contain for mixer categories of short stop (all events below 60 seconds), supply faults and weighing interference and for bagging machines: corresponding short stop events, bag closing/sewing problems and lack of possible discharge to palletizing. These events are then fitted to a distribution with a statistical software tool, and the following results are obtained and shown in table 5.1.

Similar analysis is performed for changeovers, i.e. delays needed to change production from one product to another. Although it is known that for bagging machines these times are sequential (depending on the type of products), no classification for that exists in the OEE system and the differences are believed by the managers to be small. Thus, a single distribution is given to all BTH machines, and the results are put into table 5.1 below:

Table 5.1: Short stops and changeovers distributions

Equipment	Uptime between failures [s]	Time to repair [s]	Changeover time [s]
Main mixer	Exponential(1426)	Log-normal(3.12, 0.93)	Pert(120, 210, 480)
BTH1	Exponential(185.5)	Log-normal(1.91, 1.20)	Weibull(2.21, 289.56)
BTH2	Exponential(380.1)	Log-normal(2.26, 1.22)	Weibull(2.21, 289.56)
BTH3	Exponential(651.2)	Log-normal(2.93, 1.17)	Weibull(2.21, 289.56)

The numbers from table 5.1 are calculated in several different steps. First of all, overall time between failures in not recorded by the OEE system when short stops are measured, thus mean time between failures is determined from total operating time, total downtime and number of occurrences, and assumed to be exponentially distributed. Results are put into table A.1 on page 77, based on the equation (5.1), and the rounded values are used for simulation.

$$MTBF = \frac{\text{Total\_Staffed\_Time} - \text{Total\_Downtime}}{\text{Number\_of\_Occurences}} \tag{5.1}$$

Moreover, there are no precise measurements of the main mixer changeover times, as there is current interlinking between bagging and mixing, which causes the changeovers to be longer. Because of limited information and after consulting with a company specialist, Pert distribution is chosen with most likely occurrence of 210 seconds.

Finally, the remaining values are fitted in search for their statistical distribution, using 95% confidence level and the Kolmogorov–Smirnov test. Results are put into table F.3 on page 117 and are significant only for BTH1-3 changeover, which is the only well-fit distribution (see also Figure F.1). However, thorough investigation into other statistical distributions showed that the log-normal one is best suited for the OEE time to repair (TTR) data, and after rounding is used in the simulation. Plotting histograms for TTR values showed clearly that they are not distributed exponentially and similar method to the mean time between failures could not be used. Although with so many values available one could draw directly a random value from the set, without fitting them to a distribution, this approach is considered suboptimal for clarity, data analysis and possible model alterations. Another solution would be to use a sum of multiple distributions or trying to split them into different short stop categories, and fitting them separately.

5.4. CONTAMINATION IN SLOTEN

Factory in Deventer is facing a significant increase of cross-contamination, because of the considerable rise in material transportation length in between the main mixer and system exits, if the new plant outline is to be implemented. The material, which is always in a form of powder, mostly consists of fat, milk, various protein sources and other ingredients necessary to provide for nutritional needs of the specified animals. In this terms the product portfolio is quite similar and is treated as such. For Sloten there are 17 specific nutrients defined (16 of which are used in simulation due to lack of data on moisture content). These are:

Animal Fat in Fat	Ash	Colourant	Copper	Fat
GMO	GMO in GMO Protein	GMO Soy Flour	Iron	Lactose
Probiotic	Protein	Protimax	Soyabean Protein	Vitamin A
Vital Wheat Gluten Dry	Moisture			

It needs to be noted that ash as a nutrient refers to any inorganic content, such as minerals, present in the feed, rather than leftover from the combustion process. Also, since much of the derived nutrient specification and limit levels has not yet been established by the company, such cases are treated as not defined and excluded from comparison.

5.4.1. CONTAMINATION MEASUREMENTS RESULTS

A general curve expressing all measured contamination is presented in Figure 5.2, shown as a ratio of foreign product content with respect to the collector material in function of mass flow. Due to a common frame

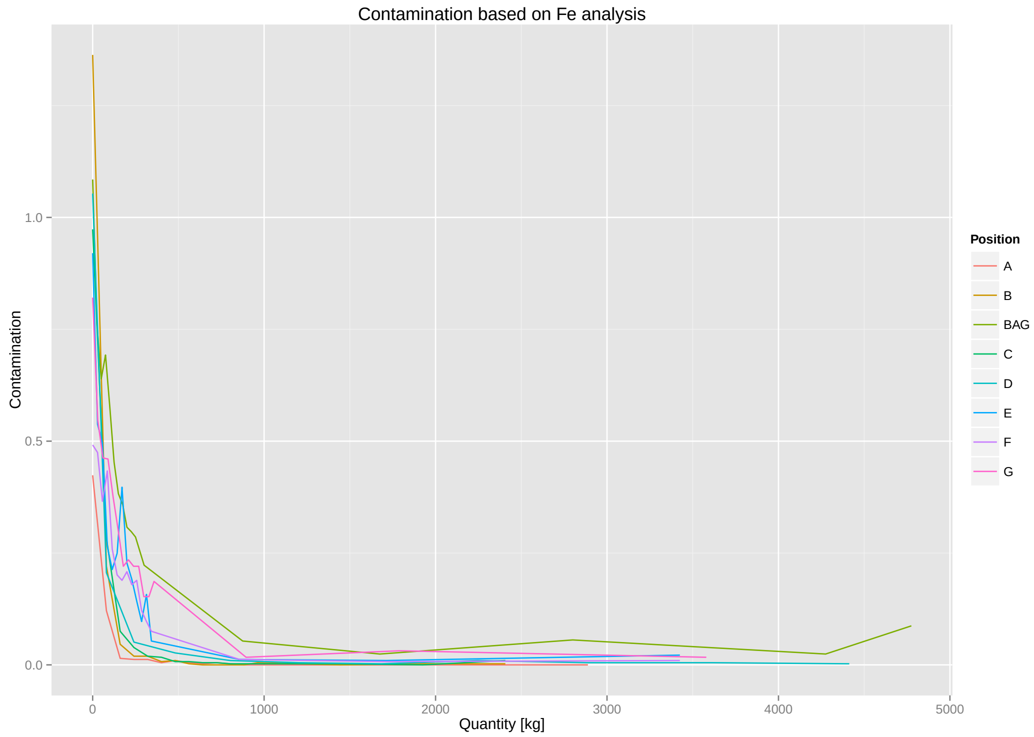

Figure 5.2: Measured contamination lab results for all sampling points

of reference, one would expect that the contamination ever increases from point to point, and cannot be lower than for the previous point. This is unfortunately not the case and there are several identified reasons for that. First of all, there are additional mixing effects in the equipment, especially silos, meaning that the material flow through it is not on FIFO basis. While the composition of the inflow material contamination has a decreasing exponential character, it amasses unevenly, and then discharges in a different manner (Wu et al., 2009, Cleary & Sawley, 2002). This results in observed peaks in Figure 5.2, especially from point E onwards. Moreover, the uncertainty of manual sample drawing is considerable and impossible to determine, and the iron and protein content analysis is subjected to some error as well. The laboratory testing the samples have not provided the possible margin of error for the method.

The acquired curves are exponentially fitted as described before and put into table 5.2, using sum of squared deviations method. For goodness of fit see table A.9 on page 79.

Table 5.2: Fitted parameters for cross-contamination curves as a function of processed material quantity

	a_1	a_2	a_3	a_4	Carry-over total [kg]	Carry-over added [kg]
A	0.384	-0.0178	0.04	-0.004	31.573	31.573
B	0.95	-0.021	0.05	-0.0035	59.524	27.951
C	0.94	-0.017	0.06	-0.002	85.294	25.770
D	0.94	-0.016	0.06	-0.001	118.750	33.456
E	0.935	-0.008	0.065	-0.0007	209.732	90.982
F	0.935	-0.008	0.065	-0.0006	225.208	15.476
G	0.92	-0.007	0.08	-0.00055	276.883	51.675
BAG	0.9	-0.0065	0.1	-0.0005	338.462	61.579

5.4.2. SIMULATED CONTAMINATION CURVES

Contamination in product batches leaving specified intervals is simulated by recreating the investigated route as much as possible. There is a slight difference in length of taken pneumatic conveyors (in total simulated route is shorter), and the bagging machine is assumed to have the same characteristics, although one of a different type was used. The contamination is expressed as percentage content of different than specified product within the batch to the same base level, which in this case is 0, by not taking into account contamination arisen from the main mixer and before. Sum of squared deviations method is used to determine the goodness of fit and the parameters are shown in table 5.3.

Most of the curves are very-well fitted with exception of points E, F and G, where the initial measurements showed lower contamination than in the previous sampling points, which would violate made assumptions. However, the simulated curves and the fitted ones are very similar to each other, as shown in table F.2 on page 117 in Appendix.

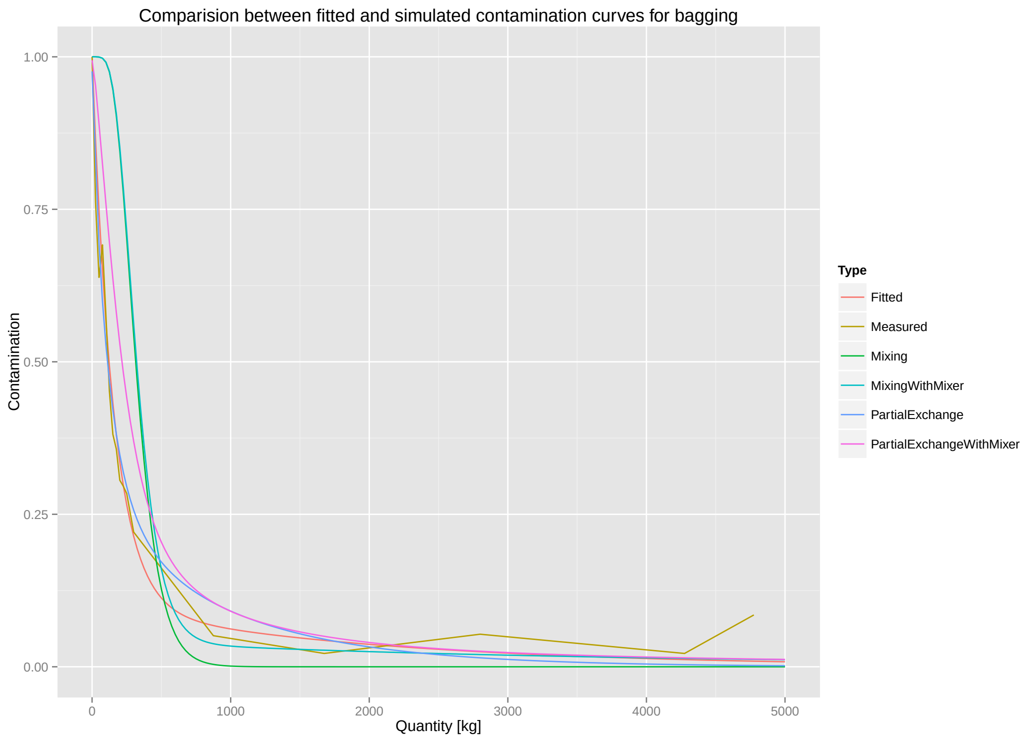

Figure 5.3: A comparison between measured, fitted and simulated contamination at the bagging level

An example fitting at bag level is shown in Figure 5.3, comparing it to the simulated and measured curves. Partial mass exchange and mixing models differ significantly in shape, though having exactly the same area underneath the curve. Mixing model collects a lot of residue in the first part, leading to an almost clean material after 1000 kg flow. This is not consistent with Sloten's experience and measurements, leading to greater confidence in the partial exchange model. However, by adding contamination in the mixer, which was not plotted in the trials, the results are more alike.

Table 5.3: Accuracy of the simulated contamination curves with respect to measured contamination

Point	A	B	C	D	E	F	G	BAG
SS Total	0.1728	1.7298	0.9043	0.9833	0.8724	0.3888	0.6963	1.4541
SS Regression	0.1623	1.5860	0.8733	0.8946	0.6366	-0.2250	0.4390	1.4045
SS Residual	0.0106	0.1438	0.0310	0.0887	0.2358	0.6138	0.2573	0.0497
R Squared	0.9389	0.9168	0.9657	0.9098	0.7297	-0.5787	0.6304	0.9658
StDev	0.0249	0.0920	0.0427	0.0898	0.1214	0.1959	0.1268	0.0541

Moreover, simulated results for all investigated points, including a random component and cut-off point, are shown in Figure 5.4, in attempt to recreate peaks and valleys of the measured curves for deviation parameter $\sigma = 0.4$. The cut-off points are set at 2000 kg, except for points A and B, where they were set to 0.

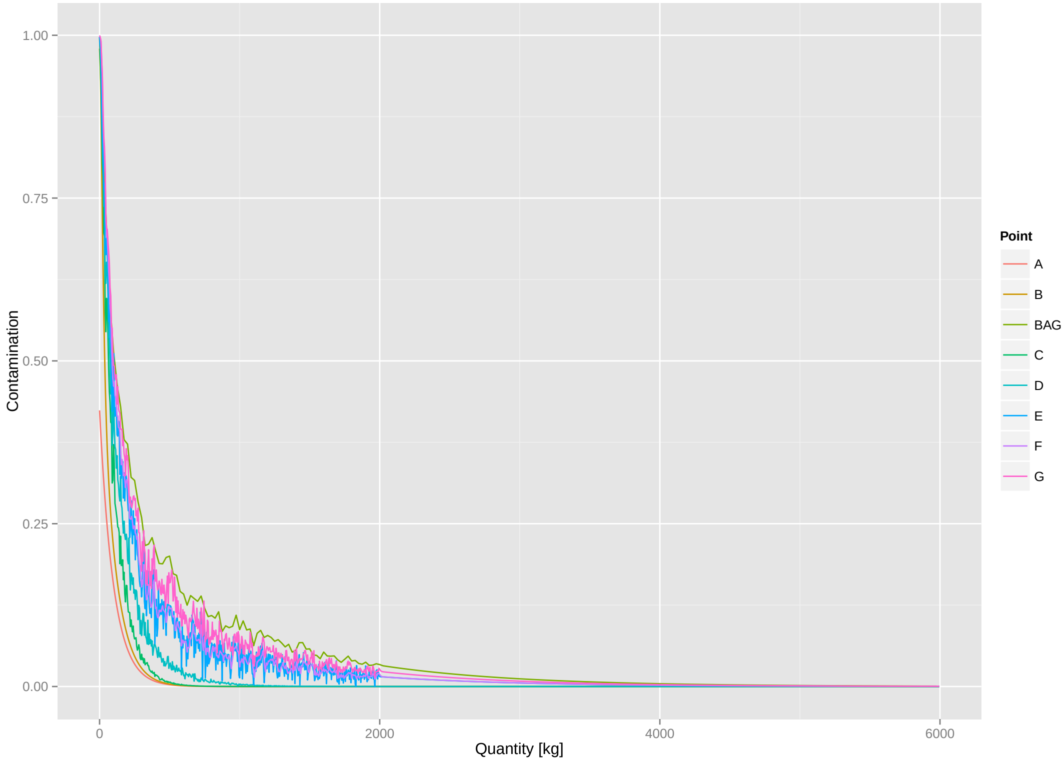

Figure 5.4: Simulated contamination with random component for all measurement points

As the mixing involved regards solid particles, some dose of 'ripples' on the function plot are expected, based on literature (e.g. Wu et al., 2009)) and experience of Sloten's specialists. Although Figure 5.4 does not resemble Figure 5.2 well, it is believed that with more measurements they would be more alike. Perhaps by introducing trends in the exchanged amount, and not treating material exchange independently the curves would be smoother and fit better to measurements. Either way, the risks (extent of contamination) represented by both curves should be similar, even they do not resemble one another exactly. That is, because the total area beneath the curve is the same in both cases and due to multiple (at least 10) application of the cross-contamination calculations that smoothers the outcome.

5.5. SCHEDULING

The following section explores the definition of various scheduling rules, the model is capable to use. By scheduling in this case is meant sequencing daily set of orders before mixing and making decisions on silo allocation. Then, using dispatching rules to make a choice of which product to bag next.

Scheduling is a vital part of the process, as a proper one can significantly improve throughputs and limit the amount of cross-contamination. It is expected, that there is no universally good solution to include both, and certain trade-offs have to be made (Blackstone et al., 1982). However, with simulation one can try to explore the best settings for each, in search of the reasons behind. In the end, a proper scheduling can help deliver better quality products to the customers in more timely manner or in bigger quantities.

As the current scheduling methodology is entirely based on planner's experience, without a proper procedure and having only restrictions on sequences, an entirely new approach for Sloten is taken, by proposing relevant rules from literature, company specialists suggestions and own expertise. The latter arises from investigating model execution in the interactive mode and thinking up solution for model logic, which could be beneficial.

5.5.1. SCHEDULING CHOICES

There are three main aspects of scheduling to be investigated in the system. First of all, it is sequencing of daily orders for mixing, in order to achieve good performance, mostly in terms of contamination. As the number of orders is fixed and the changeover times between are independent of the mixed product, there is little to be done to increase throughput. However, order sizes have significant impact on the possible allocated silo, providing that there are at least a few available to choose from for any given order, or ability to finish it within the current shift.

Silo allocation is important to find a good fit between order size, or size of all consecutive orders with the same recipe, and silo capacity so that a good one is chosen, a need for splitting orders is limited and there is a higher chance that the next order in line has space to be allocated to.

Finally, bagging order is vital especially for throughput, as it is the bottleneck of the system, and limiting product changeover would be beneficial for increasing efficiency. On the other hand, all products need to be bagged either way, and there need to be a changeovers between them, so the impact rather comes from choosing the right bagging line (BTH1-2 or BTH3), as long as there is material available to bag and no machine starving. Thus, there is a preference that there are multiple silos to choose from available, meaning that mixing leads bagging by some time. Moreover, at this point to limit contamination, one can take advantage of the mixing sequence and similarity of products, or try to minimise the tardiness of products.

Implemented scheduling rules are defined in Appendix in section C.5 on page 89, and the screen capture from SN for user input of the rules is shown in Figure D.6 on page 98. In the following section the reasons for defining these rules are given.

SEQUENCING

Sequencing is altering the order of items within specified set, and can be understood as queuing them for a certain task. In this case, the mixing sequence is the one to be influenced by rearranging the sequence from the daily planning. In general there are two steps to sequencing in this case: order sorting and recipe or nutrient incremental adjoining.

At first, the order is sorted in accordance to a pre-specified rule, such as smallest order size first or biggest bag first. Then, products with the same recipes can be shifted together with the same rule, or more complex nutrient similarity approach can be used to prepare the sequence. Naturally, the orders might remain unchanged, if desired.

Adjoining nutrients is an attempt to find a sequence that would result in lowest outcome nutrient difference among consecutive products and therefore the smallest number of off-specification bags. It is noted, that the best would be a directed search, or possibly even full factorial analysis as the number of orders per day is limited, through the entire daily plan in order to minimise the overall relative nutrient difference. However, as the utilised software is not capable of doing so, and programming an actual sequencing algorithm would be too time-consuming, an incremental method is used. This is also due to a lack of data on most of the product nutrients, which makes the full sequencing algorithm premature. The incremental method differs from the search as it chooses the best option and makes it fixed, cumulatively ending up with a sequence. However, this sequence is most likely not the best one there is. A description of the implemented method is shown in Figure E.3 on page 104 with a short description next to it.

DISPATCHING RULES

Dispatching rules allow to choose the most preferred option from the available ones, based mostly on the current state of the system with possible simple predictions. These rules are utilised for both silo allocation and bagging order.

The implemented method of choosing a silo is pictured in a flowchart E.9 on page 110 in Appendix. Empty silos and not-full silos with the same recipe are subjected to allocation dispatching rules. In general, silos with the same recipe are preferred to any other silos, providing the scheduling rules are met, and if not, the particular silo is rejected. This can be as a result of a different order type or not being able to fit entire order in that silo. Preference is then included as a multiplier to a minimisation search for the best one according to the silo matching rule, which can be based on size fit, shortest distance or disregarded. The search function implemented in Simio then is thus:

$$\begin{aligned}\min[&(1+100\cdot \text{Candidate.Silo\_Model.NutrientDissimilarity})\cdot \text{SiloAllocationMatch[1].SiloMatch}\cdot(1+\\&+(\text{Candidate.Silo\_Model.ContaminatingProduct}!=\text{RecipeTable.RecipeNumber})+1000\cdot\\&\cdot(\text{Candidate.Silo\_Model.HighLevelMark}<(\text{ManufacturingOrders.OrderQuantity}+\text{CapacityNeeded})))]\end{aligned} \tag{5.2}$$

As shown in equation (5.2), hard-coded fixed rules with assigned fixed weights (determined empirically) are multiplied by the matching rule SiloAllocationMatch[1].SiloMatch, determined by the user and nutrient similarity function. Nutrient similarity is set to 0 if it is not calculated, as according to the chosen rule. Because that can be 0, 1 is added not to bring down the equation result to 0. Finally, function strongly penalises different contaminating recipes, not currently present in the silo, and prefers silos that have higher capacity than the order.

Before bagging can be started, an appropriate silo needs to be chosen first and then discharge evaluated. Scheduling rules can force some checks to be performed earlier than others. This is done in the order: late products, BTH3 only products (coloured or for 10 kg bags) and then silo groups (designated to machine, common or all silos). For all of these dispatching rules are executed, similarly to the case of silo allocation with minimisation function for a search. See also Figure E.12 on page 113. Equation (5.3) is shown as an example search for BTH3 machine:

$$\begin{aligned}\text{BTH3\_SiloMatching[1].BTH3Rule}\cdot(\text{Math.If(Candidate.Silo\_Model.TimerDischargeRate.Enabled}, 10000, 1)+\\ +(\text{Candidate.Silo\_Model.DischargeSize} > 2))\cdot\text{Math.If(SchedulingAlternatives[7].Include},\\ \text{Math.If(BTH3.ContaminatingRecipe} == \text{Candidate.Silo\_Model.RecipeInsideNumber}, 0.5, 1), 1)\end{aligned} \tag{5.3}$$

First of all, the search function is multiplied by the matching rule, which can be e.g. smallest order first, biggest silo content or earliest mixing time. Then, there is a strong preference not to choose a silo which is currently discharging, although in some cases that might be necessary, e.g. for parallel machines or joining to bag the last product for the day. Then, BTH3 either way prefers smaller bags and, if chosen, will prefer matching recipes with the one previously bagged.

For a reference on all implemented scheduling rules see section C.5 on page 89 in Appendix.

5.6. Quality of Gathered Data

An important aspect of the investigation, is assessing the quality of data used as an input to the simulation model. Although it is very difficult to determine the range of possible errors made when using these values, this section presents the total extent of knowledge about the used data. There are two sources of quantifiable information about the system – historical statistics gathered by the company, and measurements performed specially for the project.

The measurements conducted in the factory were carefully prepared beforehand, and the crew was informed about their tasks. Nevertheless, some identified mistakes were made and possibly also other. As the access points to the equipment were located throughout the facility, no proper supervision could be maintained over the entire conduct. Employees, in pairs for each of the sampling points, had to, using stopwatches to determine intervals, manually draw samples from the material flow. With a considerable difficulty in timing, the acquired samples might have been taken at a wrong instance, leading to increased uncertainty. Unfortunately, the extent of this error cannot be measured. Moreover, as for measurement point D, due to human error, samples were taken in entirely wrong intervals, and there were fewer of them. Further sources of uncertainties in these measurements come from: other human errors, stops in discharge, lack of homogeneity in samples and laboratory conduct. Then, whether gathered samples are representative to the mixture in that location and time is also unknown. Finally, no precision of the laboratory analysis of the collected samples is given. Acquired data about the contamination is then fitted with exponential curves, which also have their precision (as described in table A.9). The simulated curves in a model have a different relation to the measured ones (see table: 5.3), which even further increases uncertainties about cross-contamination.

Nutrient content data is incomplete and full information is given for roughly 20% of the product portfolio. Remaining products have some of their information filled but not all. Only for Probiotic, colourant, Protimax, Vital wheat gluten and copper, all of the specification data fields are given but not all the limits. With full information about the nutrients, it is expected that the nutrient-based choices would be entirely different.

OEE data, although considered most certain as gathered by automated system and not prone to human errors, also exhibits some issues in certain aspects. When attempted to extract average production data many discrepancies were seen, e.g. repeated quality of products above 100%, unrealistically low equipment utilisation or recorded production with unstaffed line. Because of that, the OEE data is used only to obtain information about the short stops and changeover duration. With multiple data points and consistent structure (see tables A.2 and A.3), the quality is considered high. It is possible though, that there is a systemic bias in recording, yet nothing could be identified. The other way to extract specific production data, is using historical summaries, measured manually on the job floor and recorded day by day. Although this data is definitely not perfect, having the same working time for all the machines, which is most likely not true, and some significant outliers, including ones that are impossible to achieve in reality (e.g. bagging speed over 400 bags/hour), this is the only remaining source.

Finally, data regarding equipment properties, including for instance piping length, sizes or silo capacity, is approximated by company specialists. No technical as-built drawings are available for equipment properties, save for general piping and instrumentation drawings without great detail. As such, especially lengths, in particular for designed parts, are inexact. Also, the impact of equipment angles of inclination to the ground is not taken into account, while there are a lot of vertical, sloped or horizontal connections.

5.7. Verification and Validation

This section describes the efforts in verification and validation of the simulation model, basing on the approaches presented in Kelton et al. (2013), Sargent (2007). As the model is developed to suit the purpose described in chapter 1, its validity has to be determined with respect to that purpose. However, thorough model validation for the full domain of intended applicability is often too expensive, and thus selective tests are performed until sufficient confidence is achieved (Sargent, 2007).

The general approach to model validity was establishing trust by involving the company experts from the start in conceptualization and implementation of the model, and relying on their remarks about how the problem needs to be tackled. This is important for conceptual model validation and usefulness perception, in the case where it is impossible to have a third-party validation or another model for comparison.

5.7.1. Conceptual Model Validation

The first step to confirm the validity of a model is assuring that employed theories and made assumptions are correct, and that the problem is adequately expressed by the conceptual model's structure, logic and relationships (Sargent, 2007). These are introduced in section 3 and especially the class diagram from Figure 3.3 on page 18. At this stage, the experts are asked to perform face validation of proposed structures, boundaries and logic for each of the sub-models separately and then assess the consolidated model. Over the course of several meetings, involving different experts, proposed solutions are discussed and agreed upon. Data analysis of historical performance and other quantitative investigations, to e.g. extent of contamination or field tests of conveyor speeds, are also presented, and compared with the proposed mathematical functions modelling individual model features. This is how the initial versions of responses shown in Figure 5.3 are created and improved.

5.7.2. Model Verification

Model verification requires checking whether the simulation model executes in the designed way, i.e. if it accurately translates the design into the implementation. This stage can be further divided into two steps: general verification and verification tests, where only the latter is formalised. The first involves running the simulation in the interactive mode (with animation) and monitoring the flow of entities, values of model variables and time-dependent charts. Also checking model for specific events and monitoring whether the model executes as desired. After the initial verification several more formal tests are performed and their inputs and results recorded. These include degenerate analysis and traces basing on a dynamic testing approach and their details are included in Appendix F.1 on page 115.

5.7.3. Simulation Model Validation

Model validation is the most important step in determining the usefulness of the model, as any further analysis of experiments should be based on the premise that these indeed sufficiently well describe the possible model outputs, given the experiment inputs. Here, as the company specialists have been involved in model development from the start, their perceptions about accurateness of capture of the problem are vital. Furthermore, validation includes parameter variability tests and component/feature individual comparison with field tests or historical data. As the factory layout has not been changed yet, a comparison of the actual production performance and the simulated output cannot be made. The following sections describe the key activities during the validation phase. Details, including a quantitative analysis can be found in Appendix F.2.

Expert Validation

Expert validation has been undertaken with company specialists involved in the project. It consisted of two main parts: face validation and experiment result discussion. It concentrated on getting acceptance to modelling approach, and establishing trust in the future results.

The process began with a presentation of the simulation execution in the interactive mode in Simio. At first, the model components were explained so that the people involved could connect the model layout to the factory. Then, the model was started and material flow initiated. A set of labels, colours and displays was specially added to support understanding, and provide reason behind what was happening. Consequently, almost an entire day of production was simulated to show how material is transported through the system, delayed in between to leave through one of the exits.

The second part involved a discussion of preliminary results and comparison with a general, high-level historical data. An early version of the result presentation set-up, described in section 6.1, was used to support the process. General throughputs achieved by the simulation were within acceptable limits by the company experts, even though the are some differences between the current and the future production organisation, resulting in a different performance.

After the meeting, the company specialists were provided an opportunity to explore and get familiar with the simulation model on their own, which they did. Upon inquiry, their thoughts on execution correctness and agreed upon representation of reality were positive. The general consensus allowed to regard the model as valid.

COMPONENT VALIDATION WITH HISTORICAL DATA

This section contains validation data based on the case od Sloten. Since the layout of the system is changed considerably, expected performance validation of the entire system cannot be made. However, some measures can be compared and the differences between them explained.

PRODUCTION MODEL

The most important performance indicator is speed at the bottlenecks, i.e. bagging. Data on the performance of all bagging machines BTH combined, is obtained from the client, and concerns years 2013 and 2014 gathered in daily intervals. Data collected in the base case scenario on achieved throughputs is put into table F.4 on page 117. The following Figures 5.5 and 5.6 show box plots comparing these results.

In general, performance obtained in the simulation is much better than the measured one, especially when looking at the number of processed bags. Measured data has plenty of outliers, including some when performance is better than the maximum possible, which constitutes for recording error. Some are also very low, meaning there could possibly be an extended downtime, caused by e.g. machine breakage. Moreover, the average measured value is lower due to the single reference shift time for all machines, unrealistic for such a long period, and downtimes due to interlinking with the main mixer.

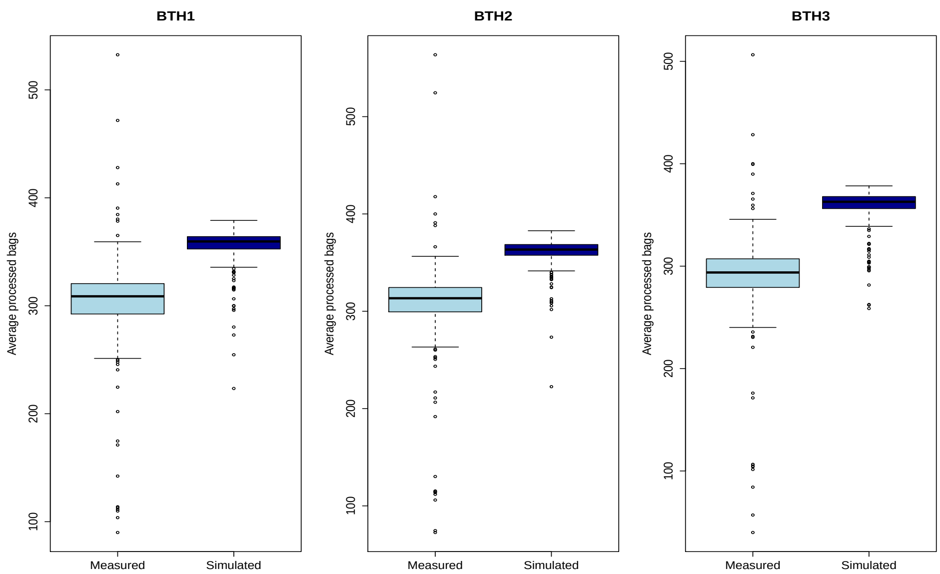

Figure 5.5: A comparison between the average measured (2013) and simulated packaging throughputs in terms of bags

When expressed in terms of processed kilograms of material, the differences are smaller, especially for machine BTH3, but only because in the simulated setup this is the place to process 10 kg bags, while historically this equipment has been used only for 20 and 25 kg packages. The BTH3 processed quantity is the only of the six presented comparisons where the simulated value is not bigger than measured, with 95% confidence, see table 5.4. Statistical tests performed were Welch two-sample t-test with one sided hypothesis.

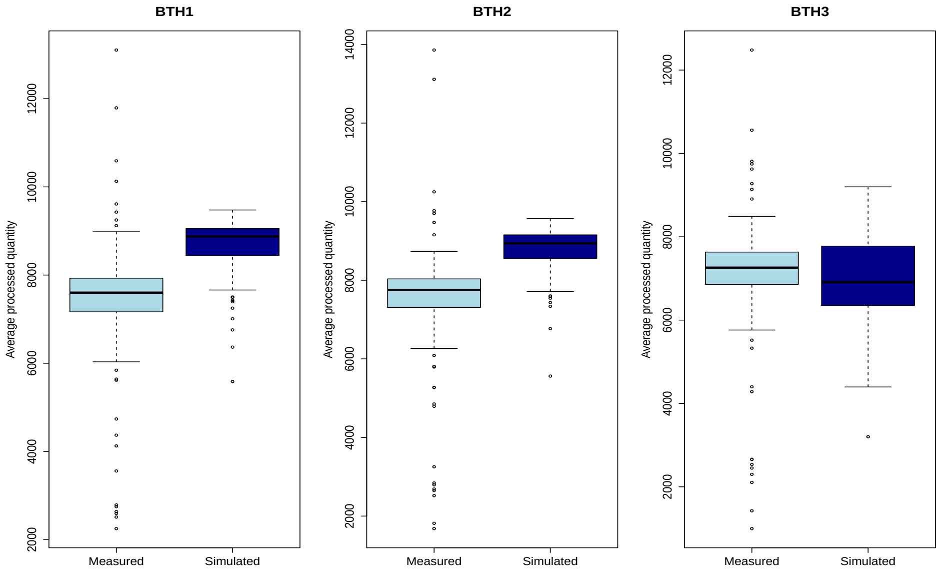

Figure 5.6: A comparison between the average measured (2013) and simulated packaging throughputs in terms of processed quantity

Company specialists, when confronted with the expected base-case scenario performance and its relation to historical data, expressed satisfaction with presented results and hope that it would be so when implemented. According to their expectations as well as evidence from the simulation, the performance is likely to increase considerably. However, the extent of the increase is uncertain, and thus no validation can be made to support achieved results.

Table 5.4: Statistical t-test comparing measured and simulated throughput values

Alternative hypothesis	t-value	df	p-value	95% conf. interval
H_1 :BTH1_Bags_Simulated > BTH1_Bags_Measured	16.504	239.97	**< 2.2e-16**	48.45214: Inf
H_1 :BTH3_Bags_Simulated > BTH2_Bags_Measured	15.973	278.29	**< 2.2e-16**	48.49943: Inf
H_1 :BTH3_Bags_Simulated > BTH3_Bags_Measured	10.686	297.40	**< 2.2e-16**	63.43501: Inf
H_1 :BTH1_Quantity_Simulated > BTH1_Quantity_Measured	15.561	310.50	**< 2.2e-16**	1147.779: Inf
H_1 :BTH2_Quantity_Simulated > BTH3_Quantity_Measured	14.873	296.43	**< 2.2e-16**	1140.839: Inf
H_1 :BTH3_Quantity_Simulated > BTH3_Quantity_Measured	-1.045	462.00	0.8517	-264.1085: Inf

CROSS-CONTAMINATION MODEL

Compared simulation results from trials presented in Figure 5.3 use slightly different route than originally. As there was just a single trial performed, this section cannot offer more than it is shown in table 5.3 on page 37, for the accuracy of simulated contamination curves to the measured ones. Pollution in orders is inspected based on charts like 5.7, where per each order the average amount, of all replications, of material over limits (red) is compared with the accepted quantity (green).

5.7.4. VALIDATION SUMMARY

All in all, the level of confidence in the model is high, and it is considered valid by the involved company experts. Performed tests prove that it suits the purpose and is able to assist with the answers to relevant research questions from chapter 1, and as defined in chapter 3.

Nonetheless, as for any model, additional tests could be performed to further increase this confidence. There are several options to choose from, while still assuming that involving a third party or building another model of the problem is too expensive for implementation. An interesting alternative is e.g. so called

Figure 5.7: An example chart of contamination per manufacturing order

Turing test, testing company specialists whether they can distinguish model outputs from actual system performance. Since the factory layout is not reorganised yet, it is too early for such analysis. Obviously, statistical tests for the actual system output and model results, would be most useful but are unachievable at this stage. They would be a vital step for more generalised purpose of the model and application to other facilities.

This section concludes the design phase, where the final simulation model is define, based on the case company example. Moreover, cross-contamination measurements are discussed, scheduling rules designed and data quality examined. Finally, the model is verified and validated. It is further used in chapter 6, to explore possible impact of the devised scenarios, i.e. certain arrangements of the input variables, on the dependent variables. The results are discussed in chapter 7, where also a connection to the literature is made.

6
Experimentation

This chapter explores what is the impact of the chosen independent variables on the dependent variables, called KPIs. Experiments are grouped in five sets, in which there are multiple scenarios defined, i.e. unique combinations of the input variables. For each group specific values of the parameters are given, along with reasons for choosing them. Due to a large number of possible combinations, of almost 500 billion for full factorial analysis, just for different scheduling options, and long simulation execution time, the investigation is limited to a certain number of viable scenarios. Replication runner is capable of running 2–4 concurrent replications and the standard investigated production period is 3–4 weeks. The analysis is based on an actual set of Sloten bagging orders from January 2015, which have assigned fixed due dates.

A funnel approach is taken to design groups of scenarios, which within a group have varied only a part of the investigated input parameters (independent variables). Thus, at first a base scenario is defined (see section 6.3), which has a fixed set of independent variables. Then, two sensitivity analysis scenario collections are performed: one (section 6.4.1) looking at performance without including cross-contamination calculations, with varying silo parameters and discharge speeds, and another investigating the disparity in different sequencing as well as silo allocation approaches on resultant contamination (section 6.4.2). These are followed by another group, analysing the impact of varying additional silo number and size, which is succeeded by an analysis of various scheduling rules definitions. Finally, a refined set of very specific inquiries into e.g. particular scheduling rules, and including random component for cross-contamination, is investigated. The choice to approach the problem in a given way is aimed to reduce the number of different scenarios to run, which is important not to drag on the analysis as well as to limit extensive computing time.

All of the scenarios are compared between each other based on pre-defined general KPIs, as defined in section 3.4.1. All results are put into tables, where for each KPI the average value, standard deviation (SD), median and number of measurements are recorded. For details on specific results see Appendix G on page 118. These values, as well as figures placing various scenarios dependent variables in comparison to each other, are presented for each set of experiments in this chapters. The analysis, i.e. drawing conclusions from the experiment results is done in chapter 7.

6.1. Scenario Navigator Setup

A proprietary software of Systems Navigator, called Scenario Navigator is used to define an environment capable of cooperation with Simio, in terms of defining system inputs, managing run of scenarios and displaying the results. Being able to store data from multiple scenarios, it is useful for analysis and exploring possible options. Tables stored in the program are linked to the simulation engine via *.csv files and the text files produced by the simulations are read after the completion of each scenario and kept in a database. Obtained data is then used to create graphs, gauges and data tables for the user, either directly or via SQL queries to filter more specific entries or higher level indicators. For further details, see Appendix D.1. Some of the figures used in this chapter are screen captures from the tool.

6.2. Required Warm-up Periods

Warm-up period is a time before the simulation reaches its steady state. As the model execution always begins with an empty system, it is vital to reach this point first, and then start gathering relevant statistics (Kelton et al., 2013). In this case warm-up period is essential to fill intermediate silos, so that there are products to be bagged immediately, and also to get rid of the initial unknown residue in the equipment.

When running without cross-contamination analysis, only the first part is important and thus a single day of warm-up period suffices. As the mixer has much higher capacity than bagging at the end of the first day there are several silos filled. For runs with contamination, it is vital that there are multiple products going through all equipment, especially conveyors. Some of them are used rarely, like e.g. bulk stations, and the time needed to sweep the initial contamination is considerable. Thus the warm-up period is set to 3 working days and although the initial contamination may not gone completely, it is small enough to consider negligible.

For considerations of the replication number as well as the chosen contamination negligence point see sections A.3.2 on page 80 onwards in the Appendix.

6.3. BASE SCENARIO

This section presents the initial point of the investigation, a so called base scenario, from which the whole analysis diverges. The following settings are used for all performed experiments, unless otherwise specified. Initial model parameters, i.e. independent variables, are put into table 6.1, and mostly are an input from the company specialists or current equipment settings with no error margin. Stochastic input variables, the same for all scenarios, are directly taken as in table 5.1. Moreover, independence among all input parameters is assumed, though especially for scheduling options some are interrelated variables.

Table 6.1: Model input parameters set for the base scenario

Parameter	Unit	Value
Silo to BTH Discharge Rate	kg/h	20000
Silo to Bulk Stations Average Discharge Rate	kg/h	15000
Silo to BigBag Discharge Rate	kg/h	12000
Polems to BigBag/BTH3 Discharge Rate	kg/h	15000
BTH1 nominal bagging speed	bags/hour	400
BTH2 nominal bagging speed	bags/hour	400
BTH3 nominal bagging speed	bags/hour	400
Big bag nominal bagging speed	bags/hour	5.5
Maximum allowed daily overtime (predicted)	h	1
Minimum order size left for pre-emption	kg	15000
Contamination cut-off point	kg	0.01

No	Rule	Include
1	Combine matching recipes in a given day for mixing	☑
2	Allocate silos based on all consecutive orders of the same recipe	☑
3	Avoid splitting small orders among multiple silos	☐
4	Prefer splitting large orders into parallel silos to combining recipes	☑
5	Put orders of the same recipe but different type into separate silos	☐
6	Allow preemptions	☑
7	Strongly prefer matching recipes for consecutive bagging	☑
8	Prefer for BTH3 to bag colored or 10kg size packages first	☑
9	Always combine recipes in silos. Allow splitting into parallel silos only	☐
10	Try redirecting Mixer-->Polem discharge if Bigbag filling is interfering	☑
11	Prefer bagging late products first	☑

Figure 6.1: Scheduling parameters chosen for the base case experimentation scenario

Base case scheduling parameters are put into Figure 6.1 and table 6.2, depicting which rules are initially thought, after consultations with relevant planning personnel, to be advantageous to the production efficiency, especially for a high throughput.

Table 6.2: Model scheduling parameters set for the base case experimentation scenario

Scheduling rule	Value
Mixing order	Smallest Orders First
Silo match	Best Size Fit
BTH1_2_SiloGroupPreference	Common Silos First
BTH3_SiloGroupPreference	All silos
BTH1_2_DispatchRule	Biggest Order First
BTH3_DispatchRule	Smallest Order First

There are other input parameters, not presented in this section, due to their considerable number, which are kept fixed for all experiments. They include other discharge or transmission speeds, secondary equipment properties, piping lengths etc. The exact values are kept constant in the SN tool or are hard-coded in the Simio simulation model.

6.4. EXPERIMENT DESIGN

The following sections contain funnel-based groups of designed experiments as well as explanations why are certain values of the independent variables chosen. For each set, a certain number of input parameters are fixed, often as a result of previous experiments outcome, while some others are varied.

6.4.1. INITIAL SENSITIVITY ANALYSIS

The aim of the initial experiments is to perform a high level analysis on production throughput, without including cross-contamination calculations. Changing discharge rates from silos is done to determine if these are bottlenecks and should be increased, as the powder transportation should not limit equipment throughput. Moreover, an initial investigation into the performance with additional storage silos is to be made as a sensitivity analysis, to focus further inquiry and reduce number of variables. The following independent variables are altered in the first phase of the experiments:

- Silos to BTH machines discharge rate
- Silos to big bag line discharge rate
- Number of additional silos
- Capacity of additional silos
- Silo recipe restrictions

EXPERIMENTS DESIGN

Recipe restriction reflects the current operations in Sloten, where two silos, number 21 and 22, are designated for specific recipes, in this case for recipe 3290 and 3211 respectively, and then no other product can be placed in them. Production operators believe it to be convenient, so it is desired to assess the impact of their habits if this situation continued in the new plant layout. Then, reserving silos for specific recipes reduces system

Table 6.3: Initial experiments inputs without contamination investigation

Scenario	Discharge Rate BTH [kg/h]	Discharge Rate Bigbag [kg/h]	Additional Silos Number	Additional Silos Capacity [kg]	Reserved Silos
NC_A	20000	12000	0	-	NO
NC_B	18500	12000	0	-	NO
NC_C	22000	15000	0	-	NO
NC_D	20000	12000	0	-	Silos 21 & 22
NC_E	20000	12000	2	52000 / 25000	NO
NC_F	18500	12000	2	52000 / 25000	NO
NC_G	22000	15000	2	52000 / 25000	NO
NC_H	20000	12000	2	52000 / 25000	Silos 21 & 22
NC_I	20000	12000	4	52000 (2) / 25000 (2)	NO
NC_J	18500	12000	4	52000 (2) / 25000 (2)	NO
NC_K	22000	15000	4	52000 (2) / 25000 (2)	NO
NC_L	20000	12000	4	52000 (2) / 25000 (2)	Silos 21 & 22

flexibility, diminishing choices for silo allocation, and impacting the number of available jobs for bagging machines as a result. The full set of independent variables values is presented in table 6.3.

EXPERIMENTS RESULTS

Acquired data is put into tables in Appendix from G.1 on page 118 to G.12. Additionally, bagging throughput in terms of average processed bags per hour is displayed in a box plot in Figure 6.2. Black vertical line inside the distinguished rectangular represents the median of the results. Lower and upper borders of the box signify respectively 25th and 75th percentile, further dashed lines expected range of the data, and possible circles farther along the line show outliers[1]. Bagging throughputs for Figure 6.2 and the following ones, are

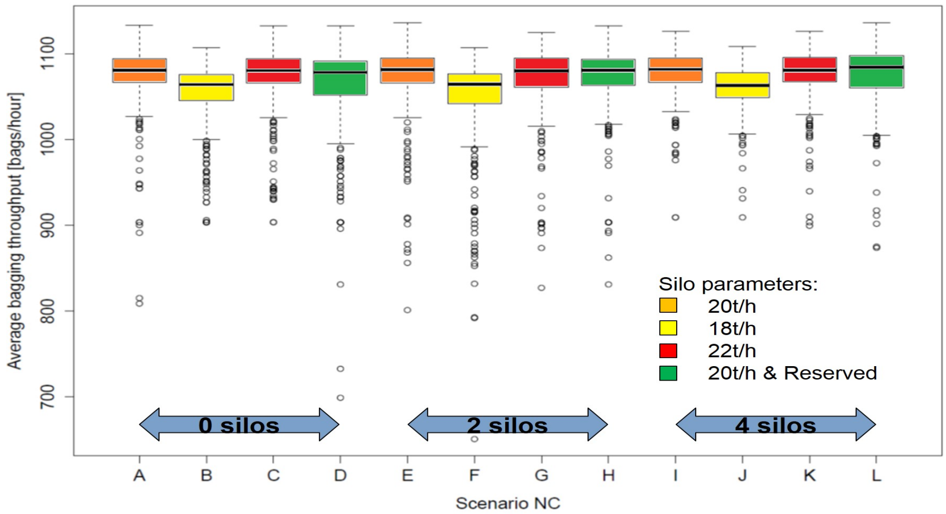

Figure 6.2: A box plot presenting average hourly packaging throughput in experiment runs without including cross-contamination calculations

calculated as an average of a day for given machine and then added up, just as in equation (6.1):

$$Average\_Throughput = \frac{BTH1\_Daily\_Bags}{BTH1\_Time\_Working} + \frac{BTH2\_Daily\_Bags}{BTH2\_Time\_Working} + \frac{BTH3\_Daily\_Bags}{BTH3\_Time\_Working} \tag{6.1}$$

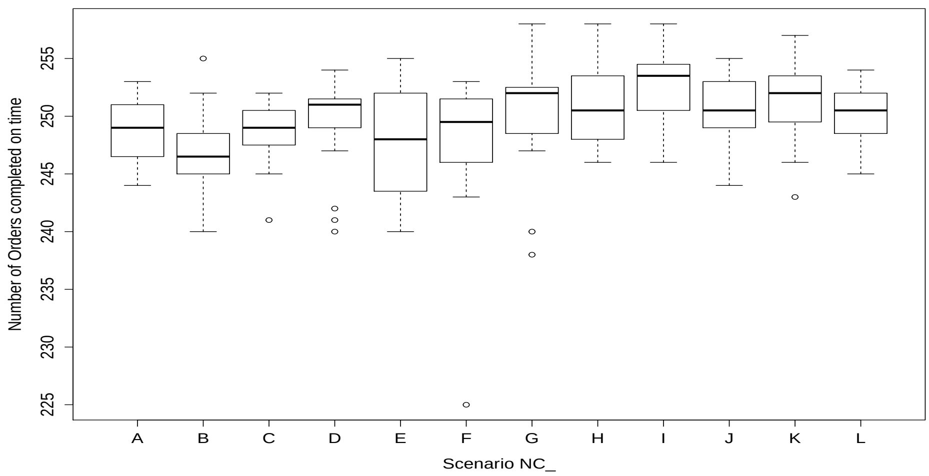

Figure 6.3: A box plot for comparison of orders completed on time

[1]For details see R package documentation http://www.rdocumentation.org/packages/graphics/functions/boxplot

Then, timely order completion comparison, using another box plot is presented in Figure 6.3. There are 261 orders to be completed, most of which are expected to finish within the run time-frame, but there is no single run where all orders are completed on time.

6.4.2. CROSS-CONTAMINATION INVESTIGATION

The second part of the initial sensitivity analysis is determining the impact of mixing sequencing, defined in section 5.5.1, and nutrient-based silo allocation, as in equation (5.2), on the total contamination. When the parameter 'Nutrient-based silo allocation' is set to 'YES', it is calculated based on schematic displayed in Figure E.3 on page 104, and if it is 'NO' the value of Candidate.Silo_Model.NutrientDissimilarity = 0. Recipe based sequencing (combining recipes) is at first sorting the daily orders according to a specified 'Mixing order' rule, also done for nutrients, and then grouping all products with the same recipe together, starting from the first one for a given day. Order sequencing with option 'combine nutrients' bases on the same principle as described in section 5.5.1.

It is expected that mixer sequencing has a considerable impact on the total amount of excess contamination, as any choices done for this set have direct repercussions in mixer allocation and bagging order. Moreover, most of the storage space is in the main silos numbered 14 to 23, and to reach any of them there is a long common route for the product, up until the end of the main elevator, an possibly even further. There are large screw conveyors there, which are measured to have a relatively high amount of material residue, comprising roughly half of the measured total residue for the investigated route (described in section C.4).

EXPERIMENTS DESIGN

The base scenario from section 6.3 is used to explore the impact of nutrient or recipe based allocation. Special controls are added to the model to disconnect nutrient based sequencing and silo allocation. All scenarios are run including (pre)mixer residue of 166 kg, and the set of experiment differentiated values for independent variables is listed in table 6.4.

Table 6.4: Initial cross-contamination experiments inputs

Scenario	Order sorting	Order sequence	Nutrient-based silo allocation
MassC_A	Largest bags first	Combine nutrients	YES
MassC_B	Largest bags first	Combine nutrients	NO
MassC_C	Largest bags first	Combine recipes	NO
MassC_D	Largest bags first	Combine recipes	YES
MassC_E	Largest bags first	None	NO
MixC_A	Largest bags first	Combine nutrients	YES

By comparing the results of the experiments presented in table 6.4, a sensitivity analysis to order sequencing and silo allocation can be made, assessing what factor has a bigger impact on the total amount of off-specification product. Additionally, experiments from MassC_A to MassC_E are run with the partial mass exchange cross-contamination model, while MixC_A is using the mixing one, and the same remaining input parameters as MassC_A. Thus, assessment on how much worse, for the total amount of off-specification product, is a slower release of the residue product, can be made. According to the company specialists, the newest state-of-the-art software, used in another Nutreco factory, utilises a full mixing based material behaviour in the process. As such, comparing it with a measured behaviour can indicate the extent of error made with this assumption. Being able to compare these two models can provide argumentation whether closer scrutiny needs to be paid to this phenomenon.

EXPERIMENTS RESULTS

Determining the impact of sequencing on overall contamination is vital to understand the implications and extent of it, as well as to show how much savings can be achieved with a simple ordering scheme. A box plot for total contamination in all packaged product is shown in Figure 6.4. Specific results for each scenario are put into tables from G.13 on page 120 to G.18.

6.4.3. ADDITIONAL SILOS EXPERIMENTS

A vital part of the investigation is determining the impact of different plant layouts on production performance. In this case, design interventions are limited to the number and size of additional intermediate storage silos, based on the proposed factory layout of Sloten, shown in Figure 5.1. There are 11 existing silos,

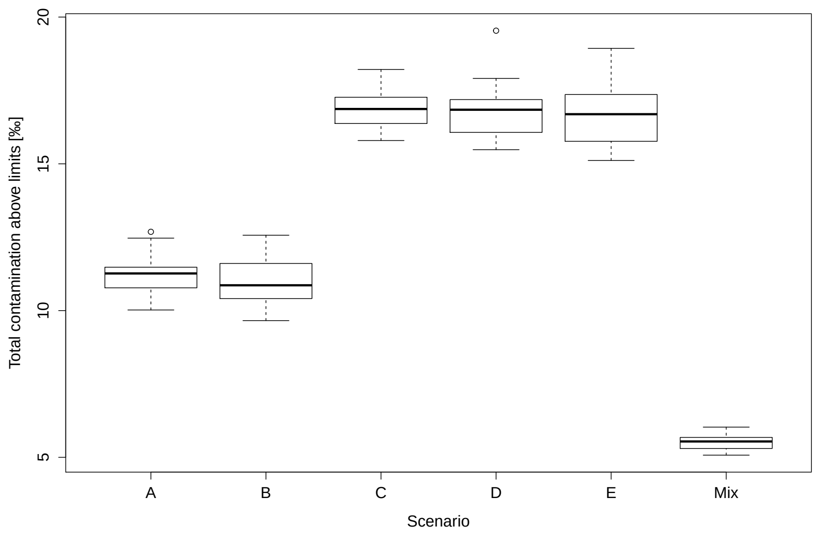

Figure 6.4: A box plot for comparison of impact of sequencing on cross-contamination

varying in size and connections that are included in the analysis as fixed input. Then, up to eight additional silos are added, with predefined constraints. Thus possible silos 51, 52, 61 and 62 are parallel to each other and connected only to packaging line 1, comprising bagging machines BTH1 and BTH2. Remaining potential silos 53, 54, 63 and 64, can only discharge to BTH3 machine.

This set of experiments can also be viewed as a sensitivity analysis of the varying number of additional silos and their size, because the factory layout interventions only regard a single dimension.

EXPERIMENTS DESIGN

Since the joint capacity of machines BTH1 and BTH2 is bigger than of BTH3, it is likely that the first ones might benefit more from increased silo capacity, and thus several experiments vary silo sizes with shift to that side. There are some chosen alterations to the scheduling rules of the base case scenario from section 6.3. Figure 6.5 shows a screen capture of used scheduling alternatives. Moreover, BTH3 bagging rule also deviates from the base scenario and is set to "Smallest Remaining Material to Package". These complete the final set of the independent variables.

No	Rule	Include
1	Combine matching nutrients in a given day for mixing	☑
2	Allocate silos based on all consecutive orders of the same recipe	☑
3	Avoid splitting small orders among multiple silos	☑
4	Prefer splitting large orders into parallel silos to combining recipes	☑
5	Put orders of the same recipe but different type into separate silos	☑
6	Allow preemptions	☑
7	Strongly prefer matching recipes for consecutive bagging	☐
8	Prefer for BTH3 to bag colored or 10kg size packages first	☑
9	Always combine recipes in silos. Allow splitting into parallel silos only	☐
10	Try redirecting Mixer-->Polem discharge if Bigbag filling is interfering	☑
11	Prefer bagging late products first	☐

Figure 6.5: Scheduling parameters chosen for silo number and capacity impact investigation

Table 6.5 contains varied silo capacities, expressed in kilograms, of the additional investigated silos, the only alterations done within this set. If the value is set to 0, then the silo is not included. Moreover, the silo high level marks were set 1000–5000 kg lower. For capacities of 25000 kg, the high level marks are set to 24000 kg, for remaining silos below 80000 kg they are 2000 kg lower and for the biggest silos 5000 kg lower.

Table 6.5: Altered independent variables for the exploration of the impact of additional silos and their capacities on production performance

Scenario	Silo_51	Silo_52	Silo_53	Silo_54	Silo_61	Silo_62	Silo_63	Silo_64
MassC_F	0	0	0	0	0	0	0	0
MassC_G	52000	52000	0	0	0	0	0	0
MassC_H	0	0	32000	22000	0	0	0	0
MassC_I	22000	22000	22000	22000	0	0	0	0
MassC_J	42000	32000	32000	22000	0	0	0	0
MassC_K	52000	52000	32000	22000	0	0	0	0
MassC_L	80000	62000	42000	32000	0	0	0	0
MassC_M	130000	105000	52000	32000	0	0	0	0
MassC_N	52000	52000	32000	22000	25000	25000	25000	25000
MassC_O	52000	52000	32000	22000	25000	25000	0	0
MassC_P	32000	32000	32000	32000	32000	32000	0	0
MassC_R	32000	32000	32000	32000	0	0	0	0

The investigation explores only a small part of the solution space that is expected to be beneficial to production performance. Silo sizes from table 6.5 are chosen based on early company specialists prediction and then further varied in size, mostly increased. The biggest proposed silo from scenario MassC_M is specially selected for the set of production orders used with the experiments, so that the largest order would fit in it entirely without splitting.

EXPERIMENTS RESULTS

Obtained results for all scenarios are put into tables in Appendix from G.19 to G.30 in the same manner as before. Additionally, scatter plots are provided in Figures 6.6 and 6.7 to visualise the average dependent variable values for the total contamination as well as average hourly bagging throughputs as functions of the total silo capacity. Additionally, the dots representing the results are coloured to show how many silos are used.

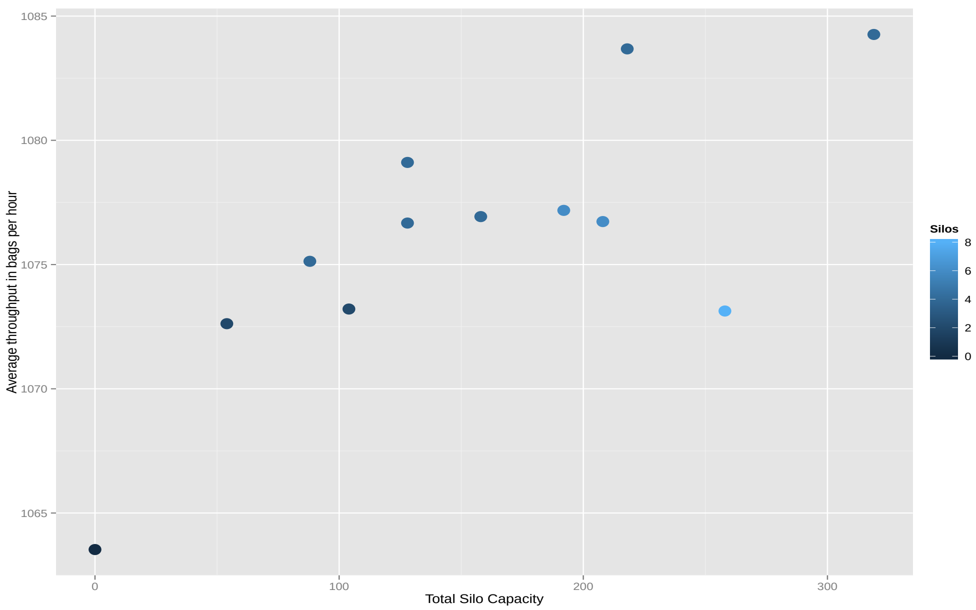

Figure 6.6: A scatter plot displaying average results for throughput with respect to varying silo capacity and number

Total contamination from Figure 6.7 is shown in parts per thousand and represents the ratio of the total amount of material considered off-specification to the total packaged quantity.

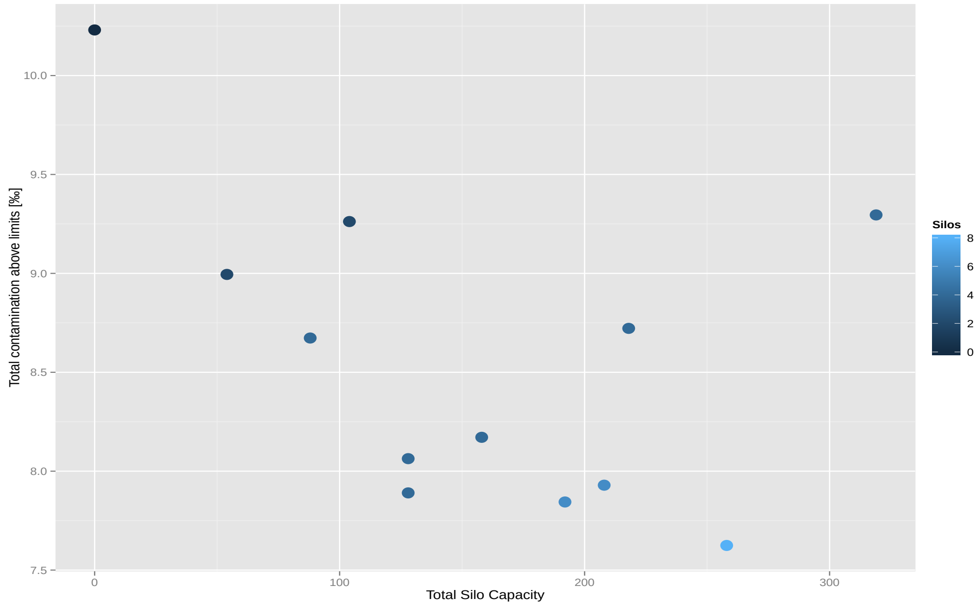

Figure 6.7: A scatter plot displaying average results for contamination with respect to varying silo capacity and number

Furthermore, the two plots from Figures 6.7 and 6.6 are combined in one to show the total contamination as a function of bagging throughput in Figure 6.8.

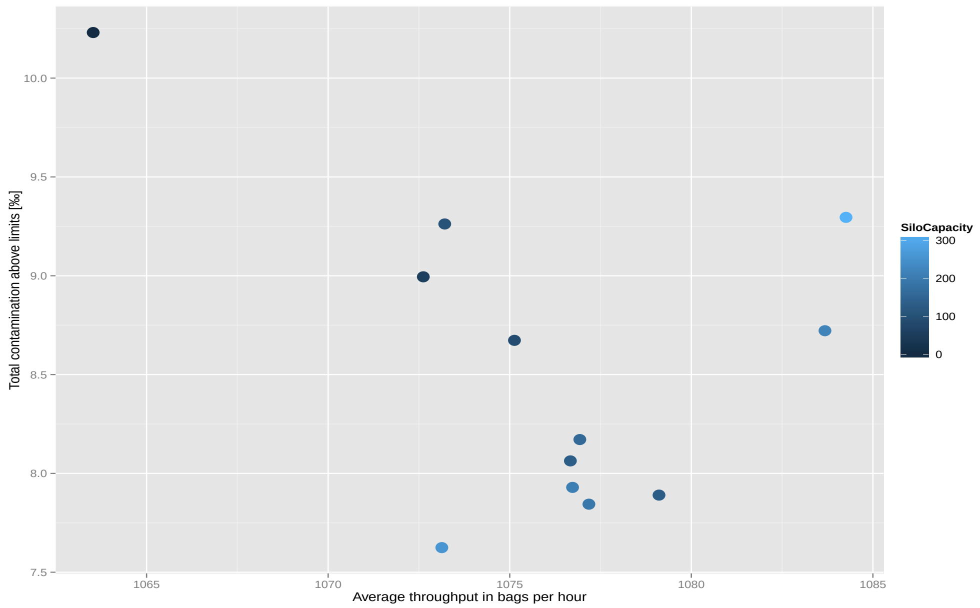

Figure 6.8: A scatter plot displaying average results for contamination with respect to achieved throughput for silo parameter analysis

Finally, box plots for comparison of completed orders and ones finished on time are included in the Appendix in Figures G.2 and G.3 respectively.

6.4.4. SCHEDULING RULES EXPERIMENTATION

The following group of scenarios concentrates on assessing the impact of different scheduling logic on the production performance. They utilise specific silo parameters from one of the scenarios from section 6.4.3, namely MassC_K, having four fixed silos with capacities of 52, 52, 32 and 22 tonnes. It is expected that there is a considerable impact of different scheduling rules on all the KPIs and that the reasons for the differences among them can be identified.

Yet again, experimentation can be viewed as a sensitivity analysis, this time exploring the expected trade-offs between aspects of production performance. Thus the main reason for choosing the following sets of independent variables is identifying the extent of impact of scheduling on the average throughput as well as corresponding amount of the off-specification product.

EXPERIMENTS DESIGN

There are a number of independent variables that are varied within this set of investigated scenarios, all of which are scheduling rules. Although the number of scheduling possibilities just for different combinations of the rules is large, of almost 500 billion, there are only six experiments performed. Table 6.6 contains numbered scheduling rules as in Figure 6.1 and proposed scenarios. If the rule is included, the cell contains 'YES', otherwise 'NO'.

Table 6.6: Scheduling rules chosen for scenarios exploring their impact

Scenario	1	2	3	4	5	6	7	8	9	10	11
Scheduling_A	YES	YES	YES	NO	NO	NO	YES	NO	NO	YES	NO
Scheduling_B	YES	YES	YES	NO	NO	NO	YES	NO	NO	NO	NO
Scheduling_C	YES	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO
Scheduling_D	YES	YES	YES	YES	NO	YES	NO	NO	NO	NO	NO
Scheduling_E	YES	NO	YES	YES	YES	NO	NO	YES	NO	NO	YES
Scheduling_F	YES	YES	YES	YES	NO	YES	NO	YES	NO	YES	YES

Chosen dispatching rules, that are also varied, are put into table 6.7. The mixing order for all is 'Smallest orders first', and the nutrient based allocation is also always included, because it, based on results from section 6.4.2, reduces the total contamination significantly.

First two scenarios in the set are aimed at achieving low contamination, by taking advantage of the mixer sequence, where dispatching rules for bagging machines set to 'earliest mixing time'. The following two are set to increase the average bagging throughput, by taking advantage of the different capacities of lines 1 & 2, and the final two provide reference for the first two by having a combination of independently reasonable choices, that together do not fit too well.
All of the values are based on the input from company specialists, literature study from section 2.5, as well as own exploration of the model in the interactive mode.

Table 6.7: Dispatching rules chosen for scenarios exploring impact of scheduling

Scenario	Silo match	BTH1-2 silo pref.	BTH3 silo pref.	BTH1-2 dispatch	BTH3 dispatch
Scheduling_A	Best size fit	All	All	Earliest mixing time	Earliest mixing time
Scheduling_B	Best size fit	Designated	Designated	Earliest mixing time	Earliest mixing time
Scheduling_C	Best size fit	All	All	Biggest silo content	Smallest silo content
Scheduling_D	Shortest route	All	All	Biggest order	Smallest package
Scheduling_E	Shortest route	All	Common	Biggest order	Smallest quantity left
Scheduling_F	Best size fit	Common	All	Biggest order	Earliest mixing time

As such, within this set there are fifteen varied input variables. Although independence among them is assumed, there are quite possibly notable interconnections. These are not explored.

EXPERIMENTS RESULTS

The results of the experiments are put into tables in Appendix from G.31 on page 125 to G.36. Additionally, a similar graph to 6.8 is prepared for scheduling investigation and shown in Figure 6.9, but grouped by scenario name (ScA is short for Scheduling_A etc.). Different colours in the scatter plot signify scenarios whose independent variable values are defined in tables 6.6 and 6.7.

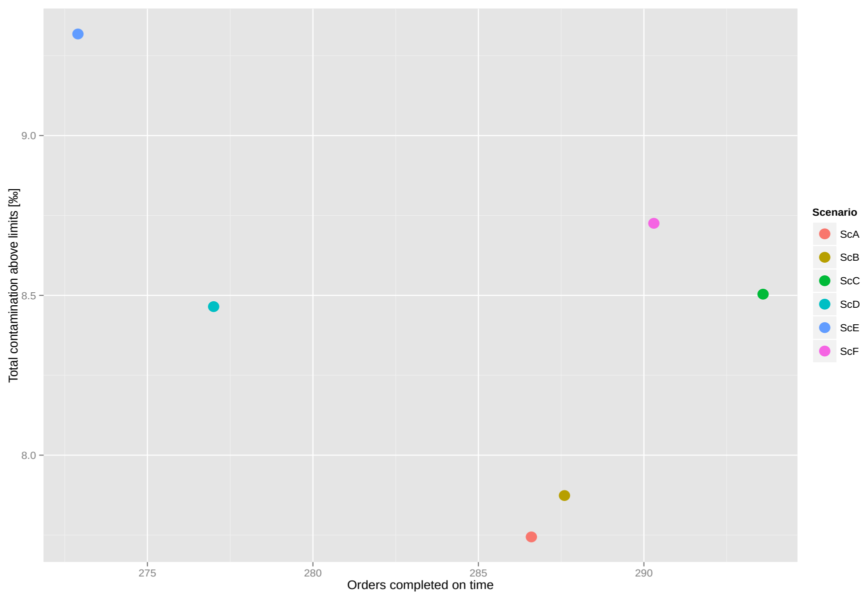

Figure 6.9: A scatter plot displaying average results for contamination with respect to achieved throughput for scheduling analysis

Moreover, a box plot showing the total average packaging throughput per hour for the investigated group is shown in Figure 6.10.

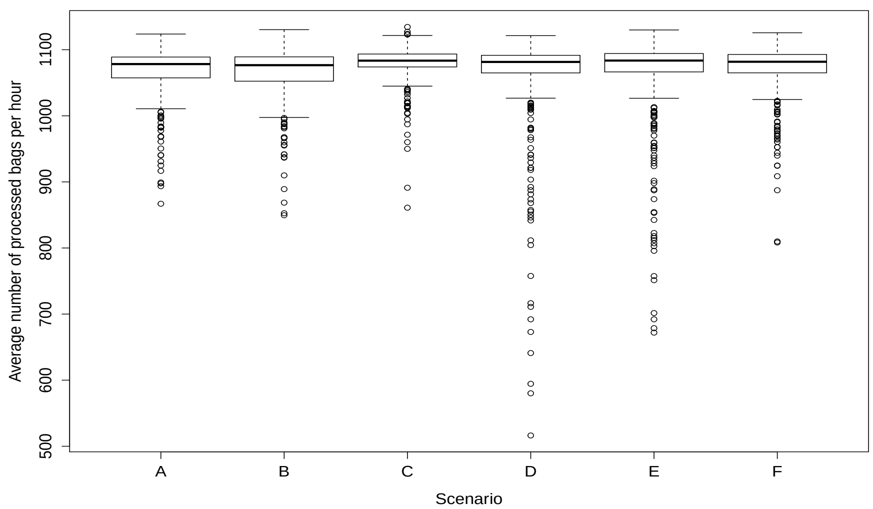

Figure 6.10: A box plot displaying average results for bagging speed per hour for each of the investigated scenarios

Similarly to the previous section, box plots for comparison of completed orders and ones completed on time are included in the Appendix in Figures G.5 and G.6 respectively.

6.4.5. RANDOM COMPONENT INVESTIGATION

The final set of scenarios includes the parametrised random component for cross-contamination calculations. The leading assumption, on top of ones made previously, is that the exchanged amount, as described in equation (4.8), differs per product batch according to the normal distribution, where the expected value is EAP, with a standard deviation of $\sigma \cdot EAP$, but altogether constrained not to result in negative values. Doing so creates ripples in the cross-contamination curve, similar, but lower and much more frequent as measured (shown in Figure 5.4 on page 38). The following experiments explore the effects of this randomisation on the total amount of off-specification material.

RANDOM COMPONENT SIZE

Scenario MassC_J (see section 6.4.3) is taken as the source for the set of independent variables, because it has relatively good results for both throughput and contamination. This is thus a starting point for comparison with $\sigma = 0$. Then, by increasing the value of the random component σ the ripples appear and become higher, which might have an effect on total contamination. The following two experiments are given the same input variables as scenario MassC_J and only differ in the random component value, as defined in table 6.8. This way a comparison can be made to results without the random component, and two scenarios including it. Additionally, the mixing cross-contamination model is also explored to provide a frame of reference for method comparison. For scenario MixC_B the random component is not applicable.

Table 6.8: Random components chosen for analysis

Scenario	σ	Cross-contamination model
Random_A	0.2	Partial mass exchange
Random_B	0.5	Partial mass exchange
MixC_B	-	Mixing

To sum up the design of this set, scenario Random_A differs from MassC_J by introducing a random component for cross-contamination $\sigma = 0.2$. Then, experiment Random_B has it increased to $\sigma = 0.5$. Finally, scenario MixC_B has the same input parameters as Random_A with exception of the cross-contamination model, which is set for the mixing one, as the name suggests.

RANDOM COMPONENT SIZE EXPERIMENT RESULTS

The results from scenarios Random_A, Random_B and Mix_B are put into tables 6.9, 6.10 and 6.11 respectively. Additionally, the results, including further experimentation with the random component is put into plots, presented in the Appendix G.5 on page 127.

Table 6.9: Experiment results of scenario Random_A

Scenario	**Random_A**				
KPI	Average	SD	median	no. measurements	Unit
Avg throughput bags	1077.61	38.42	1085.99	320	bags/h
Avg throughput quantity	24821.37	1351.91	24939.92	320	kg/h
Orders completed	304.05	1.16	304.50	20	-
Orders completed on time	292.40	5.73	292.50	20	-
Avg contaminated order ratio above limit	0.08903	0.00837	0.08814	20	-
Total contamination above limits	0.0080	0.0006	0.0078	20	-

Table 6.10: Experiment results of scenario Random_B

Scenario	**Random_B**				
KPI	Average	SD	median	no. measurements	Unit
Avg throughput bags	1077.61	38.42	1085.99	320	bags/h
Avg throughput quantity	24821.37	1351.91	24939.92	320	kg/h
Orders completed	304.05	1.16	304.50	20	-
Orders completed on time	292.40	5.73	292.50	20	-
Avg contaminated order ratio above limit	0.08753	0.00849	0.08563	20	-
Total contamination above limits	0.0080	0.0006	0.0078	20	-

There is a number of additional scenarios including the effects of the random component together with various scheduling rules. As they are not directly devised to answer the research questions, they are put into the Appendix G.5 on page 127, with short analysis. Their results though, often appear in figures providing comparison among multiple scenarios.

Table 6.11: Experiment results of scenario Mix_B

Scenario	**MixC_B**				
KPI	Average	SD	median	no. measurements	Unit
Avg throughput bags	1079.11	30.47	1084.61	320	bags/h
Avg throughput quantity	24873.79	1278.97	24913.92	320	kg/h
Orders completed	304.25	1.26	305.00	20	-
Orders completed on time	293.65	3.64	294.00	20	-
Avg contaminated order ratio above limit	0.04018	0.00171	0.04056	20	-
Total contamination above limits	0.0036	0.0001	0.0036	20	-

FLEXIBILITY EXPLORATION

In general, it is expected that by introducing additional silos the flexibility of the system would increase, as there would be more freedom to make choices. But then, reserving certain silos for specific recipes should decrease this flexibility to reduce the total contamination. The following experiments try to provide quantifiable information to assess whether this expectation is correct, by introducing first scenario with 8 additional silos and measuring the values of the dependent variables. These are then analysed and six specific recipes, which are connected to products which are likely to be contaminated, are picked and silos are reserved for them.

Silo sizes are the same as in scenario MassC_N, but scheduling rules differ, as these are based on scenario Scheduling_A to have low contamination. The exact values of chosen independent variables for scheduling are put into tables 6.12 and 6.13.

Table 6.12: Dispatching rules for scenarios Random_H and Random_I with silo reservation investigation

Mixing order	Silo match	BTH1-2 silo pref.	BTH3 silo pref.	BTH1-2 dispatch	BTH3 dispatch
Smallest order	Best size fit	All	All	Earliest Mixing	Earliest Mixing

Table 6.13: Scheduling rules for scenarios Random_H and Random_I with silo reservation investigation

Rule	1	2	3	4	5	6	7	8	9	10	11
Value	YES	YES	YES	NO	NO	NO	YES	NO	NO	YES	NO

Moreover, a random component of $\sigma = 0.2$ is included. The specific silos and recipes that are reserved in scenario Random_I (6 silos in total) are shown in table 6.14.

Table 6.14: Chosen combinations of silos reserved for specific recipes in scenario Random_I

Silo Number	15	20	22	23	52	54
Reserved Recipe	3100	3113	3130	3149	3301	3412

Then the final two scenarios are fully defined.

FLEXIBILITY EXPLORATION RESULTS

The results from the investigation are put into tables 6.15 and 6.16

Table 6.15: Experiment results of scenario Random_H

Scenario	**Random_H**				
KPI	Average	SD	median	no. measurements	Unit
Avg throughput bags	1074.17	28.57	1079.21	320	bags/h
Avg throughput quantity	24769.10	1426.32	24977.36	320	kg/h
Orders completed	303.60	1.36	304.00	20	-
Orders completed on time	291.75	3.14	291.50	20	-
Total contamination above limits	0.08179	0.00669	0.07926	20	-
Ratio of material above limits to total processed	0.0073	0.0004	0.0073	20	-

Table 6.16: Experiment results of scenario Random_I

Scenario	**Random_I**				
KPI	Average	SD	median	no. measurements	Unit
Avg throughput bags	1052.19	56.29	1073.53	320	bags/h
Avg throughput quantity	24178.45	1816.54	24472.04	320	kg/h
Orders completed	301.00	2.86	301.00	20	-
Orders completed on time	284.25	7.29	284.00	20	-
Total contamination above limits	0.08079	0.00668	0.08057	20	-
Ratio of material above limits to total processed	0.0068	0.0005	0.0069	20	-

Additionally, the Appendix contains scatter plots for all experiments including the non-zero random component. Figure G.8 on page 130, to depict the relation between the total contamination and the average throughput, in Figure G.9 to show the order completion, and finally in Figure G.10 to show the relation of the total contamination to the average contaminated order ratio above limits.

6.5. EXPERIMENTATION CONCLUSION

This section concludes the experimentation phase. In total 46 experiments are performed in five scenario groups in chapter 6, following a funnel approach. The reasons for the choice of independent variables, in short to determine the impact of plant layout and scheduling interventions on production performance, are discussed, and the values of dependent variables (KPIs) given in Appendix G. Moreover, figures displaying selected charts of different KPIs in a scenario groups are included, to visualise the obtained data.

The following chapter provides an analysis of those results as well as recommendations arising from the experimentation.

7
Results Analysis

This stage deals with an interpretation and assessment of the results from the experiments performed in chapter 6. As described by van der Zee & van der Vorst (2005), a proper and universal way to compare various scenarios is needed to fairly judge their performance. The analysis is based on KPIs defined in section 3.4.1.

Statistical tests performed in this section are done with 95% confidence. T-tests, unless otherwise specified, are Welch two-sample ones, where equality of variances is not assumed. For variables where there are 20 values available additional F-tests are calculated to determine equality of variances (see column 'var equal' in result tables in Appendix G). When equality of variances is confirmed the pooled variance is used to estimate the variance, otherwise the Welch approximation to the degrees of freedom is calculated.

7.1. Results Presentation

Just as in case of experiment inputs, an extensive set of processed data is included in the SN tool for results visualisation. This comprises of six screens and multiple charts, gauges and table to provide the user with relevant information, allowing to make design (and in the future operational) decisions. Typically, when possible, information displayed is based on the average of multiple replications, and if needed, tables with raw data are available for preview. One of the important features are resource charts that can display machine utilisation in time intervals per different replications. Thus, important data is communicated in easy to understand, visual form. Several screen captures of the aforementioned SN tabs are presented in section D.2 and further.

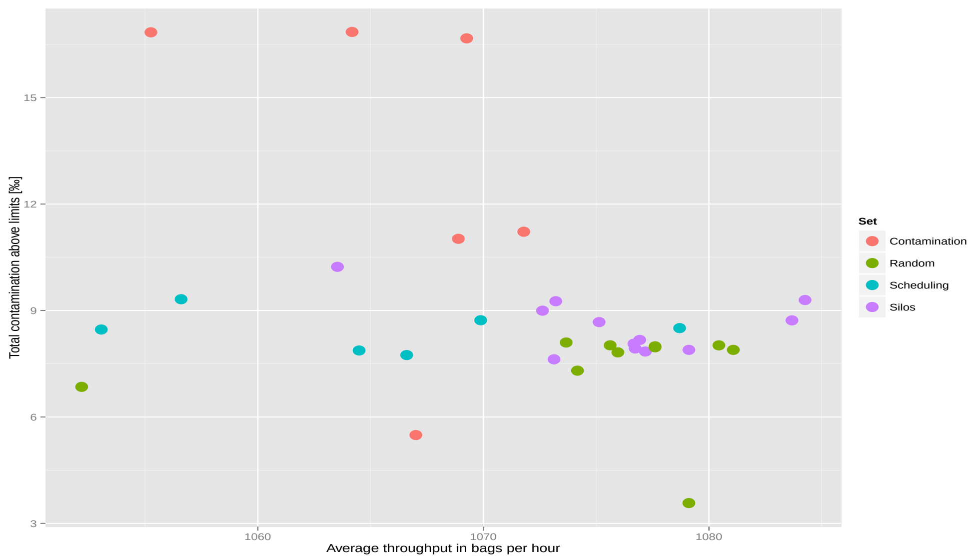

Figure 7.1: All scenarios plot for total contamination as a function of the average throughput

Moreover, Figure 7.1 shows a scatter plot of all scenarios including cross-contamination analysis for the average total contamination, shown against the average packaging throughput as a means to compare results among different scenario groups.

7.2. Initial Sensitivity Analysis Discussion

Initial experiments designed in section 6.4.1 are focused on finding the starting point for a more oriented search. The aim is to perform limited sensitivity analysis on adding extra silos, varying discharge speed, and reserving some silos for specific recipes. All done without including cross-contamination in the investigation. For more detailed description see section H.1, and for statistics see tables from H.1 on page 132 to H.10 on page 133.

There is some evidence to suggest that the more silos the more orders finished on time, and the higher average throughput. However, in total it is rather inconclusive. The only piece of convincing results refers to the difference in the average throughputs, when the silo discharge speed is lowered from 20 tonnes per hour to 18. In all three corresponding cases, with different silo number, the average throughput is significantly smaller. Likewise, when increasing the discharge to 22 tonnes per hour, the average throughput in all three cases is not significantly higher than for 20. This can be clearly seen in Figure 6.2. When comparing the same scenarios with the only difference of reserving silos, two out of three have a significant difference in means when comparing orders finished on time. Moreover, one in three is showing similar significance in the average achieved bagging throughput.

In the end, from the initial analysis, it can be concluded that the model is not highly sensitive to the varied parameters.

7.3. Impact of Cross-contamination

Experiments aiming to determine the impact of sequencing based on nutrient similarity on production efficiency are shown in table 6.4 on page 49. The goal is to determine the contamination characteristic with different methods of mixer order sequencing and nutrient based silo allocation.

Investigation into the total contamination in bagged products is shown in Figure 6.4, which clearly indicates, together with performed t-test shown in table H.11 on page 133, that mixer sequencing based on nutrient similarity is significantly better (lower contamination) than simple recipe joining or no intervention, except for order sorting. Surprisingly, recipe joining is not significantly better than no specific sequencing. This can be because of limited knowledge about the nutrients and their limits, based on which the final contamination is assessed, or even an outcome due to the used order set. What is vital, nutrient based sequencing is a much better method to keep contamination low.

Also as expected, the total contamination when using the mixing cross-contamination model is much lower than for partial mass exchange one. This is due to the steepness of the release curve, as a result of which, the foreign residue is concentrated in the early batches after the change of product. Of course, the same amount of material is carried, but in the mixing model the early batches are more contaminated than in the partial mass exchange model, resulting in quicker disposal of the residue.

Figure 7.2 shows a scatter plot of the total contamination in the bagged material as a function of the average contamination in polluted orders, which have at least one off-specification bag. Additionally, error bars are added to signify 95% confidence intervals. Clearly, there is a strong connection between the average pollution and the total contamination, almost linear based on Figure 7.2, and the lower the contamination, the smaller the uncertainties.

Finally, no evidence that allocating silos based on nutrient similarity has limiting effect on contamination could be found, when comparing scenarios MassC_A and MassC_B as well as MassC_C with MassC_D. It is possible, that there is no such correspondence for the given system, or it is due to the limited choice of silos when starting to mix a new order. With increasing number of silos this effect could be noticeable. Moreover, since most of the residue is concentrated in equipment before the silo, it is possible that further carry-over has little effect on final contamination.

7.3.1. Cross-contamination Model Comparison

To compare the developed models and asses the possible error made by using a wrong one, data on off-specification order ratio is extracted and put into table 7.1.

Nutreco specialists claim, that the best state-of-the-art automatic production support tools, available in the corporation and commercially on the market, measure inflow material and use a mixing model for pre-

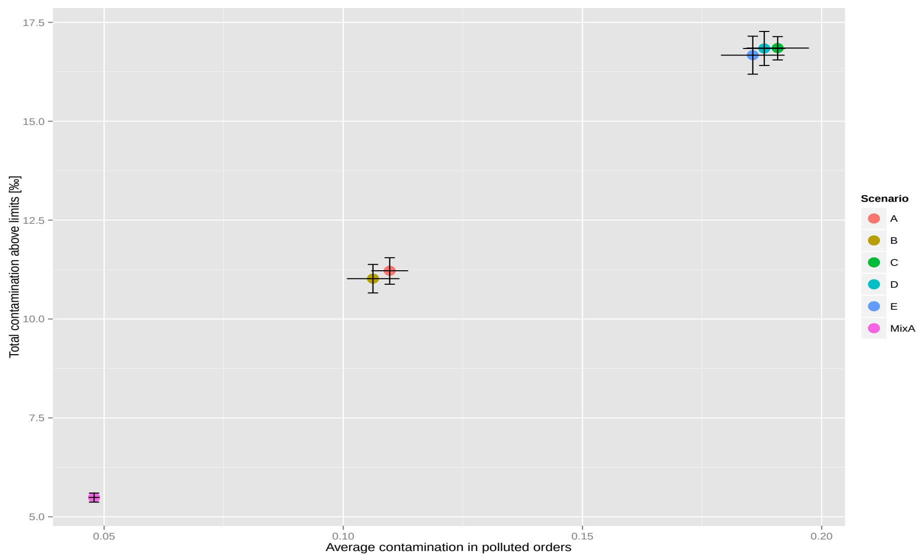

Figure 7.2: Scheduling parameters chosen for the base case experimentation scenario

diction of the flow progress. Assuming that the developed partial mass exchange model provides an exact prediction of the process, the error made when using the mixing model instead can be estimated.

Table 7.1: Statistics on order above limits ratio for different cross-contamination models

	MassC_A	MixC_A
n	696	714
mean	0.10955	0.04790
st dev	0.09948	0.02972
median	0.08750	0.04063

Thus, the expected value of the difference between all possible sample means is equal to the difference between population means:

$$E(x_1 - x_2) = \mu_d = \mu_1 - \mu_2 \tag{7.1}$$

The standard deviation of the difference between sample means σ_d is approximately equal to:

$$\sigma_d = \sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}} \tag{7.2}$$

When calculated the values are:

$$\mu_d = 0.06165 \tag{7.3}$$

$$\sigma_d = 0.00393 \tag{7.4}$$

The 95% confidence interval for the difference is thus from 0.06144 to 0.06186. The discrepancy accounts thus for over 6% of the contaminated order size, that is misjudged as within limits, while assessed off-specification with a more accurate prediction method. Relatively to the order ratio, this is an almost 130% increase, which deems such mixing models unreliable for estimation.

7.4. Layout Interventions Impact

Experiments designed in section 6.4.3 deal with assessing the impact of introducing additional intermediate storage in between mixing and bagging. Chosen independent variables are listed in table 6.5, and the results in tables from G.19 on page 122 to G.30 on page 124. Statistical tests for order completion, total contamination and average throughput are put in tables H.12, H.13 and H.14 respectively.

Based on Figure 6.6 there seems to be a relationship that when silo capacity increases, so does the average throughput. It is stronger for the overall capacity than for silo number. The plotted relationship shows that with further increase of silo capacity, the relative increase of the average throughput decreases, and seems to approach asymptote at over 300 tonnes. Fewer bigger silos have a higher positive effect on the average throughput than more smaller ones.

Similarly, Figure 6.7 shows the relationship of the total contamination and additional silo size. Here, the relationship does not seem to be so straightforward. In the beginning, with an increasing additional silo capacity the total contamination decreases, but after it has reached around 200 tonnes, it starts increasing rapidly. But when looking at the silo number, the link is ever decreasing – the more additional silos, the lower the total contamination.

Both of these relationships can be explained. For capacity, the total contamination initially decreases because of increased flexibility in choosing the intermediate storage, as well as lower chance of splitting orders among multiple silos, which could result in higher contamination. But with increasing silo capacity, the total material residue in the system increases as well. At some point, the benefits from better fitting the orders outweigh the drawbacks of putting a few relatively small orders into too big silos. As such, there is a increased risk of higher contamination with very large silos.

Then, Figure 6.8 shows a scatter plot of the total contamination as a function of the average throughput. Another version of this chart, including error bars for 95% confidence intervals is shown in Figure 7.3, to depict the uncertainties to the means shown in the plot, arising from the simulation.

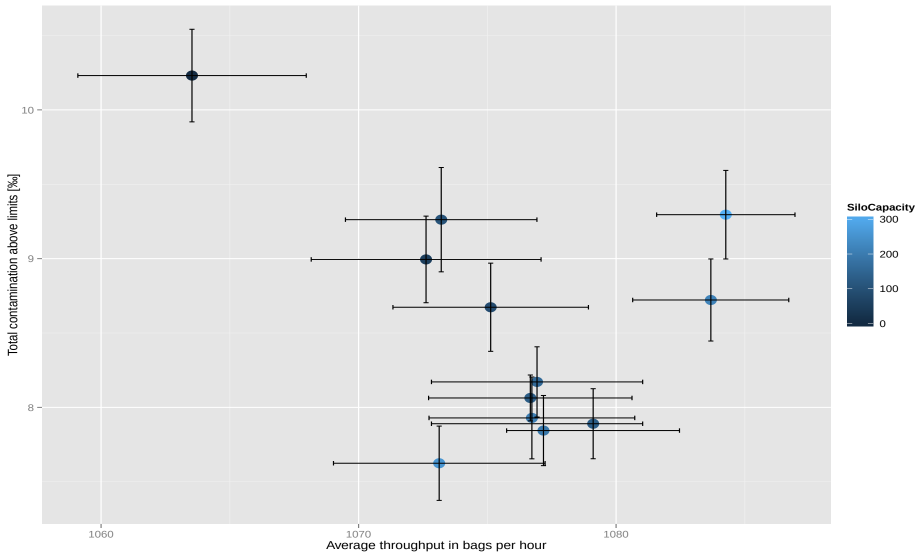

Figure 7.3: A scatter plot displaying average results for contamination with respect to achieved throughput with error bars for 95% confidence intervals in silo parameter analysis

Based on Figure 7.3 there is a region, with relatively low contamination and high average throughput, not very sensitive to changes in silo parameters. Even large variations in additional silo capacity have little effect on the average throughput, which is relatively less than 2% between the lowest and the highest achieved. On the other hand, the relative difference in the total contamination amounts up to 35% relative difference.

Finally, statistical tests, the results of which are put into tables H.12, H.13 and H.14, are performed with assumption that the bigger the total silo capacity, the higher the average throughput, more orders completed on time and less total off-specification material. This is the case only in the beginning, when increasing additional silo capacity from 0 to about 100 tonnes (2 or 4 extra silos). Further on, the sensitivity of response decreases.

7.5. IMPACT OF SCHEDULING ANALYSIS

An analysis of the impact of scheduling rules on the production efficiency is performed to assess possibility o positively influencing certain parameters and determining coupled trade-offs. The results are put into tables from G.31 to G.36 on page 126.

Figure 7.4 depicts a scatter plot with error bars, where the average total contamination is plotted against the average bagging throughput. Since the scheduling interventions are based on scenario MassC_K, it is also included in the plot. Most importantly, it is shown, that a proper choice of scheduling rules can, up to some point, increase multiple factors of production efficiency. Scenarios Scheduling_D and Scheduling_E have both higher contamination and lower throughput than scenarios Scheduling_A or Scheduling_B. But, at some point, with this method of scheduling logic there seems to be a trade-off relation between lower contamination and higher throughput. Additional experiments are needed to explore this relation, but basing on this preliminary analysis, there might not be a set of scheduling rules achieving best results in all aspects.

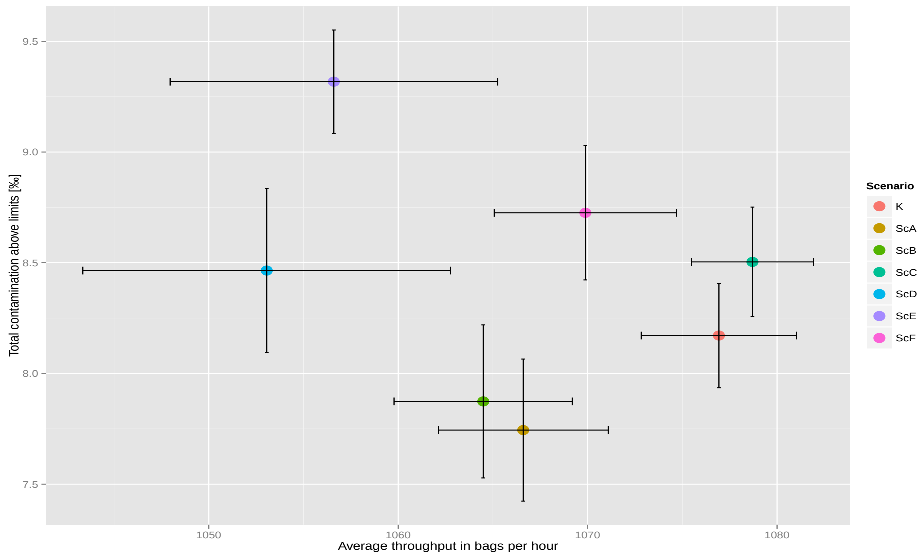

Figure 7.4: A scatter plot displaying average results for contamination with respect to achieved throughput with error bars for 95% confidence intervals in scheduling analysis

To add to the insight, a plot similar to 7.2, exploring the same relationship between total contamination and the average contamination in polluted orders, is shown in Figure 7.5. This time, the corresponding relation is not close to linear. On the contrary, no visible correspondence between these two factors can be distinguished. Nevertheless, from the limited performed analysis, which does not include scheduling optimisation, there are several conclusions that can be made.
Taking advantage of the mixing sequence is beneficial to low contamination. Chosen dispatching rule for bagging 'Earliest mixing time' sufficiently well performs this function, with significant lead of mixing before bagging. Thus increasing chances that cross-contamination occurs between products of similar nominal composition and as a result the participating products are not too heavily affected. Of course, as all scheduling choices, it is not optimised, and comparison with an optimum schedule cannot be made.

Attempts to increase the throughput are, in this case, based on the specific factory layout, and difference in capacities between packaging lines. By diverging larger orders to line 1 with higher capacity, the number of needed production changeovers decreases, as there are two machines on line 1 in contrast to line 2, where there is only one. However, when this methodology is utilised, the number of available orders to bag in the intermediate silos is an important factor, and the low contamination logic can no longer be utilised. It can be thus concluded, that there is a trade-off between these two factors, and it should be up to the scheduling decision maker, to choose one preferred or provide a function weighing these (e.g. total perceived monetary cost). Only then, can there be judgement made on which rule is the best.

However, there is an important limitation in the analysis – it is performed based on a single set of manufacturing orders. Although these are taken directly from the facility to increase realism, it is possible that for a different set the results could be entirely different. In the end, this inquiry is to give predictions and increase insight into the process, and not give the best scheduling solution, which is the outcome not only of scheduling logic and manufacturing orders, but also operational circumstances, which are not explored in this investigation.

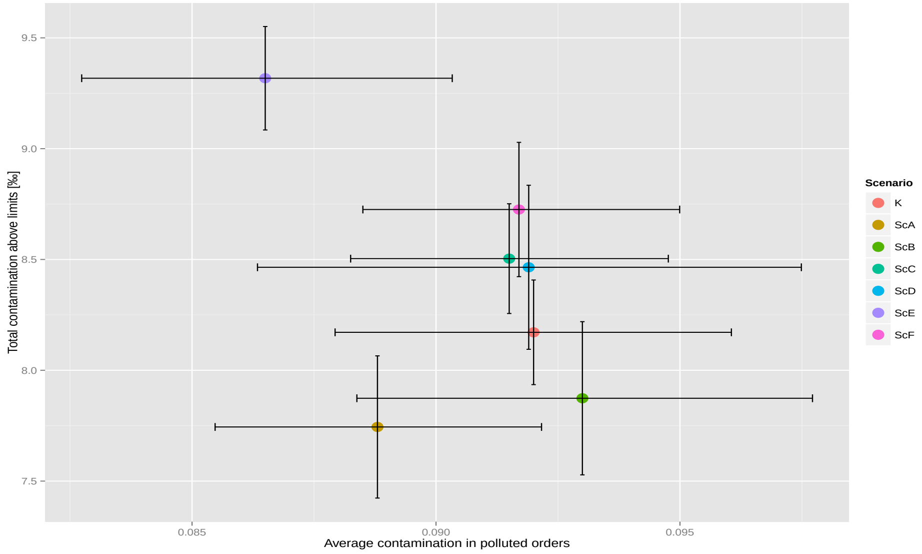

Figure 7.5: A scatter plot displaying average contamination in polluted orders with respect to the total contamination, including error bars for 95% confidence intervals in scheduling analysis

7.6. RANDOM COMPONENT INVESTIGATION ANALYSIS

Random component for cross-contamination calculations is introduced in attempt to recreate similar peaks and valleys in the contamination curve as measured, and assess the impact of uncertainties in single calculations on the total amount of cross-contamination.

7.6.1. SIZE OF THE RANDOM COMPONENT EFFECT

Figure 7.6 shows a scatter plot of results from chosen scenarios investigating the random component size effect on the average throughput and total contamination.

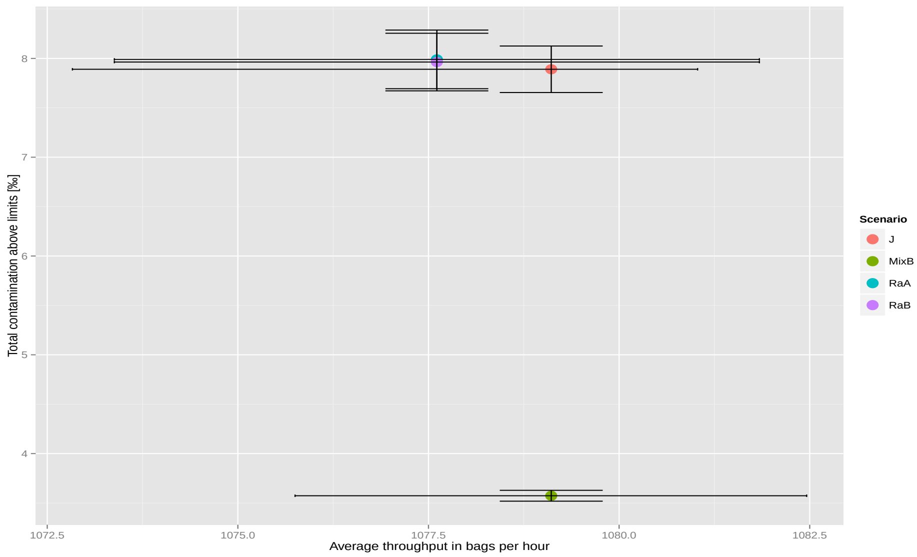

Figure 7.6: A scatter plot displaying average contamination in polluted orders with respect to the total contamination, including error bars for 95% confidence intervals in random component analysis

Random component has a slight influence on the total contamination. Scenarios MassC_J and MixC_B, which do no include the random component have the exact same achieved throughput, but different total contamination because of utilised cross-contamination models. If that was not the case, the validity of the model should be questioned, because a technique called common random numbers (CRN) is utilised i.e. different scenarios run with the same random value stream, from which the values are drawn. Similarly, scenarios Random_A and Random_B have the exact same throughput but slightly different contamination.

As all of the scenarios are run with the same set of independent variables for throughput and scheduling, it should be expected that, due to the CRN the achieved throughput is the same. This is not the case as random value streams are not differentiated for stochastic variables and scenarios including the random component draw from this stream much more frequently, and the correlation to runs without the random component is not maintained. In the future, utilised random value streams for different stochastic variables should be separated.

When the random component is included, the contamination changes. However, based on the t-test shown in table H.16 there is no significant difference in means among the results achieved without the random component and when it is set to $\sigma = 0.2$ or $\sigma = 0.5$. Similarly, no difference for throughput can be determined for any of the scenarios in this set.

The reason for little difference between using a non-zero random component and not including it, might arise due to investigation into total effects of contamination and not specific changes in the release curves. As the total amount of residue swept is the same for both models, the total number of off-specification bags are not affected by slight changes in the individual contaminations.

That is why a more in-depth inquiry is performed looking at specific orders. Scenario Random_B has 668 recorded polluted orders, while there are 659 such orders for Random_A, for all 20 replications. Comparison shows, that out of them in 281 cases the order contamination is simulated to be the same, 158 times contamination in orders from Random_B is greater that equivalent one for Random_A and 229 is the other way around.

It can be concluded that additional efforts in modelling are required to better recreate the contamination curve. Devised method, even assuming that additional assumptions are valid, is not a means to adequately model the issue. However, it gives a few important indications, mostly that the assumptions made about constant value of specific equipment total residue is in all likelihood not valid. Cross-contamination has a very complex character, which is only in the early stages of analysis and additional data is needed to more accurately model the process.

7.6.2. Flexibility Exploration Analysis

The final analysis concentrates on the impact of reserving silos on contamination. It is established in section 7.3, that the biggest impact on total contamination comes from initial order sequencing, which should be done based on consecutive product nutrient contents.

Tables 7.2 and 7.3 provide one-sided t-tests on the difference of the average throughput and total contamination when six arbitrarily chosen silos are reserved for recipes, which compose some of the contaminated products from scenario Random_H.

Table 7.2: Comparison of impact of silo reservation on the average throughput for 8 silos

Hypothesis	n	mean	SD	t	df	p	95% conf. interval
H_1 :Ra_H>Ra_I	640	1063.18	46.01	6.2206	473.137	**5.452e-10**	16.1614: Inf

Table 7.3: Comparison of impact of silo reservation on total contamination

Hypothesis	n	mean	SD	var equal	t	df	p	95% conf. interval
H_1 :Ra_H>Ra_I	40	0.00708	0.00052	TRUE	3.049	38	**0.002083**	0.00730: 0.00685

It can be thus concluded, that although the effect is small, there is a statistically significant, with 95% confidence, decrease in contamination when silos are reserved for some recipes to prevent cross-contamination in them. In parallel, because of that action, there is a significant decrease in the average achieved throughput as a cost of lower number of off-specification products. Indeed, there is a trade-off relation between flexibility in terms of free choice of intermediate storage silo and production efficiency factors of contamination and throughput.

7.7. PROPAGATION OF ERRORS ESTIMATION

Below considerations assume that all investigated variables are independent, and that their errors have a normal probability distribution. For the numerous observations, according to the central limit theorem, this is an acceptable assumption.

7.7.1. CHANGEOVER TIME ERRORS

Changeovers CH are independent delays that happen after the end of processing of a product at a machine, as defined in section 5.3.2. Then, the uncertainty of function basing on these delays is a linear combination of the exact number of observations for a given machine n, and given by equation:

$$f_{CH} = n \cdot CH \tag{7.5}$$

Then the standard deviation of the total error is :

$$\sigma_{f_{CH}} = |n| \cdot \sigma_{CH} \tag{7.6}$$

For example, in scenario Scheduling_C there are on average 111 changeovers for BTH3 machine. Then, for $\sigma_{CH} = 123.75$ seconds, the total deviation is:

$$\sigma_{f_{CH}} \approx 3.82 \quad [hours] \tag{7.7}$$

While the total average changeover time for the period is:

$$f_{CH} \approx 9.92 \quad [hours] \tag{7.8}$$

7.7.2. SHORT STOPS INACCURACIES

Short stops are cyclic combinations of two factors: time to failure and time to repair, each with their own independent uncertainties. Then, the expected time of the cycle is:

$$S = MTBF + TTR \tag{7.9}$$

And the total function can be expressed:

$$f_S = n_{MTBF} \cdot MTBF + n_{TTR} \cdot TTR \tag{7.10}$$

Having the same number of occurrences of failures and repairs the standard deviation of the resulting function is:

$$\sigma_{f_S} = n\sqrt{\sigma^2_{MTBF} + \sigma^2_{TTR}} \tag{7.11}$$

Then, knowing that the standard deviation of an exponential function is equal to the mean, the final formula can be written:

$$\sigma_{f_S} = n\sqrt{MTBF^2 + \sigma^2_{TTR}} \tag{7.12}$$

As the time to repair is approximated by a log-normal distribution in table 5.1, the non-logarithmized values need to be calculated. Denoting distribution parameters μ_{log} and σ_{log} the mean and standard deviation of the variable's natural logarithm respectively, the sought for values are:

$$\sigma_{TTR} = \sqrt{(exp(\sigma^2_{log}) - 1) \cdot exp(2\mu_{log} + \sigma^2_{log})} \tag{7.13}$$

$$TTR = exp(\mu_{log} + 0.5\sigma^2_{log}) \tag{7.14}$$

Then, based on table 5.1, parameter summary for error propagation is constructed in table 7.4.

Table 7.4: Error propagation parameters for short stops

	Mixer	BTH1	BTH2	BTH3
μ_{log}[s]	3.12	1.91	2.26	2.93
σ_{log}[s]	0.93	1.20	1.22	1.17
$MTBF$ [s]	1426.00	185.50	380.10	651.20
TTR [s]	34.90	13.87	20.17	37.13
σ_{TTR}[s]	40.92	24.90	37.36	63.57
S [s]	1460.80	199.37	400.27	688.33
σ_S[s]	1426.49	187.16	381.93	654.30

The total number of short stops is not recorded in the simulation, and thus only estimation for a single cycle is given.

7.7.3. Cross-contamination Uncertainty Evaluation

There is no function to describe cross-contamination of a product batch given. This section tries to derive a generalised way of expressing it, and discuss a method of error approximation. An expansion of the method presented below, not for a single product batch but for an entire order, would be vital to further use in mixed integer linear programming methods for optimisation.

Contamination in a product batch C_B is then a sum of contamination picked up in the mixer and swept further along the route until bagged. The following consideration assumes using the partial mass exchange model, without the random component and all designations as in section 4.4.1. Then, assuming exactly known route for the product, the function can be given as:

$$C_B = C_{Mixing} + C_{Route} \tag{7.15}$$

The mixing contamination, given that the batch enters it uncontaminated, is then a function of the residue, its composition, total material quantity in the mixer and batch mass, see equation (4.18).

$$C_{Mixing} = f(TR, R_i[item, quantity], n, M) \tag{7.16}$$

And the route contamination is a sum of es crossed equipment segments S, denoted by function g_S:

$$C_{Route} = \sum_{S=1}^{es} g_S(TR, R_i[item, quantity], EAP, M) \tag{7.17}$$

It is also possible that contamination in a given segment or even entire route is negative, thus decreasing the total contamination. Then, assuming that material quantity in the mixer and mass of a batch are exact, without uncertainties, and that the current residue composition in a piece of equipment $R_i[item, quantity]$ is a derivative of previous exchanges with exactly known starting value, the only uncertain variables are TR and EAP. The contamination functions, presumed differentiable with respect to uncertain variables, are in fact sets of non-linear combinations of the variables that need to be linearised by e.g. Taylor series expansion. Furthermore, neglecting correlations between variables, and adding denotion S to route segments parameters, the standard deviation of the formula yields:

$$\sigma_{C_B} = \sqrt{\left(\frac{\partial C_{Mixing}}{\partial TR_{Mixing}}\right)^2 \sigma^2_{TR_{Mixing}} + \sum_{S=1}^{es} \left[\left(\frac{\partial C_{Route}}{\partial TR}\right)^2 \sigma^2_{TR} + \left(\frac{\partial C_{Route}}{\partial EAP}\right)^2 \sigma^2_{EAP}\right]_S} \tag{7.18}$$

As in (Ku, 1966, see equation 2.10)

7.8. Variance Reduction

Most figures presented in this chapter are drawn with 95% confidence intervals, implying that the true mean lies somewhere between the minimum and maximum value, not necessarily being as calculated. This is due to the stochastic nature of some of the input variables and different outcomes of the scheduling rules. Ideally, this interval should be as low as possible to signify high certainty of the achieved output, providing there is no bias in data. In the presented case the intervals might be viewed as large. However, the figures are scaled so that the differences between achieved outputs are clearly visible. Figure 7.7, a version of Figure 7.1, shows the dependent variable ranges from zero, and does not allow for distinguishing much. Plotted 95% confidence intervals indicate, that the relative difference in achieved values is not high, often hardly distinguishable on the plot.

Yet, it is still possible to reduce the variance by increasing the number of performed replications. All experiments, the results of which are presented in Figure 7.7 are run with 20 replications, while increasing this number even further would decrease the intervals (see also section on how number of replications is chosen in Appendix A.3.3). By default Simio uses the same stream of random numbers for a given replication, so that wherever possible the advantage of common random numbers (CRN) technique can be taken.[1] Differentiating random number streams in the simulation, currently running with a single stream, would have positive effect on variance reduction.

[1] See *Simio Reference Guide* for details, topic "Simulation Replications" in version 7

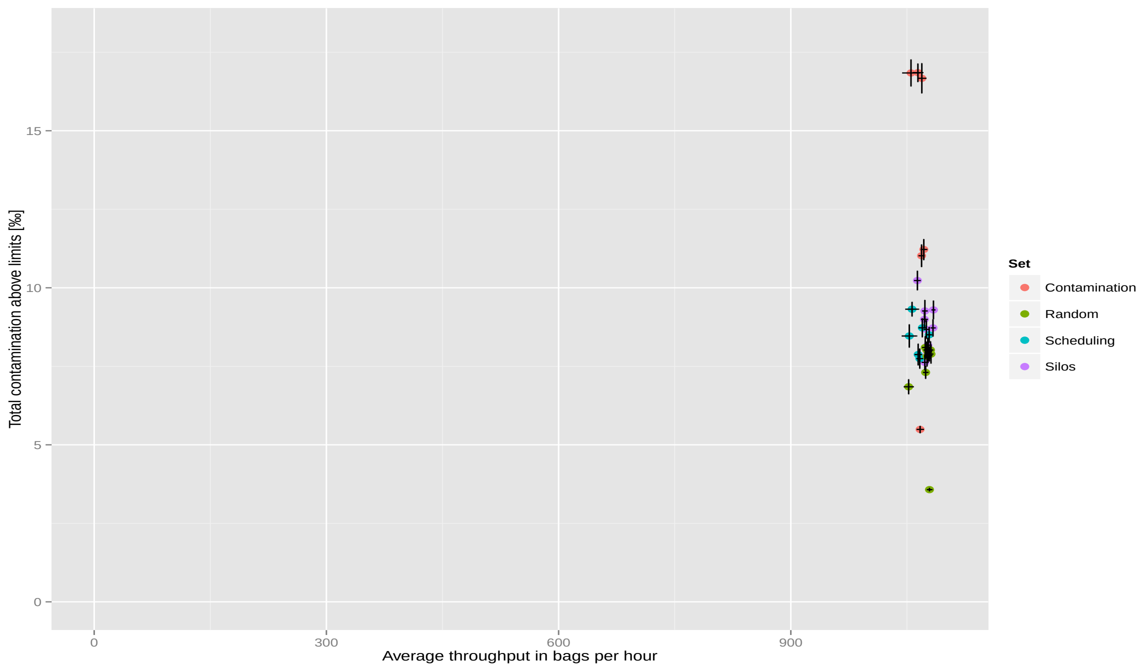

Figure 7.7: A scatter plot indicating the average variance for investigated scenarios

On the other hand, due to differences in manufacturing order list, and consequences of machine starving time, changeovers, shift duration for a given day etc., the gain cannot be very high. A single change in sequence or silo allocation of a single order can result in it taking a polluted path and skewing the results for total contamination, while in another replication with a different random value stream such situation might not happen. Box plots for throughput from chapter 6 depict a significant number of outliers, which are not going to disappear with simple increase of replications.

7.9. RECOMMENDATIONS

The experiment analysis chapter is concluded with a set of general recommendations, that are relevant to similar cases, including cross-contamination calculations. For case specific recommendations see section C.7, and for thoughts on future research direction see section 8.4.

First of all, the research shows that it can be extremely useful to include investigation into cross-contamination effects in production environments. By managing to explore product contamination in this way, an additional aspect of the production performance can be analysed, which is a supplementary layer to typical consideration providing a lot of useful information, that could help decision makers in their responsibilities. Thus for most, or possibly all industries with cross-contamination problem, it is recommended to include a form of such analysis.

Cross-contamination character is directly connected to the equipment properties, especially the total amount of residue remaining in the system. The more short-term residue, the more carry-over between products and the larger the cross-contamination. Reducing this amount would have a direct and significant influence on lowering the amount of off-specification product. This can be done by e.g. choosing a different piece of equipment, one which has a better cross-contamination characteristic. During the measurements it was determined, that a pneumatic conveying system has much less residue than screw conveyors. Just as for Sloten, replacing all the screw conveyors with pneumatic ones of sufficient transportation capacity could reduce cross-contamination problem, for any other system choosing machinery with consideration of this factor could help avoiding extensive pollution. Conveyor manufacturers often claim that there is a very low residue in their products[2], but do not provide any measurements of that characteristic. Including comprehensive analysis for many bulk products would be very expensive, or even impossible, but some indication

[2]Based on several internet folders scrutiny

of the extent would be useful in assessing which manufacturer to choose.

Discrete event simulation is a useful way to attempt predicting performance of a future production system, which is not yet fully defined. It allows for relatively easy addition of extra features and exploring impact of uncertain values, by means of sensitivity analysis. Moreover, it is possible to include stochastic variables in DES and assessing their joint influence on dependent variables. It is thus recommended to be used as one of the methods of validating a system design.

Acquiring such deep understanding of the cross-contamination issue, will most certainly help making more informed decisions on both system design as well as daily operations. Taking it further to create a decision support scheduling tool, that is integrated into the planning landscape, and that is used to assist planners in making scheduling decisions, would be very beneficial. Such appliance, able to quickly assess different scenarios, could help find a scheduling arrangement most suited for a particular period, given specific preferences that are difficult to formalize (like breaks, convenience, preference, experience, workforce skill impact etc.). Cross-contamination analysis undoubtedly should be included for cases of similar systems.

Finally, investigating a problem, whose composing system has a large number of input variables, because the system does not exist in reality, is not ideal. To deliver more valid results, it would be better to perform the analysis on an existing setup, and not combine two different analysis goals in one. But then, assessing the effects of layout interventions would probably not be the goal, and the analysis would have much more operational character.

8
Conclusions

This chapter first gives the conclusion of the project findings, then author's reflection on the research, and finally identifies several important directions for future research. First of all, a discussion divided into scientific part, including research questions answers, and practical implications is given.

8.1. Discussion

This research presents a unique and novel method, which describes how to model cross-contamination in a discrete event simulation. Typical models analysing production systems do not include such feature. Although its creation is connected to multitude of assumptions and the use has its limitations, by including such considerations an improved insight into the problem of cross-contamination in high technology production environments can be created. In this way, organisations can better explore and understand how technology can be used, to deliver products of better quality, in the end contributing to improving outcomes, such as customer satisfaction, corporate productivity, profitability and competitiveness.

Performed cross-contamination measurements to determine the magnitude of the problem tell about the general character of the release curve, and confirm its similarity to axial dispersion problem (Liao & Shiau, 2000). As Leloup et al. (2011) stated, the tracer-collector method is an adequate means of measuring the extent of the issue, and by adding intermediate sampling points a lot more information can be determined. Two cross-contamination models built based on this investigation are generic, and could be utilised in other models or models of different systems.

The achieved results show, that such scrutiny should be included, and more effort needs to be put to solve the problem of quality decline as a consequence of cross-contamination. Analysing the effects of various interventions in the chosen case shows, that both system layout and production scheduling have a considerable impact on production efficiency.

8.1.1. Research Questions Answers

Eight auxiliary research questions are formulated in section 1.3, to focus the study efforts. The answers for them are gathered throughout the research, allowing in the end to phrase them:

1. *What is cross-contamination, and why is it important for multi-product factories?*

Cross-contamination is a process of mixing material residue, left by preceding products, into the next processed batch. Short term residue is leftover product that sticks to surfaces it is transported through. Because of the flow and friction, material adhered to them gets loose and is picked up with a stream. Its place is then taken by some of the powder coming through (Leloup et al., 2011).

It is assumed, because of lack of detailed analysis, that the amount of residue in a particular location is roughly constant once it is built up, providing the properties of handled material are similar, mostly in terms of particle size, viscosity and friction parameters. Some aspects are difficult to model as there is some amount of chaotic mixing involved. Though it is expected that such assumptions are in the end not valid.

In multi-product factories cross-contamination might result in a decline in product quality, which can further lead to issues concerning product safety (Fink-Gremmels, 2012). Handling a large number of products on the same manufacturing line poses a higher risk of cross-contamination, forces them to put bigger effort to production scheduling (Toso et al., 2009) and often requires additional treatments, like cleaning, rework, or possibly even reject affected portion altogether.

2. *What are the relationships between factors influencing cross-contamination?*
Developed model distinguishes two major components affecting the magnitude of cross-contamination: the total amount of residue located in the equipment, and the way this material is released to the incoming product. Although this is not a complete list, the model is capable of sufficiently well recreating behaviour determined during measurements in the case factory.
Then, the more residue in the system, the bigger the total extent of cross-contamination, i.e. more products are affected. But the precise character of sweeping material residue with the flow is determined by the shape of the release curve, which is recreated by one of two cross-contamination models in the developed simulation. Comparison made between mixing and partial mass exchange cross-contamination models shows, that the way residue material is incorporated into the next product has a tremendous effect on final material composition. In essence, it can be taken very quickly and amassed in front of a batch, or more slowly released and affecting larger portions of material.
As Fitzpatrick et al. (2004) determine, distinguishing investigated powders based on cohesiveness and friction angles, would lead to better prediction of the possible behaviour. Further inquiry into the total amount of residue, as well as to shape of the release curve, is undoubtedly needed.

3. *What are the effects of cross-contamination, and how are they relevant?*
The effects of cross-contamination can be divided into three categories: neutral, unwanted but acceptable and forbidden. Neutral is when mixing happens between the same or very similar materials, and the resulting mixture upholds all relevant quality standards. In this case, cross-contamination occurs, but its effects are limited, if at all distinguishable. In some cases, transferred carry-over contains material that is not specific to the manufactured product or results in concentrations that are different than intended, but still acceptable. In such cases, the total product quality declines but there is no reason to reject the product altogether. It might have to change its product category, destination (client) or require rework of some magnitude, but is going to be still regarded as sales product.
Finally, there is a chance that some forbidden material is transferred cannot be there, either because of quality standards or safety reasons. Such product must be discarded and creates significant losses for the company. That is, if it is actually discovered as the quality control of related issues is often lacking. In the investigated case, cross-contamination of animal feeds poses risk of even poisoning target animals (Zervas et al., 1990).

4. *When is a product considered out of specification?*
A final product is considered off specification when it does not meet quality standards that it was initially intended to. In the case of Sloten and other similar businesses, there are several company-specific categories of final mixture contents, based on which the products are evaluated. There is a certain level of specification contents of each of the components ,or nutrients in this case, that are added to create the product, and some level of acceptable deviation from this specification, called lower and higher threshold levels. If either of this thresholds is breached, just for one out of many investigated components, the product is considered out of specification.

5. *How to express product-residue mixing in a mathematical way so that it can be used as a general approach for expressing product contamination?*
A means of quantifying cross-contamination is devised and modelled. Two alternative methods, basing on principles of segmentation, quantity conservation, product similarity and proportionality, are devised. Succeeding in sufficiently well recreating measured release curve shows, that it is possible to create calculation method for one-by-one indirect reassignment of some material contents between consecutive discretised product batches. One that is mathematically sound, can be used to investigate an actual production system, and in the end help in better understanding of the involved issues.
The devised general approach is a series of independent material exchanges, in essence mixing, happening whenever a material batch leaves distinguished segment of the system. The mixing model always results in homogeneous composition of a product batch and residue in the equipment, while the partial mass exchange model has an extra parameter saying how big portion of both product batch and equipment residue is mixed together. In the end, it is a necessary intermediate step for further investigation (Sen & Ramachandran, 2013).

6. *Can cross-contamination phenomenon be modelled in a discrete event simulation paradigm?*
Cross-contamination can definitely be included in a DES model, complementing typical investigation into

production with a directed analysis into the issue. By expressing batch contamination and equipment residue in tables where specific components and their quantities are saved and handled, a generic way of keeping track of the current components and proportionally mixing them is devised. The biggest limitation is that it requires a fixed size, small material batches, which results in considerable computing time. Moreover, so far the ability to recreate peaks and valleys observed in the measurements is rather narrow. Further work is needed to improve on the method and increase its usefulness, as the ability to include and assess uncertainties can provide a better insight to the process (Mula et al., 2006).

7. *What are the effects of additional buffer capacity in manufacturing on cross-contamination and production capacity?*
Production efficiency comprises many factors relevant for companies. In general it is concerned with achieving the greatest output with the lowest input, but due to its multiple aspects, and also because of changing goals, it is often difficult to explicitly present. For Sloten in this research, there were two most important aspects: line capacity (in terms of finished product throughput) and resulting product contamination. Flexibility manifests as the ability to use multiple pieces of equipment for different products (multi-purpose allocation) and appropriate conveying connections to suit it. Moreover, relatively small lot sizes, agility, quick response to customer and WIP quantity, are all aspects of this adaptability. Normally companies try to limit the trade-offs between performance and flexibility by understanding, measuring and constantly improving their process (Sandborn & Vertal, 1998). Sometimes these are understood literally when a minimum in a perceived cost function is sought for, especially in daily operations. But when a chance arises, for example before bigger organisational changes, some seize the opportunity to introduce more systemic improvements in pursuit for simultaneous increase of several performance indicators.
Additional buffer capacity introduces more flexibility to the process but also more complexity in scheduling. Adding more silos can help in increasing line capacities, as there is then more work in progress and better scheduling choices can be made. For the investigated case where a bottleneck is at the end, capacity increase is minimal, only due to a better distribution of products among the machines and slight reduction of changeovers. However, this occurrence is very specific to the investigated system and might not happen in another, which has to be analysed separately.
Increased buffer capacity can have a positive effect on the total contamination, where it can be used to reduce the negative effects of cross-contamination by choosing a different intermediate storage, which was previously used for the same or similar material. Providing the silo size is similar to the order, which is not split among multiple storage places, the resulting contamination can be limited. However, large increase of storage capacity poses a risk of much higher contamination, as it increases the total amount of residue in the system. Fitting relatively small orders in too big silos might result in excessive impurities and in general poses a risk of higher contamination.

8. *Which scheduling rules are beneficial for reducing the extent of cross-contamination, and what is their impact on production capacity?*
Most of all, proper sequencing of products can reduce the negative effects of cross-contamination. By making sure that consecutive products in given intervals of the production lines are similar, such mitigation can be attempted. In the investigated system, scheduling choices of first incrementally sequencing most similar orders, then fitting them tightly in a single silo with a neutral material residue, and finally packaging them in an order as close to the mixing sequence as possible, are best.
When certain choices to reduce the overall contamination are made, they have their tow on achieved capacity, i.e. they limit the available remaining choices and might constrain achieved capacity. Yet, for the investigated system the negative effect, although statistically significant, was low, and possible gains from less contaminated materials, in the view of company specialists, outweigh the slight decrease in throughput. However, a quantitative analysis into the total connected costs needs to be made to accurately depict the difference, and possibly confirm this assessment.

To sum up and answer the main research question, there are many effects of cross-contamination on the amount of off-specification goods in a multi-product factory when varying buffer capacity and scheduling rules, most of which are adverse to product quality. The investigation concentrates on the impact of scheduling interventions as well as varying buffer capacity, and determines that both these sets have a significant ramifications on off-specification goods.

In essence, cross-contamination is unavoidable in a multi-product factory, but its negative effects can be mitigated. Biggest impact comes from production sequencing, a specific scheduling aspect, which, if done properly, can limit the negative repercussions of cross-contamination. In the investigated system most of the residue is located in the beginning of the process and thus the initial sequence is so important. But in fact, all choices need to consider the effects of cross-contamination.

To a large extent facility layout and available space are relevant as well, mostly because of the total amount of residue in the system, that has a direct connection to the extent of cross-contamination, and as a result number of off-specification products. When designing or altering a production system an analysis into specific contamination issues is needed, because once it is created there operational (scheduling or procedural) interventions to contain it are more limited.

Yet, as Erenguc et al. (1999) claims, all aspects of production efficiency should not be seen as each other trade-offs but be simultaneously prioritised in search for the best solution. Although a comparison with an optimum schedule cannot be made, scheduling via dispatching rules seems as a good enough and relatively simple method for scheduling (Jeong & Kim, 1998).

8.2. PRACTICAL RELEVANCE

There are operational actions to be performed that help limiting the adverse effects of cross-contamination. Since it is impossible to avoid it, scheduling similar products next to each other have very strong positive effect on this matter. Then, including intermediate storage silos increases flexibility in the system and can positively influence both throughput and total contamination. However, introducing large intermediate storage silos poses an increased risk of higher cross-contamination and larger number of off-specification products, due to higher total material residue in the system. Flexibility increase might be as a result done at a cost of increasing risk of contamination. It is expected, that several varied in size silos and proper scheduling can outperform silos of equal size, allowing to fit production orders more tightly in them. Furthermore, reserving silos for certain product can decrease contamination, but at a cost of decline in flexibility, and possible limited deterioration of the production throughput. The validity of the results is too limited to generalize further, as the analysis is made based on a single system and a single set of manufacturing orders. Still, it provides a valuable insight into the uncharted territory of the cross-contamination phenomenon.

A simulation study can help establish boundaries for non-existing production layouts and create insight into its design. Thus making it possible to make more informed decisions in the design phase, for aspects like included number and size of intermediate storage silos. By analysing potential performance of a future system with a relatively cheap method, conceptual changes can be introduced, based on the acquired data to support the design process, and deliver a better solution in the end. Depending on the case of Sloten, it can be concluded that an informed design of a facility can most definitely help in limiting trade-offs between production efficiency and flexibility. Utilising simulation to help determine the impact of different layouts and scheduling rules with special regard to cross-contamination helps to create insight into the process, and to give the decision makers quantitative data on proposed solutions. Although the changes in layout are not fundamental, they are easily implemented in the simulation and can create a difference in performance.

In many cases, also partially for investigated Sloten's facility in Deventer, cross-contamination poses a serious threat to food safety issues, and a thorough investigation into it is vital for delivering high quality, trustworthy products. This method has a potential to mitigate some of the risks that are characteristic to multi-product manufacturing lines. Surprisingly, very little data is available on cross-contamination, and highly theoretical concepts, from e.g. fluid dynamics, have little practical use. The behaviour of cross-contamination is not transparent and a lot more needs to be done to precisely predict its actual character. It is crucial, when dealing with food, to provide safe, dependable product and a means of its automatic prediction would be valuable to the industry. Ideally, during cross-contamination it is the nutrients and not products that should take part in the exchange and be recorded. Then, the number of different fields to record for every product batch as well as equipment residue would be known and equal to the number of distinguished nutrients. There would also be no need for recalculation into different frame of reference or to neglect some products when their content drops below certain threshold. However, the requirement for that is for all nutrients in a product to be registered, expressed as percentage content and sum up to 100%. This was not possible for Sloten to achieve for the project, and the data was acquired on nutrients was near the end of the design phase, so the product representation was in the end chosen as a good enough substitute.

8.3. REFLECTION

This section aims to provide a few personal thoughts on the completed project and give perspective on the way things progressed.

Working on the verge of academia and industry is very alluring and challenging. It requires looking at a problem from different perspectives, and creating a more complete picture of the problem, while each of the viewpoints is mostly concerned with only a part of it. Having two 'masters' implies additional work to satisfy both parties, and to present the same facts differently, in a way that is better understood and preferred by them. For a long run it could get frustrating, but I was more amused by, curious of and even a bit worried about the gap that separates these mindsets.

In this research simulation is used to perform quantitative investigation into the problem of production efficiency trade-off for versatility, in an animal feed manufacturing industry. Showing that till certain level all parameters can be improved simultaneously, and after that there is a clear trade-off relation, is from perspective better outcome than anticipated when the project commenced. Simulation as a methodology is a very powerful means of determining possible performance in systems that are too expensive to investigate or not existing. Discrete event simulation in particular is a robust and precise method that should be used much more often in research as well as for process improvement.

Lack of proper literature on the topic made it more difficult to commence with the project, especially with the design of cross-contamination models. This gap of knowledge should be filled to help to understand and counteract these as well as enable future process improvements. I hope that I have contributed to this notion, as solving real problems and drawing general conclusions that could help further, is probably the most stimulating and rewarding occupation one can have. I am thus hoping to be one day able to go a step further and apply the principle in the food industry. Yet, it is my belief that with more solid theoretical background for cross-contamination phenomenon and more knowledge about the tracer–collector measurement methodology beforehand, it would be possible to influence the factory contamination trials conduct to gather data of higher quality.

Managing to devise a model of cross-contamination nevertheless was gratifying, especially that its final form is very simple, customizable and does not base on complex theories from chemical engineering field or fluid dynamics. Method seems quite neat, powerful and allowing for further development.

Surprisingly, the biggest challenge to finalise the thesis came from my favourite part – writing. Being normally able to endlessly spew fairly cohesive and well written text on virtually any topic, I had to constrain myself to the rigidity of a scientific report, and to writing in a plain, easily understandable manner. What a nightmare it is, not to be able to use humour, digressions, vague allusions, or to lesser extent, other languages (*quidquid Latine dictum sit, altum videtur*). Constant revisions of text so that it is more clear, better understood and cohesive are, despite their obvious need and value, the biggest discouragement from trying it again. If ever facing a binary choice between a scientific text and a work of fiction, I will most certainly choose the latter. The reason is, perhaps, that my thesis is written for, at least in theory, scientific community, and my own scribblings are primarily directed to my selfish ego...

8.4. FUTURE RESEARCH

As the research presented in this report is describing area, which was never investigated thoroughly before there are a lot of possible directions to take for further analysis. Most likely, animal feed industry is going to expand, increasing their complexity of operations while trying to limit costs and increase production. The following proposal of future research possibilities is divided into two parts: method improvement (scientific) and method application (practical).

8.4.1. ACADEMIC RELEVANCE

Presented model and research are the first step in understanding and predicting what happens or could happen during production in terms of cross-contamination, and what mechanisms describe this phenomenon. There are therefore, several distinct areas of inquiry to be listed. First of all, a further analysis of actual and perceived trade-offs arising from cross-contamination effects should be made. To enhance the approach taken for this research and allow for better analysis of the trade-offs between production efficiency and versatility, several improvements could be made. Firstly, an inquiry into the trade-off perceptions of managers and their view of the importance of cross-contamination of several facilities would be extremely useful in determining the willingness to face them to find a mutually beneficial solution, if possible. Moreover, the trade-offs expressed during the analysis do not have clear weights and have to be interpreted subjectively by decision makers. While this not necessarily has to be a bad thing, a more objective performance indicator, such as reducing trade-offs to monetary value and interpreting costs.

Moreover, a clear single objective could prove useful in the future for optimisation. If cross-contamination carries hidden quality depreciation, as analysed in this report, then attempts can be made to minimise this cost or overall cost in system design, or operational scheduling.

In order to optimise, a generic scheduling approach, capturing the essentials of cross-contamination effects, needs to be developed. Current solutions involving non-triangular setup times for cleaning (Toso et al., 2009) are insufficient, and need to be improved to include acceptable limits of carry-over, possibly distinguished for sensitive ingredients. Such method would be much more difficult to define than the usual mixed integer formulations in similar problems, and most likely much more demanding computationally.

Furthermore, improving the modelling method to capture the relevance of physical properties of the material, its flow and the equipment, to create a universal description of the problem, if that is even possible, should be attempted. Representing exact chaotic movement of particles might be extremely difficult, and the benefits coming from it limited. In substitution, a smooth curve with a safety factor could be used to sufficiently well model the phenomenon. Then, to include a differentiation among product properties, the assumption made of constant residue in the system needs to be set aside, and the mass balance kept for the system in total, not for each of the material contents exchange.

Finally, as cross-contamination occurs especially with edibles, a more thorough risk analysis into its effects on health should be made. Current methods involve reactive measures to determined liabilities, while with a proper investigation method, a hazards could be identified and eliminated before they occur, with significant benefit to public safety.

8.4.2. PRACTICAL APPLICATIONS

In terms of application a natural advancement seems to expand analysis to other powder-based systems that encounter similar problems. First of all, for other feed production facilities, in which characteristics and complexity of issues is different, to establish a more general method, applicable to the entire industry and tested on multiple cases.

Furthermore, research can be expanded for human food with much stricter regulations and possible safety repercussions than in the animal feed case. As the industry is much bigger, the possible use is also greater. Being able to reduce lot sizes and gain a lot of flexibility, while limiting efficiency loss, would definitely be interesting to plant managers, that could more quickly respond to market needs without bearing considerable costs.

Moreover, the method could be applicable for non-edibles like metal powders, chemicals, plastics & polymers or minerals. There are many industries that use common conveying equipment for various products without realising or caring for resulting pollution. An analysis into its extent could help design better systems or use them in a more efficient manner.

There are also possible extensions to the simulation model, that could better capture characteristics of the real system and provide improved insight into it. Built simulation model could be further expanded by adding or improving features listed below:

- Dynamic silo allocation with additional checks during mixing (e.g. when current silo full),
- Perform nutrient similarity sequencing based on a directed search or full factorial analysis,
- Taking into account specific product properties (e.g. viscosity, friction) to distinguish products from each other to determine impact of that on cross-contamination extent,
- Including nutrient analysis for all products,
- Include nutrient similarity check for bagging dispatching rules,
- Adding prediction possibilities for bagging dispatching rules, including forcing idle time in anticipation of a better sequence.

Obviously, increasing validity of the model, by measuring an actual production system and not just its concept, would prove useful for confidence in results, in terms of not only throughput but further measurements of contamination. Designed model is validated based on partial data and specialists assessment, but quantitative analysis of the entire system is invaluable.

Finally, this analysis with the simulation model is a first step to an on-line scheduling tool for operations, that could include learning capabilities to capture the knowledge of planners. Being able to expand usefulness of the method, making it a composite solution, could only encourage potential users to undertake it.

All in all, possibilities for expansions are considerable and should be made in the future to provide more value to both science and industry.

Appendices

A

Model Data

A.1. Model Input Data

Table A.1: Short stops data

	Failure number	Total Downtime [h]	Total Staffed Time [h]	MTBF [h]	MTBF [s]
BTH1	6539	26.81	363.82	0.052	185.5
BTH2	4062	22.30	451.19	0.106	380.1
BTH3	1990	16.81	376.78	0.181	651.2
Mixer	1060	8.87	428.73	0.396	1425.9

Table A.2: Changeover time statistics

	Observations	Mean [s]	SD [s]	Median [s]	Min value [s]	Max value [s]
BTH1	287	277.27	128.08	271	62	658
BTH2	295	256.93	116.45	246	61	603
BTH3	310	235.00	123.53	213	62	625
Mixer	733	266.91	248.12	246	61	1048

Table A.3: Time to repair statistics

	Observations	Mean [s]	SD [s]	Median [s]	Min value [s]	Max value [s]
BTH1	5895	16.37	34.66	6	1	580
BTH2	3593	22.34	41.53	8	1	599
BTH3	1634	21.34	60.15	20	1	628
Mixer	896	35.66	51.39	25	1	661

A.2. Contamination Measurements Analysis

Several weeks after the trials the laboratory results came in and first conclusions could be made. The most important reference values were measured to be:

Table A.4: Contamination results reference points

Fe ppm	Protein %	Material
432	12.22	First material (contaminant)
20	19.46	Reference value with contamination
8	19.93	Second material (without contamination)

For each of the points A to F normally 16 – 17 samples were taken over time, which allowed to plot contamination curves for this point. Measured points, in relation to the reference sample, are expressed as a ratio, and plotted with straight-line connections between points. Cross-contamination measurements for all the points are shown in Figure 5.2 on page 36. These lines show exponential behaviour and all are based on the reference value of 20 ppm Fe, as such displaying picked contamination from the start to the measurement point and not incrementally from point to point.

MIXER CONTAMINATION ANALYSIS

Below calculations show how much residue was picked up by the second material before the mixer and inside the mixer. Assuming that the route was entirely polluted, there was some amount TR_{Mixer} of the first material with content of 432 ppm Fe at a point in the mixer, together with 5700 kg of the second material with 8 ppm Fe, that was added during the trial. Resulting uniform mixture had iron content of 20 ppm and thus an equation can be formulated as the total amount of iron needs to remain constant:

$$5700\,\text{kg} \cdot 8\,\text{ppm} + TR_{Mixer}\,\text{kg} \cdot 432\,\text{ppm} = (5700 + TR_{Mixer})\,\text{kg} \cdot 20\,\text{ppm} \tag{A.1}$$

Solving the equation the total mass of picked residue is calculated:

$$TR_{Mixer} = 166.0194\ [\text{kg}] \tag{A.2}$$

Similar calculations for protein yield over 370 kg of contamination, which is deemed way to excessive and highly improbable by the operations expert, and thus is rejected. During the project period, the main mixer was specially cleaned and weighed before and after that process. Operators reported that the difference amounted to almost 80 kg. The rest of the RM value would be picked up before the main mixer. Either way, this shows that there is a considerable amount of material residue in the system and since this is the only possible route this cannot be helped by scheduling. Redesign of that part or special cleaning in between is not considered in this research.

CONVEYORS CORRELATIONS

One of the aims of contamination modelling is ability to generalise the obtained curves to fit other, not measured equipment. That would mean finding correlations among significant parameters of the given equipment, and finding a general expressions to be applied to any other ones in the system. At first these significant parameters need to be defined and found. An example of such parameters for investigated screw conveyors is shown in Table A.5. Interval C –> D is not investigated due to fewer and inconsistent measurements.

Table A.5: Parameters of the investigated screw conveyors

screw	Mixer –> A	A –> B	B –> C
length [mm]	3000	14000	17090
diameter [mm]	500	400	380
compartments	1	2	3
rotational speed [rpm]	64	294	306
pitch [mm]	320	250	280
angle of inclination [deg]	0	90	45
particle speed [m/s]	0.3413	1.225	1.428
internal area [m^2]	7.9168	29.6968	33.2932
volume [m^3]	0.3770	0.6333	0.9785
Residue [kg]	32.7778	23.1667	30.1667

First parameters from Table A.5 relate to physical characteristics of the conveyors (or the sum if there were more conveyors in between measurement points, see the number of compartments). Further come from the measurements, and are fitted for the incremental curves. Finally, a total residue is the conveyor is estimated by integrating the curves. In search for cross-correlations among the values, an Excel in-built correlation function is used. Because of the limited number of measurements, the findings can hardly be expected to be perfect. The results are put into Table A.6 and are inconclusive.

Table A.6: Correlation parameters of the investigated screw conveyors

	length [mm]	diameter [mm]	rotational speed [rpm]	pitch [mm]	angle of inclination [deg]	particle speed [m/s]	internal area [m^2]	volume [m^3]
diameter [mm]	-0.99854	1						
rotational speed [rpm]	0.98622	-0.99371	1					
pitch [mm]	-0.79519	0.82675	-0.88452	1				
angle of inclination [deg]	0.74266	-0.77771	0.84319	-0.99661	1			
particle speed [m/s]	0.99943	-0.99979	0.99122	-0.81509	0.76471	1		
internal area [m^2]	0.99689	-0.99969	0.99618	-0.84047	0.79308	0.99897	1	
volume [m^3]	0.92165	-0.89937	0.84479	-0.49763	0.42464	0.90811	0.88824	1
Residue [kg]	-0.98542	0.97480	-0.94371	0.68044	-0.61790	-0.97915	-0.96896	-0.97423

Table A.7: Parameters for correlation analysis for all measured equipment (excluding points G and Bag)

screw	Mixer –> A	A –> B	B –> C	C–>D	D–>E	E–>F	F–>G	G–>Bag
length [mm]	3000	14000	17090	11000	12700	60000		
diameter [mm]	500	400	380	380	3600	150		
internal area [m^2]	7.91681	29.69684	33.29318	21.29772054	154.62320	28.273		
volume [m^3]	0.37699	0.63334	0.97849	0.60670	130	1.06028		
Residue [kg]	31.573	27.9508	25.7703	33.4559	90.982	15.476	51.675	61.579

Table A.8: Correlation results for all equipment parameters (as in table A.7)

	length [mm]	diameter [mm]	internal area [m^2]	volume [m^3]	Residue [kg]
length [mm]	1				
diameter [mm]	-0.24992	1			
internal area [m^2]	-0.09062	0.97461	1		
volume [m^3]	-0.16325	0.99588	0.98673	1	
Residue [kg]	-0.38089	0.98663	0.93875	0.97141	1

Although there are promising values for relation between the total residue and volume (0.97423) or internal area (-0.96896), no expected relationship could be made, because of the limited number of samples. Additional analysis needs to be made before any results are accepted and generalisation made. In the end, the non-measured intervals of screw conveyors are assigned total residue TR that is proportional to their volume and corresponding measured interval's volume. Thus, when the volume changes in the simulation, for e.g. included extra silos, the total residue changes as well.

PNEUMATIC CONVEYORS

This type of conveyors contains least amount of residue out of all the measured equipment, according to the trials. Because there was only a single long section of pneumatic conveyor investigated no correlations can be found, and the generalisation bases on the findings from screw conveyors. Assuming that residue is also in this case correlated with pipe volume then with the same diameter in all pneumatic conveyors, the amount of residue can be expressed as material per running meter. The investigated portion of the conveyor has approximately 60 m, and had 15.476 kg residue total. That yields:

$$R(l) = l \cdot \frac{15.479}{60} = 0.25793 \cdot l \left[\frac{\text{kg}}{\text{m}}\right] \tag{A.3}$$

Where l is length of a given interval.

Table A.9 shows the parameters obtained by using sum of squared deviations method to find exponential curves for contamination.

Table A.9: Accuracy of the exponential curve fitting expressed with the sum of squared deviations method

Point	A	B	C	D	E	F	G	BAG
SS Total	0.172808	1.729847	0.904290	0.983347	0.872396	0.388773	0.696348	1.454125
SS Regression	0.171882	1.597465	0.901128	0.967468	0.611294	-0.154848	0.458486	1.409095
SS Residual	0.000926	0.132382	0.003161	0.015878	0.261101	0.543621	0.237861	0.045030
R Squared	0.994640	0.923471	0.996503	0.983852	0.700707	-0.398299	0.658416	0.969032
StDev	0.007381	0.090960	0.014057	0.037993	0.127745	0.184326	0.121927	0.051466

A.3. MODELLING AND EXPERIMENTATION CHOICES

This section contains considerations on specific choices to be made for proper model execution, so that necessary input variables are chosen after appropriate deliberation. At first, modelling consideration about entity size is done, then when to neglect certain contamination and finally what number of replications to choose for reliable experimentation results.

A.3.1. ENTITY SIZE AND NUMBER

Choice for entity (dynamic object) size, a discretisation of continuous material flow into small individual product batches is done, based on the production specification introduced in chapter 5. General model as shown in Figure 3.3 assumes there is a uniform size of all product batches but does not specify its value, which needs to be explicit for the chosen system.

In the end, most of the products need to be packaged into bags having size of 10, 20 or 25 kilograms. Natural, easiest choice suggest taking their highest common divisor – 5 kg, from which contents for all these bags can be assembled. However, such selection poses a risk of having a lot of entities in a system at any given moment, which would impede execution speed. Because of cross-contamination, the entities need to store their product contents, and the record needs to be available during every exchange calculation. For that it is easier to store these values in each entity individually, but then operations of merging them into a single entity in storage would require additional logic and value storage.

Assuming that most material in the system is stored in the intermediate silos, the maximum capacity of which (in the basic case) is 535 tonnes, then by having them all filled to the maximum, they would contain 107 thousand entities of 5 kg. This is an unrealistic, 'worst case' scenario and the actual number of them in a system should be lower, as the silos are most likely not going to be full all the time. Still, considerations are done on this number, to assure smooth execution even in unlikely situations. Having this many active entities is, based on field experts experience, not possible in Simio, which would probably crash during execution. It is thus required to put the entities in storage into some form, that is less expensive for model execution or perform some actions to lessen that impact.

Additional tests with simplified Simio models are performed to determine a sufficient method for modelling. Roughly 100 thousand entities are put into several Simio constructs called a station[1] and then material flow movement to and from the stations representing silos is approximated. The speed is relatively low, but is deemed acceptable. However, additional layer is added to increase the speed, which involves process of batching entities entering a station into a single entity (called batch entity). Organisation of having a silo represented by a station, in which there is constantly a single batch entity, which has then a collection of the actual product batches that enter and leave it in a FIFO manner, is empirically deemed faster and thus utilised for the final production model.

A.3.2. CUT-OFF POINT

There is an amount of material in a given place which can be considered negligible for the outcome i.e. even if a given product is sensitive to it releasing its entirety into the product batch in subsequent stages would not change the outcome on its own. There is a chance, that composition of factors might eventually have a higher impact, but due to modelling limitations the limit when a given product is considered negligible should be established. In general higher precision comes at a cost of extended computing time and thus the cut-off limit is a variable in the model. The following considerations derive a limit deemed acceptable for the vast majority of cases. Moreover, is the limit is too high, the biggest repercussion is considering up to a few finished product bags as acceptable, whereas they should be counted as outside of specification, most likely together with earlier identified ones.

The biggest difference in between one product's specification level and the higher level of another determined for Sloten is 2880 times, which could happen only in a very extreme case. This is a difference of bacteria content between $1.44 \cdot 10^8$ cfu (colony forming units) and limit of $5 \cdot 10^4$ cfu (with specification of 0). Supposing there is total amount of X kilograms of material in a finished product batch of 5 kg. Then, basing on only this component and these two product it should within:

$$X \cdot 1.44 \cdot 10^8 < 5 \cdot 5 \cdot 10^4 \tag{A.4}$$

$$X < 1.736 \cdot 10^{-3} \quad \text{[kg]} \tag{A.5}$$

[1] See *Simio Reference Guide* for details

The biggest number of intervals in between the main mixer and bagging is 17 and thus assuming that at each of them the product batch is picking all of the contents, leaving no behind the maximum equal picked material x at each stage would be:

$$x = 1.02 \cdot 10^{-4} \quad [\mathrm{kg}] \tag{A.6}$$

This is highly unlikely as picking up entire residue without leaving anything behind is against cross-contamination modelling specification and the cut-off value should be higher. In fact, whenever given product contamination is higher that equipment residue it strives to equality with every exchange and thus the inequality from (A.5) holds for every exchange and not only totality. Still the amount of just above one gram is very conservative and is in practice relaxed to the next order of magnitude to 0.01 kg. Practical screening of results with chosen threshold of 0.01 kg and 0.0001 kg revealed no apparent differences.

There is a chance, that there are multiple trace amount of products which together constitute for significant amount of a given, sensitive nutrient and could have a negative impact on the bag acceptance determination, but this is unlikely. Although higher precision is desired, the chosen negligence threshold of 10 grams is deemed sufficient for great majority of cases.

A.3.3. REPLICATION NUMBER

Each defined scenario must be run several times with different pseudo-random number generator seeds to account for stochasticity in the model an give an accurate prediction of the expected value (or output possible interval based on some confidence level). Although in the designed model the number of stochastic variables is low and include only changeovers, short stops and possibly random exchange component for cross-contamination calculation, their impact might be profound on the performance. Mixing sequence remains fixed for a given scenario but the chosen silos and bagging order do vary from replication to replication, creating a ripple effect since it first occurs.

Therefore the necessary number of replications is investigated first manually and then using statistical tools to find an optimum number. In general, the more replications are run the more certain can one be about the results but that comes at a cost of computing power (Kelton et al., 2013). In this case for used Intel® Core™ i5-4300U CPU and 64 bit Simio with 4 parallel replications the run time is around 70 minutes without contamination calculations and exceeds 200 minutes including cross-contamination for gathered statistics of 3 weeks of production time. Therefore it is vital to limit the number of replications per scenario to a comfortable level in order to explore more than just few options.

A comparison of the results for one sample t-test for 95% confidence interval for different number of replications is given in tables A.10 and A.11 for three weeks production and a single day of warm-up period (excluded).

Table A.10: One sample t-test results for the number of late orders for 95% confidence

	Late orders		
	n=10	n=20	n=40
t-value	9.8466	13.369	20.466
d. freedom	9	19	39
p-value	4.069e-06	4.093e-11	< 2.2e-16
interval low	8.01071	8.60311	9.732637
interval high	12.789287	11.79689	11.867363
mean	10.4	10.5	10.8

Table A.11: One sample t-test results for average number of processed bags per hour for 95% confidence

	Avg Bags per hour, n = 10			Avg Bags per hour, n = 20			Avg Bags per hour, n = 40		
	BTH1	BTH2	BTH3	BTH1	BTH2	BTH3	BTH1	BTH2	BTH3
t-value	260.24	218.72	277.53	407.83	342.34	410.42	539.39	471.18	575.29
d. freedom	149	149	149	299	299	299	599	599	599
p-value	<2.2e-16	<2.2e-16	<2.2e-16	<2.2e-16	<2.2e-16	<2.2e-16	<2.2e-16	<2.2e-16	<2.2e-16
interval low	351.7474	352.0303	354.5835	354.2724	355.1371	356.1618	354.2870	355.4477	356.7238
interval high	357.1299	358.4490	359.6689	357.7080	359.2437	359.5938	356.8763	358.4232	359.1677
mean	354.4387	355.2396	357.1262	355.9902	357.1904	357.8778	355.5817	356.935	357.9458

It is concluded that having 20 replications giving well enough results of experiments with acceptable confidence interval for 5% significance level as well as manageable runtime. Thus, all performed experiments are to have 20 replications, unless otherwise specified.

B

VALIDATION DATA

This chapter contains historical information considered sensitive by the company, and is left blank in the public version.

C

CASE STUDY

This chapter provides information on the company, their goals, production process and more case-specific data hat can be addition to general summary presented in the main text.

C.1. PROJECT BACKGROUND

Sloten B.V., a subsidiary of Nutreco corporation, is a major developer and supplier of young animal feeds, taking care of these sensitive animals by meeting their specific nutritional needs with high-quality products. To optimize the capacity and efficiency in the Sloten facility in Deventer, a plan is devised for a thorough plant-upgrade, which is to be evaluated. It is desired to further analyse the capacity of the proposed plant-upgrade based on real customer order, product and production data. As it is very likely that the new manufacturing layout will require different scheduling rules or even a completely new planning approach, an in-depth inquiry into current state of the art knowledge is to follow. A discrete event simulation (DES) including stochastic effects is requested to analyse the performance, and be the base for determining additional new structural requirements and scheduling.

The company started the project as it is mostly interested in gaining insight about the future plant operations, specifically about the possible capacity of the proposed upgrade and above all – about the impact of cross-contamination on production and product quality. By having an outside party come to the factory and ask questions about their process, they believe to be stimulated to investigate the right issues and improve the manufacturing performance. One of the most important requirements in their production process is keeping strict cross-contamination procedures to prevent unwanted or excessive impurity of a product, due to collection of residue from a previously produced one and sent through the same piping system. Thus there is a desire to keep a single production for as long as possible, by e.g. joining orders and making sure that the next product in line is not in violation with the defined contamination rules. However, the consecutive products can also be sequenced in an order that mitigates the impact of cross-contamination, due to feed ingredient similarity, and some products cannot be put in sequence without a cleaning run, that takes time. Specifically, contamination has two main aspects. Firstly, due to the quality standards, the amount of different than specified ingredients cannot exceed certain threshold. Additionally, some products are susceptible to particular ingredients (which potentially may even be harmful to the animals) and are allowed to contain only much stricter, trace amounts of those. It is also desired to perform cleaning with sales products, that are not sensitive to a given type of contamination. If that is not possible, certain amount of product can be discarded, or reworked, which generates losses.

Moreover, it is requested to investigate and determine the number of needed additional intermediate storage silos and overall line capacities. In the end, basing on real manufacturing orders, a feasibility of the upgrade is to be assessed. After such, the company management will be presented with the results and will determine whether to undertake it. A schematic of the proposed production scheme is shown in Figure C.1. The new approach is to introduce more flexibility into the system and more routes. With more choices and complexity, the handling of scheduling is going to be more challenging, and the extent of cross-contamination due to longer routes greater, limiting production efficiency. Thus a thorough comparison between possibilities of the new approach and limitations of the old one is necessary to convince the management whether this is a viable improvement. Before the production can be rearranged as indicated in Figure C.1, a feasibility

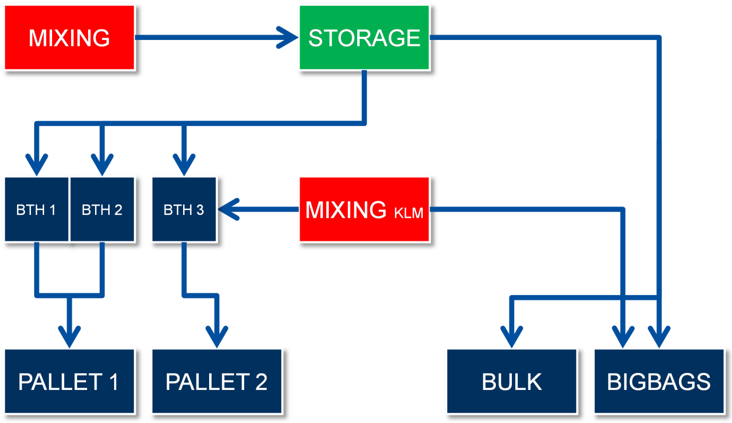

Figure C.1: A schematic of the proposed production organisation, BTH1-3 are bagging lines

study determining its performance and requirements needs to be carried out. Most importantly, assessing the level of cross-contamination that is to be expected, and preparing a suitable scheduling approach. The management identified several issues that should be addressed and improved, these are:

- Mixing speed limited by bagging lines,
- Downtime interlinking for dosing, mixing and packaging,
- Missing route options and limitations on line combinations (with negative efficiency impact),
- Low equipment utilization,
- Limited use of finished product silo.

In the end the Sloten management is to be provided with an answer on the feasibility of production process transformation, its requirements in terms of resources and scheduling as well as an assessment of possible improvements (e.g. in terms of capacity) that could result from it.

C.2. Planning and Scheduling in Sloten

Planning procedures are normally a result of organisational choices and differ among the companies. In Sloten, planning is largely detached from scheduling (sequencing of manufacturing orders within a day) with some overlapping. The process is illustrated in Figure C.2, and starts with either customer order or low stock of some, frequently sold items. The main tasks of planners is to fit these orders to daily plans in accordance to their needed lead times and lot sizes. Two days ahead the daily plan for manufacturing is released and sent to production department. Manufacturing has normally freedom to sequence the orders in the manner they see fit, providing that contamination rules are abided. As the current process is much simpler from the investigated one, due to direct connection of mixer and bagging, in the new outline there requires more choices to be made, because next to mixing sequence silo capacity for the order needs to be allocated and then the sequence of bagging from the silos. There are two main sources of manufacturing orders: customer orders and low inventory of some make-to-stock items. Planners are then responsible to consolidate orders, fit them into daily schedules, and to determine final lot sizes. Since customer orders might come with a limited advance, there is a constant need to rearrange the plan until it is released two working days ahead of the manufacturing date. All the planning is done manually within an ERP system, without specialised tools to help.

Daily production plan is then sequenced by the manufacturing crew (main mixer operators), who compose it manually according to their expertise, preference and relevant contamination rules. The contamination rules are in form of written-down guidelines, often prohibiting certain sequences and giving minimum material throughput in between them. Nonetheless, there are no strict procedures on how to prepare the daily schedule and the process is very subjective. Moreover, until recently there was no centralised contamination rules register and various responsible parties were only given seemingly relevant pieces of information with no central site for the full knowledge.

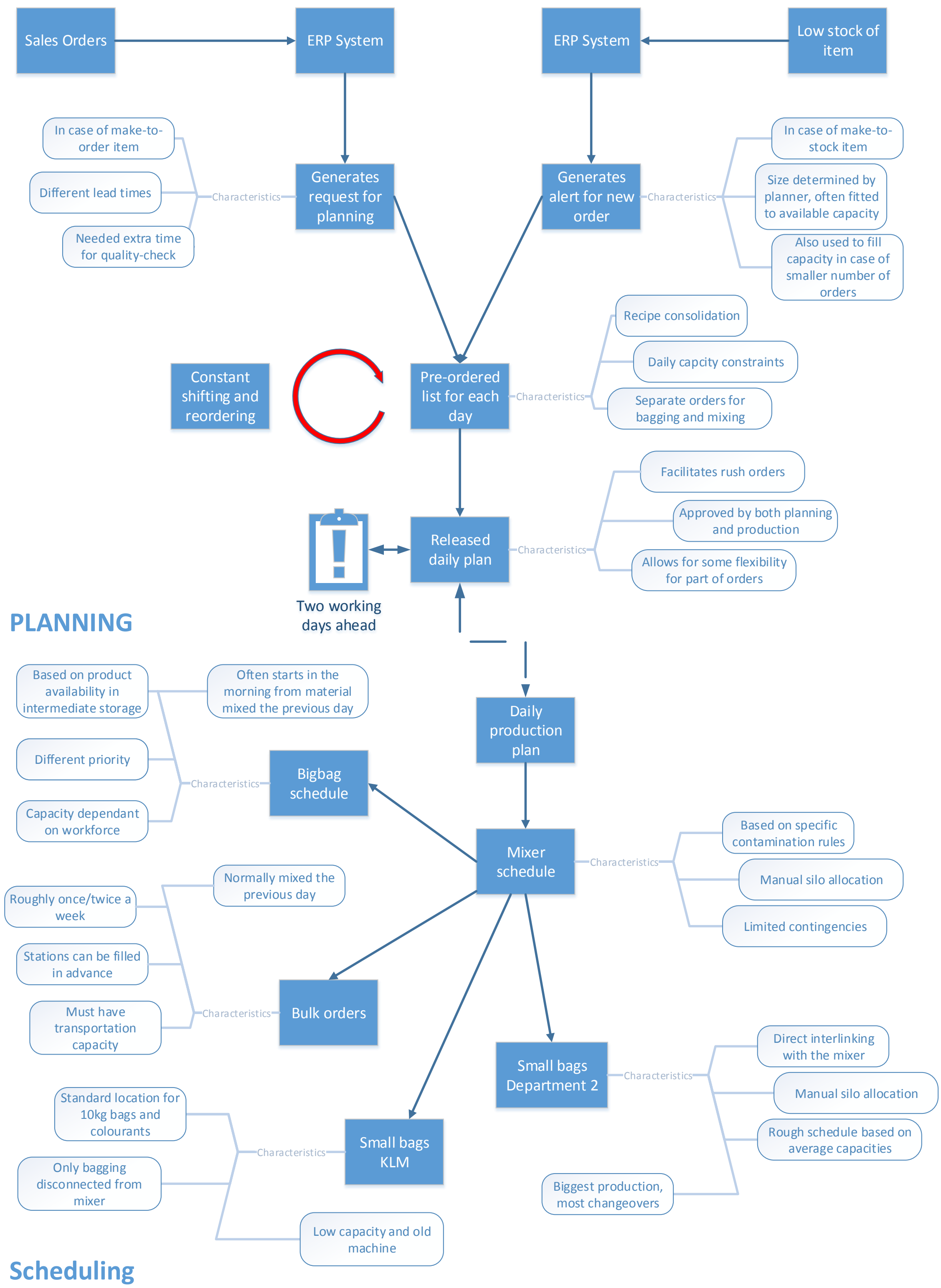

Figure C.2: A flowchart of the current production planning and scheduling characteristics

Therefore for the researched problem, the total production plan is to based on the actual historical data split into fixed due dates. Orders within a daily production plan can be rearranged freely in terms of mixing sequencing, silo allocation and bagging order, and are to be subjected to the simulation model logic and its scheduling rules. As the simulation model is to give indication on the trade-off between manufacturing versatility, flexibility and efficiency loss as well as validating a plant layout design, further investigation into planning is not necessary at this point. Nonetheless, integrating short-term planning with daily scheduling in a single APS solution could bring further benefits in terms of better production schedules.

C.3. PRODUCTION KPI DEFINITION

There are two main categories of key performance indicators (KPIs). First is connected to overall average system performance (mixing and bagging capacities, silo utilisation or working time), and the other is order specific, meaning it creates a separate set of statistics for each order (contamination, throughput). General statistics are gathered in set intervals.

GENERAL KPIS

General KPIs are mostly gathered in intervals, averaged over the measured period. It is assumed that during working hours the equipment is staffed at all times.

Mixer

Mixer works continuously during working hours. If all orders for that day are finished it continues working, providing it estimates there is sufficient time to finish the order during the shift. Records the time last order is finished and compares it with the shift ending time (can be a little late if there are many stops).
Daily statistics:

- Time available [hours]
- Under- or overtime to the schedule [hours]
- Time working [hours]
- Total downtime [hours]
- Total changeover time [hours]
- Time starving [hours]
- Total throughput during working time [kg]

Bagging

For each of the bagging machines (BTH1-3) the following set of statistics is recorded.
Daily:

- Time available [hours]
- Under- or overtime to the schedule [hours]
- Time working [hours]
- Time working bagging late products [hours]
- Total downtime [hours]
- Total changeover time [hours]
- Time starving [hours]
- Total throughput during working time [bags]
- Total throughput during working time [kg]

Hourly:

- Throughput [bags]
- Throughput [kg]

Silos

Each of the silos is measured to provide the following indicators.
Daily:

- Average weight [kg]
- Time empty [hours]
- Ratio of average contents weight to silo capacity during a non-empty time (utilisation) [-]

Every 15 minutes:

- Material weight in the silo [kg]
- Ratio of contents weight to silo capacity [-]

Before mixing start three availability categories (with sub-categories):

- Total number of silos where given order type could be stored, based on system output destination
- Number of available silos to discharge to:
  - With the same material
  - Empty
- Total usable space in available silos [kg]
- Number of blocked silos:
  - Due to contamination rules
  - Due to scheduling constraints
  - With the same material but full
  - Non-empty with different materials

In order to start mixing, there needs to be at least one available silo for allocation and the total available space in silos needs to be equal or greater to the order size.

ORDER KPIS

For each of the processed orders the following statistics are recorded.
Performance statistics for every order:

- Time started mixing [hours]
- Time ended mixing [hours]
- Time started bagging [hours]
- Time ended bagging [hours]
- Order quantity [kg]
- Order package size [kg]
- Whether order was finished on time [-]

Contamination:
The statistics for residue within equipment are not directly shown. Contamination is thus only measured separately for each bag that is leaving the system and which contents comprise of the sum of entity composition within it. The bags are then classified into two contamination categories: within or out of set contamination limits. Regarding a bag as above the limit does not necessarily mean that is should be rejected due to its quality. Once the final criteria on how to evaluate the acceptance or rejection of a given bag are made, it is desired to provide the following statistics for every order:

- Count of bags above limit
- Amount of material above limit (bag count multiplied by bag size) [kg]
- Ratio of order of material above limit (amount of material above limit divided by the order size)

OTHER STATISTICS

There are also other performance indicators recorded, that cannot be assigned to any previously mentioned category.

Report of order arrangement:
As a reporting feature, an outcome set of schedules

- A list of consecutive orders in the mixer with starting and ending times
- A list of utilised silos for each order
- A list of consecutive products at bagging machines with starting, ending times and source silo

All aforementioned statistics are shown to the user in specially designed for the purpose environment in Scenario Navigator software.

Run ending statistics:
When a simulation run is ending the following information is to be stored:

- Number of completed orders
- Number of completed orders on time
- Percentage of the simulation time when different numbers of silos were empty

C.4. CONTAMINATION TRIALS

The contamination trials were conducted in the facility on 05.03.2015. They consisted of two main steps. At first, the investigated route (shown in Figure C.3) is contaminated entirely by a product with high iron content, with nominal value of 432 parts per million (ppm). After that, a new product with a low iron content and a reference value of 8 ppm is sent through. Because the mixing process in Sloten is continuous, the trials aimed to measure in different places in the system (see Figure C.3) the amount of iron after a certain amount of material was sent through. Due to difficulties in frequent sampling, some measurements were made in quite big intervals, making a good result analysis more challenging. Contaminating with a high iron content

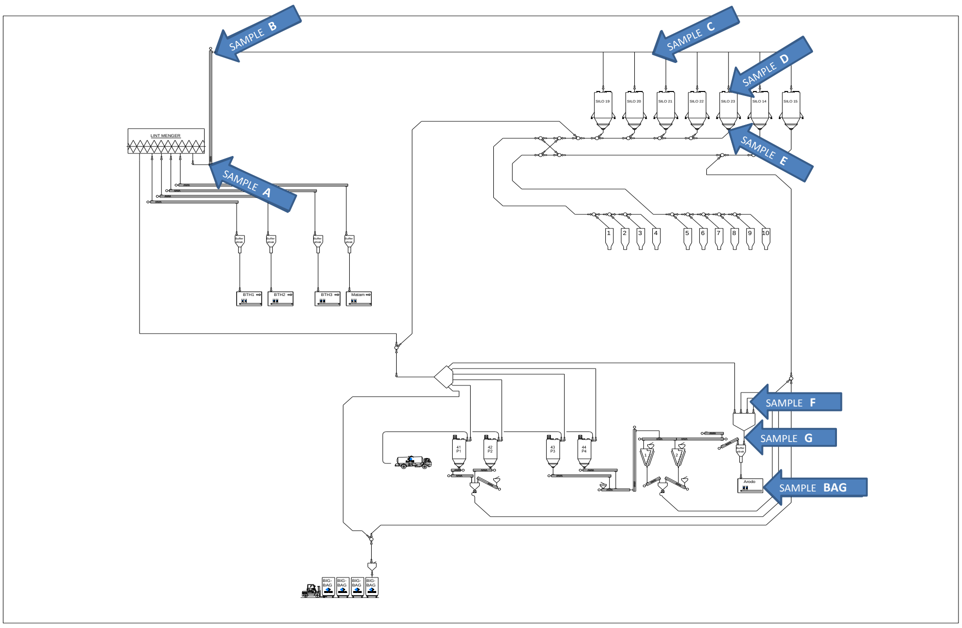

Figure C.3: A schematic of the investigated route and sampling points

material is way to leave a tracer marker within the system, that is then picked up by the incoming product. Iron content measurement is generally accepted to be quite precise and not very sensitive to measurement errors. An investigation into iron content of the consecutive product batches leaving the system allows to draw a curve of how contamination changes over time. In fact, iron was not the only tracer measured for the trial. Additionally, protein content was investigated for the same samples as drawn. Yet, because of much lower protein content difference between products and more uncertain laboratory measurement method, resulting values are considered to be less precise from the iron content analysis.

First Steps
At first, the system is completely polluted by the high iron content product. The amount of product to be sent through needed to entirely contaminate the system is taken from the experience of operations staff and based on the previous trials. The following product is then put to mixer, filling it completely and thoroughly mixed. Because there was some pollution before the mixer and within it, a reference sample is taken from the mixer

itself to establish a base for the further measurements. In order not to dilute that, there is no material dosing once the mixer start discharging, which deviates from the normal operating procedures but is required for trustworthy results.

Screw Conveyor Measurements
Then, the discharge is started and all the material is directed to the same storage (Silo 23), just as the high iron content pollutant, at a steady pace. Along the screw conveyors, four access points (A to D) were made, for sample taking. Sampling for each point started when the material reached it, and then after previously specified time intervals, same for all the points. This way was aimed to draw samples after a concurrent mass flow for each point. The phase was ended once all the material from the mixer was sent to the designated silo.

Silo and Pneumatic Conveyor Measurements
Product from silo was directly discharged to a bagging line. Because of a higher discharge capacity than bagging speed, this process was interrupted several times, based on the material level in the bagging line buffer. To draw samples from lines with high pressure, special access points were made to divert some part of the flow away to a sampling container. Such a device is shown in Figure C.4. The samples were then taken manually from points D to G and by a machine just before bagging. Labelled containers with samples from each access point were then taken to laboratory for chemical analysis to determine iron content.

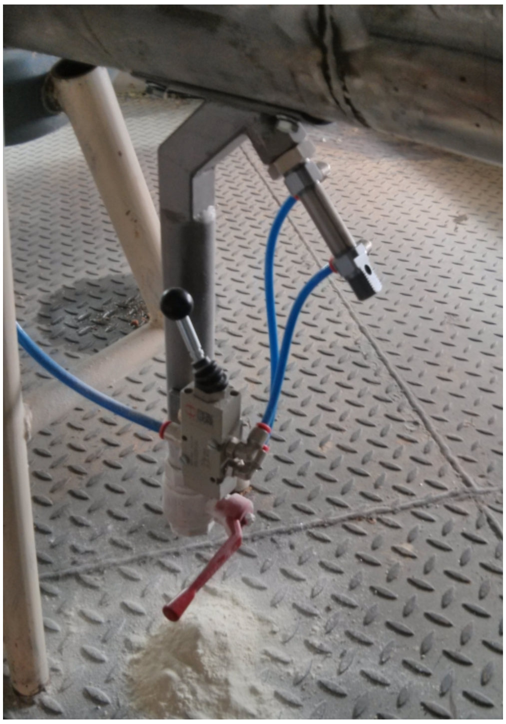

Figure C.4: A photograph of a sampling access point for pneumatic conveyor

C.5. SCHEDULING RULES

Below, all possible defined and implemented rules are listed. There are four categories of scheduling rules, connected to sequence of mixing orders, allocation of mixed products in silos and the choice of which product to package next. First category lists several alternatives that can be either applied or not and the following ones base on preferences (expressions in model) used to make choices.

Scheduling alternatives
The following list contains an independent set of alternative choices that can be used in any combination with each other. Rule 1 regards order manipulation, rules 2–5 silo allocation and the rest bagging.

1. Combine matching recipes in a given day for mixing
   To position all products with the same recipe next to each other;
2. Allocate silos based on all consecutive orders of the same recipe
   To consider finding suitable space for more than a single order ahead;
3. Avoid splitting small orders among multiple silos
   To prevent splitting small orders (less than 90 tonnes) into multiple silos. Might delay mixing;
4. Prefer splitting large orders into parallel silos to combining recipes
   To send a large order (bigger than 90 tonnes), that by default would almost certainly be split, rather into parallel empty silos than to a partially full with the same recipe and non-parallel one(s) elsewhere;
5. Put orders of the same recipe but different type into separate silos
   To prevent from combining different order types of the same recipe in the same silo. Distinguished 4 types of orders: bulk, big bag, 10 kg bag and coloured (for BTH3 only) and rest of small bag products;
6. Allow pre-emptions
   BTH3 machine in cases when BTH3 and BTH1 or BTH2 are bagging from the same silo and a new, better product is available for bagging is stopped. Product is redirected to BTH1-2 and after BTH3 changeover another product is chosen. Requires to specify the lowest remaining order size to consider it beneficial;
7. Strongly prefer matching recipes for consecutive bagging
   Forces bagging machines to foremost look for the same recipe as was bagged before and check other only if not found;
8. Prefer for BTH3 to bag coloured or 10 kg size packages first
   To prioritize BTH3-specific products;
9. Always combine recipes in silos. Allow splitting orders into parallel silos only
   Overrules points 3–5 and silo matching choice (for 'best size fit'). Forces combining of the recipes and allocates product to the chosen silo and its parallels only. Might cause significant starving time for large orders;
10. Try redirecting Mixer to Polem discharge if Big bag filling is interfering
    Tries to reduce waiting time in case mixer is to discharge to Polem silos while there is a simultaneous discharge from the main silos (14–23) to big bag;
11. Prefer bagging late products first
    Increases priority of late products. If not applied late products conform to the same rules as the rest.

Order manipulation

For each scheduled day the simulation logic can rearrange the order of consecutive products to be mixed. Firstly, it organizes them based on the list below and then applies chosen alternatives from scheduling alternatives. Rearranging the consecutive orders to mix for the given day is based on:

- Smallest bags first (bulk)
- Smallest orders first
- No sorting
- Biggest bags first
- Biggest orders first

Silo matching

When an empty silo is chosen as a potential candidate for filling with the current product, the silo matching rule is applied to rank it priority. As such, e.g. the 'best size fit' rule picks a silo that has the smallest positive difference between the silo capacity and the order size. By default, the model logic prefers silos that already have products of the same recipe inside (or used to have it) but that can be overruled by scheduling alternative choices. Possible silo matching rules are:

- None
- Best size fit
- Shortest route

Bagging rules

A bagging machine chooses a new product to package from among all that are reachable at a given moment, If there are more available it has to choose which one to pick first. Rules from scheduling alternatives are applied prior to preferences listed below. In general the aim is to utilize bagging lines for as much time as possible therefore waiting for silos to become available for discharge (that are blocked by parallel silo discharge) are not investigated. BTH3 is the only one to process 10kg bags and coloured products and there is a strong preference that BTH3 would bag other product than parallel BTH1-2. Also, there is an in-built preference to start discharging material to big bag or bulk stations prior to small package bagging machines. For each of the small bagging lines there are two choices to be made - which silos to consider first and what preference to use. There are 3 choices of the silo groups:

• *All silos* with no group preference
• *Common silos first* that can reach all bagging lines
• *Designated silos first* that can only discharge to the particular bagging line

The preferences below are then applied first to the group from above and then to the rest if there are no silos ready to discharge within the group. The preferences then are:

- Biggest order first
- Biggest package first
- Biggest silo content first
- Biggest silo content ratio to capacity first
- Earliest mixing time
- None
- Smallest order first
- Smallest remaining quantity to bag first
- Smallest package first
- Smallest silo content first
- Smallest silo content ratio to capacity first

C.6. PRODUCTION OUTLINE

A detailed schematic of production outline, including exact transportation connections is shown in Figure C.5. Marked in green is material entry point and system exits are red. Parts that are conceptualised and not yet built have dashed lines, whereas existing conveyors are distinguished between screw based and pneumatic (blue).

Every existing screw conveyor and equipment is considered separately for cross-contamination calculations. For pneumatic conveyors the calculations are done after each of the independent intervals with only a single direction.

C.7. CASE SPECIFIC RESULTS AND RECOMMENDATIONS

There are a number of specific outcomes of the study, relevant to Sloten. This section discusses briefly the results in scope of the company and gives case specific recommendations on further actions.

C.7.1. ADDITIONAL SILO EFFECTS

The results have shown that installing additional silos can, up to a point, increase line capacities, because there are:

- More jobs to choose from,
- More work-in-progress, bigger lead of mixer,
- Less chance of being blocked by parallel discharge.

Moreover, by installing bigger silos there is in general less order splitting among multiple silos, which leads to fewer changeovers and higher throughput. More silos have also effects on product contamination, in general:

- The more silos, the fewer off specification products,
- There is a point where additional silos have little effect on contamination (8 silos not considerably better than 4),
- Silo size has bigger impact on contamination than their number,
- Increasing silo sizes introduces higher risk of contamination.

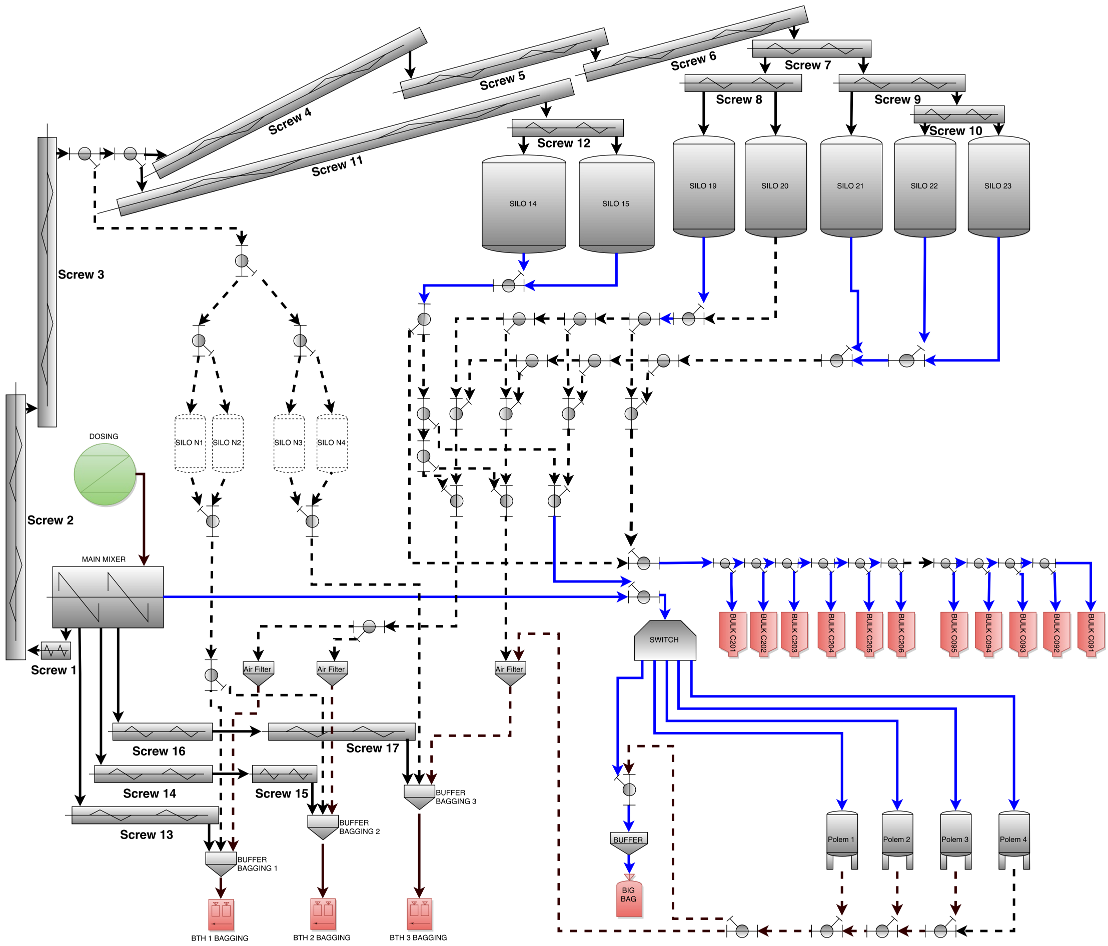

Figure C.5: A detailed schematic of proposed production organisation

C.7.2. SCHEDULING

Informed scheduling is vital for high production efficiency and should be the goal not only for Sloten, but for any manufacturing company. Any schedule is an outcome of the order set, scheduling logic and operational circumstances. Best schedule devised by a planning tool might not be superior if the algorithm does not have the full information, which it rarely has. As the planning in Sloten is done off-line in advance, the information on scheduled breaks, workforce availability etc. is not full. Moreover, scheduling is not updated once a change in production occurs. Thus, for a company an operational tool to assist with making decisions would be extremely helpful, especially when it comes to contamination.

There are certain limitations to the investigation. It was done with a single set of manufacturing orders, and by changing this set the results could differ considerably. Moreover, scheduling by dispatching rules is not a single choice, but a set of dependent selections, though for statistical analysis assumed independent. For the limited number of designed scheduling rules, there are almost 500 billion combinations of the scheduling logic alone, which is by no means all of the choices made. Moreover, there is probably no fixed set of scheduling rules that will perform best for any situation. However, the investigation gave a few good indications about what is important and/or has the biggest impact:

- Mixing sequencing is the most important aspect,
- Allocate silos based on all orders of the same recipe,
- Splitting when order type is different might be considered too, as it decrease contamination,
- Unconditional combination of recipes in a silo and never splitting orders among multiple silos is unrealistic without forced waiting time for mixer,
- Orders need to fit tightly in their designated silo, therefore varying capacity of silos is suggested,

- For low contamination choose to bag earliest mixed orders (take advantage of nutrient sequencing),
- For high throughput:
  - BTH1 & BTH2 should bag material from silos with largest amount in, or choose the largest available order,
  - BTH3 should bag coloured and 10 kg bag products first,
  - BTH3 then should go for smallest orders or smallest content in silos;
- There should be no discrimination of silo groups (designated/common),
- Pre-emptions have positive effect on throughput,
- When bagging late products is a priority, it has a slight negative effect on throughput.

C.7.3. LINE CAPACITIES

Figure C.6 shows average achieved throughput in scenario Scheduling_C (see table G.33, which is a scenario with a fairly high throughput.

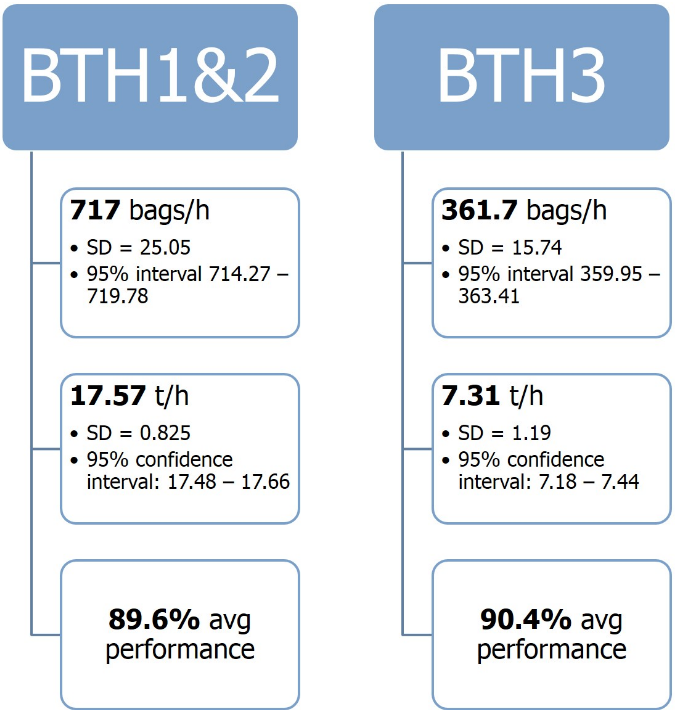

Figure C.6: A diagram of achieved bagging speeds for scenario Scheduling_C

Yearly extrapolation

To give an indication about the possible yearly performance, some calculations are made to extrapolate that. Assuming there are 240 working days in a year and the factory operates for 16 hours a day one can calculate the expected yearly value as:

$$240 \cdot 16 \cdot (17.57 + 7.31) \approx 95.5 \quad \text{[thousand tonnes]} \tag{C.1}$$

Of course, for this time-frame, adding extended machine downtime, scheduled workforce downtime, lack of orders or workforce etc. needs to be included as well, as the model investigates the issue only for a short period, and does not include several aspects that could be important in the long run. Thus, the expected extrapolated throughput should in the end decrease.

C.7.4. RECOMMENDATIONS

Based on the performed analysis with described assumptions and limitations, it is concluded that additional four silos with capacities of 30 to 40 tonnes would be beneficial for production performance. To reduce contamination varying the sizes of these silos should be considered, as the orders need to fit well in them.

First of all, in order to understand better as well as draw proper conclusions, the cross-contamination trials should be way more extensive, and possibly include more than a tracer-collector relationship. Basing on a single set of measurements can only give an approximate idea for the character of cross-contamination. Investigating several routes repeatedly with different materials with known properties is the only way to make statistically solid judgements for system properties. That could be preceded by an analysis on the material flow within conveyors and silos, possibly supported by a more thorough literature search on this topics. Moreover, cleaning the system from time to time and part by part is a way to determine the extent of amassed residue. Doing so several times, in a long enough interval, could confirm or contradict the assumption that the amount of material in the system remains roughly constant. Then, the possibility of using another type of equipment, with a different residue specification, is not discussed in the thesis. Manufacturers should have information on the possible level of leftovers in their equipment. Making it a priority to choose ones with a low specification could be a simple solution to reduce overall contamination. Definitely finding a way to exchange screw conveyors for pneumatic ones, without deteriorating capacity, would be an example, but perhaps also installing silos with smaller residue characteristic. Furthermore, cross-contamination trials were performed on a single route with just a single measurement for each mass flow for every sampling point. This is not enough for a proper scientific study and should be expanded in the future. Doing more cross-contamination measurements, including other equipment and better preparations would help in increasing prediction certainty of the results. Including factors like specific product properties and differentiating them (in terms of e.g. viscosity, friction angles, grain size) would allow extending the analysis even further and concentrate on actual product to product relations.

All scheduling decisions should be made with considerations of nutrient similarity for consecutive products, to reduce contamination and make more informed decisions. Method of matching product similarity is much more transparent and theoretically sound than the current practice of introducing ‘blocking rules‘, preventing certain combinations of products, and leaving the remaining scheduling up to the responsible persons based on their preference and experience. Especially, that there is much to gain (or lose) in terms of contamination, or specifically the number of off-specification bags of product. It is recommended to approach cross-contamination with closer scrutiny, and prioritize low contamination over higher throughput when there is a trade-off relation. Interviews with company specialists suggest that rework or rejection (scrapping) of material would be more costly than slight increase in throughput. Closer scrutiny would require assigning cost to working hours and rejected material, but is out of scope for this investigation.

It was not the goal of this research to give a single answer to which scheduling rules and particular combination of trade-offs for production efficiency are best. Instead, providing answers to the possible extent of these trade-offs and effects associated with certain scheduling choices so that the users themselves can pick the most suitable ones for them, either by choosing directly or introducing a cost function to weight them. Needless to mention, from academic viewpoint the ability to reduce cross-contamination is the most interesting one, and finding further ways to decrease it, is most strongly recommended. This could be a result of aforementioned trials but possibly also product base consolidation, or using ingredients of the same nutritional value but different particle properties.

Moreover, it is believed that with some extra effort, the current operational scheduling procedure could be utilised for the corresponding action for the new factory layout, especially because the mixer sequence is deemed the most important factor for total material contamination. No advanced APS solution is thus necessary to operate the future system. However, sloppy scheduling will pose a high risk of contamination, much bigger than it is currently, and without a scheduling tool, assessment whether a chosen schedule is close to optimum cannot be made. Thus, either a tool based on linear programming, or simulation-based exploratory software could be extremely useful to determine the possible outcome to finally help in making an informed decision for planner.

D
SN Tool

This chapter contains information on the Scenario Navigator tool developed to support experimentation and result analysis as well as for possible future use.

D.1. Scenario Inputs

The tool possesses 8 initial tabs, where vital data can be defined and scenarios prepared for execution. Below, each of them is shortly described.

Main inputs

This tab is used to input equipment and contamination parameters. The user can choose whether to include cross-contamination calculations in the run and according to which model. Also total residue in the mixer (amount of material that remains in the mixer and before it) as well as cut-off point (amount of any product when contamination in given equipment can be neglected) can be set. Relevant equipment properties comprise of bagging and discharge speeds and container level marks, among others. Additionally, maximum predicted daily overtime can be adjusted. As advanced options the user can move to altering product and recipe definitions.

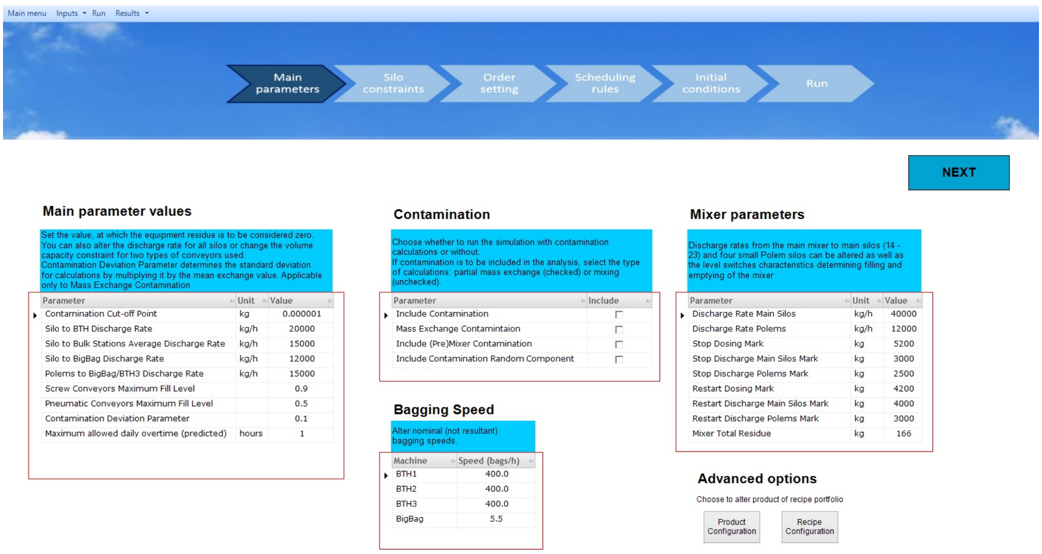

Figure D.1: SN input of the main scenario parameters

Product definitions

Tab contains a table where the whole finished product portfolio is defined. In order to add a new product, a unique number has to be given, name set, and connected to an existing recipe. Package size parameter defines the size of bags for the product to be put into, which reduces the possible system exits that can be used. Last check-box is an additional parameter, company specific, that provides an extra restriction on the possible bagging machine usage (in this case products with package size 20 or 25 and checked box will be sent only to BTH3 bagging machine).

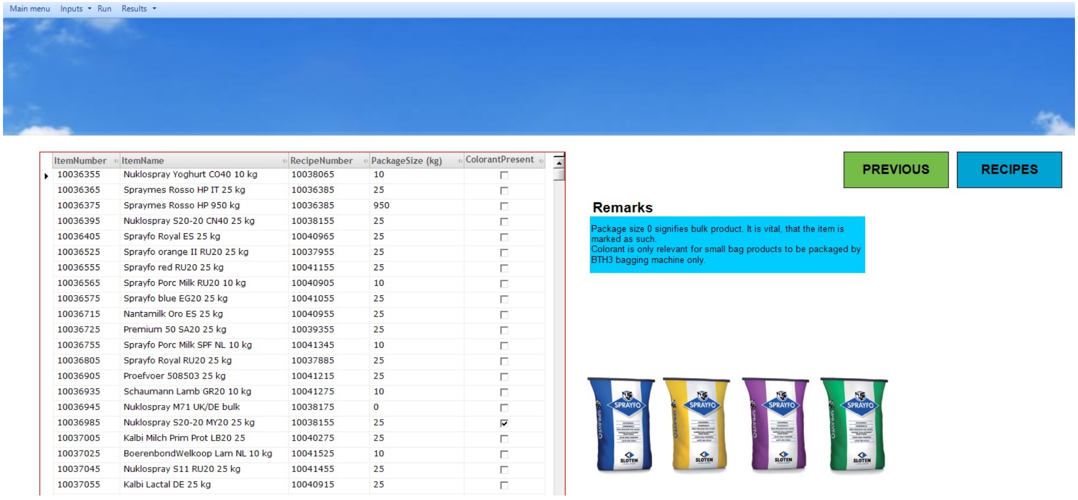

Figure D.2: SN input of the product portfolio

Recipe definitions

Recipes table connects the products that base on the same set of ingredients. As well as the products, they are identified by a unique code and have their standard names. Additionally, because of the limitations of the raw material feeding system, maximum dosing speeds to the main mixer are defined per recipe.

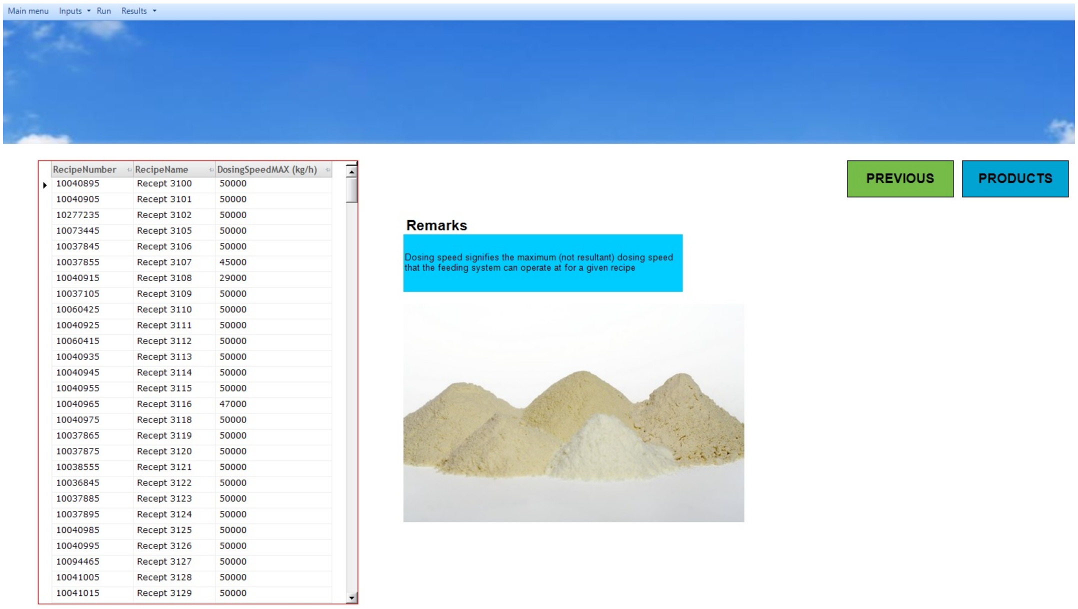

Figure D.3: SN input of the recipes for products

Silo constraints

This tab allows for change in the definitions of intermediate storage silos. For those, that do not exist in the system, the user can choose to include them in the run and what their size should be. Moreover, for any silo restrictions on accepted recipe can be established. This means, that only products with the same recipe as chosen can be sent to the given silo.

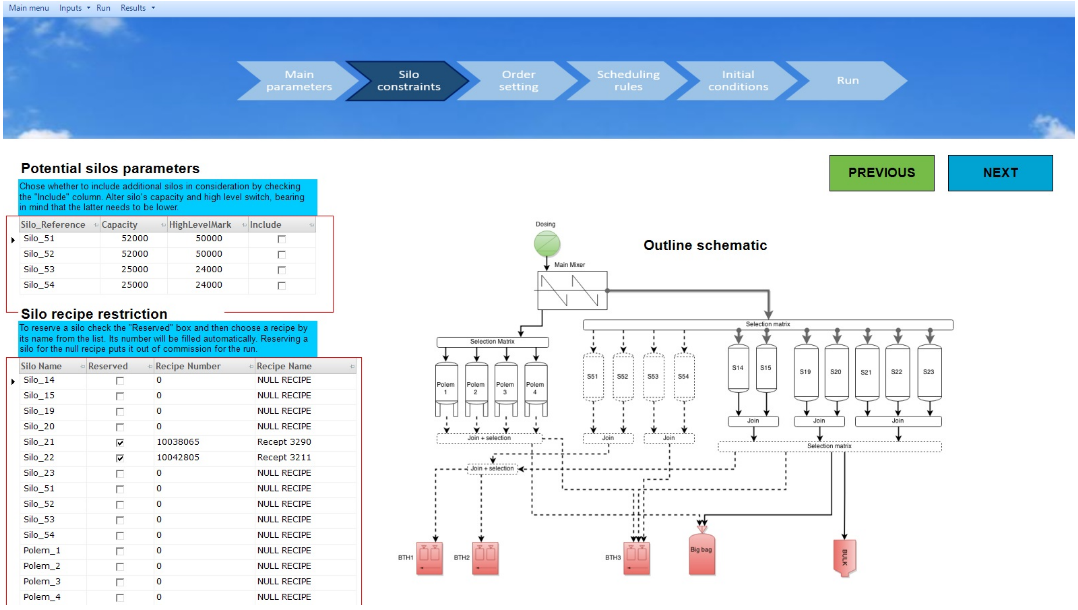

Figure D.4: SN input of silo recipe constraints

Order setting

Manufacturing orders are created by choosing a product from a drop-down list and then entering its quantity and due date. Unique identification number, called MO number, and used to distinguish between orders, is given automatically. These orders are then used by the simulation an handled in accordance to their assigned due date.

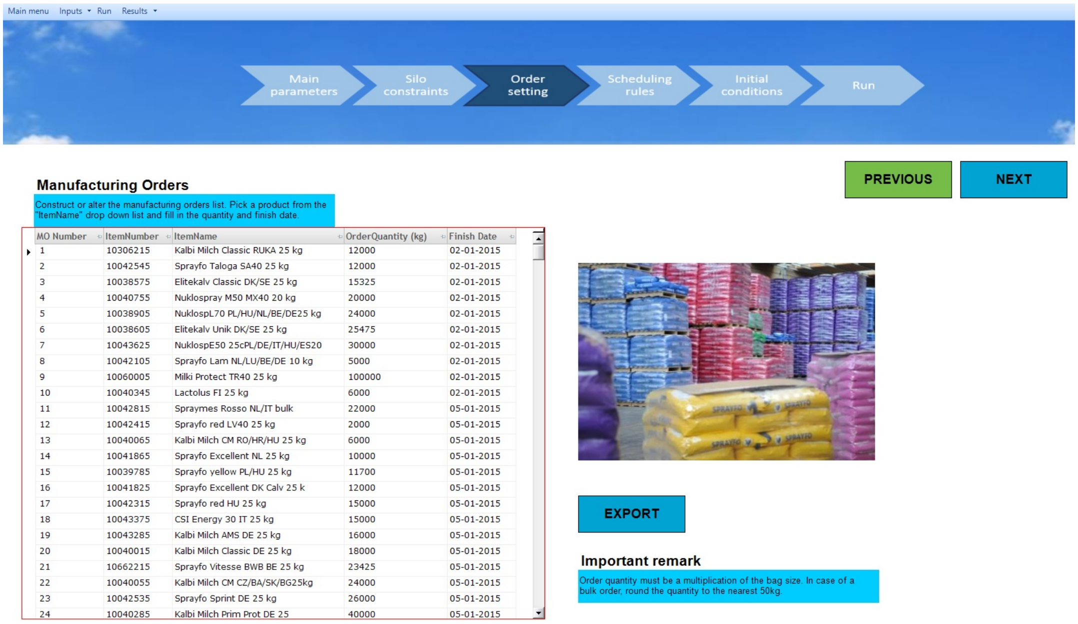

Figure D.5: SN input of a manufacturing orders set

Scheduling rules

One of the most important features of the model is assigning scheduling rules to equipment, and measuring their performance in search of rules of thumb that could help in daily operations. Thus the user has a choice on all possibilities defined in C.5 by entering a boolean value for certain alternatives and picking a rule from a drop-down list for others.

Figure D.6: SN input of the scheduling rules

Initial conditions

An additional feature of the model is an ability to define initial silo contents, that have been previously mixed, and are waiting to be processed further. This component is treated entirely as an extension and a possible use in operations. The table contains a list of orders and their locations, where mixed products are awaiting that is not connected to the actual order list. By using initial silo contents the warm-up period could be reduced.

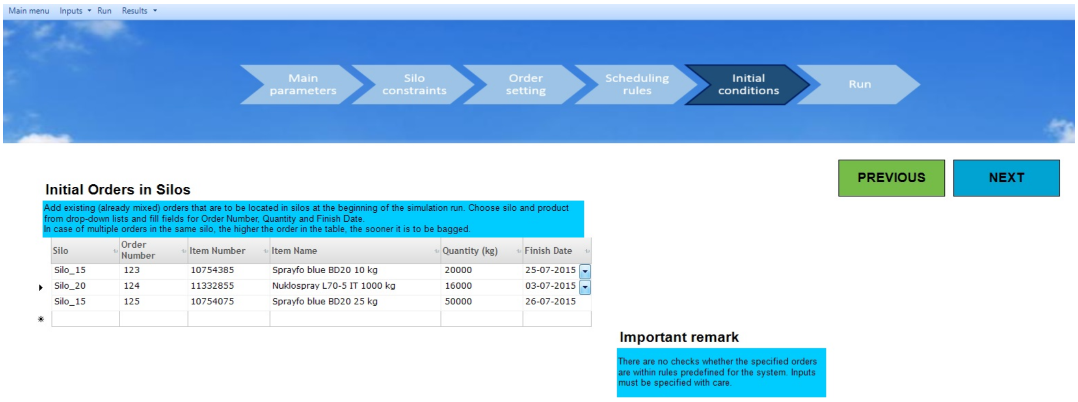

Figure D.7: SN input of the initial conditions

Run settings

Finally, the scenario run settings need to be defined. These include starting date and duration of the run, warm-up period, number of replications as well as the simulation model to be used, if those differ. On top of that the user has a possibility to exclude data gathering for some of the parameters if desired. The following dashboards in the tool relate to results visualisation and analysis.

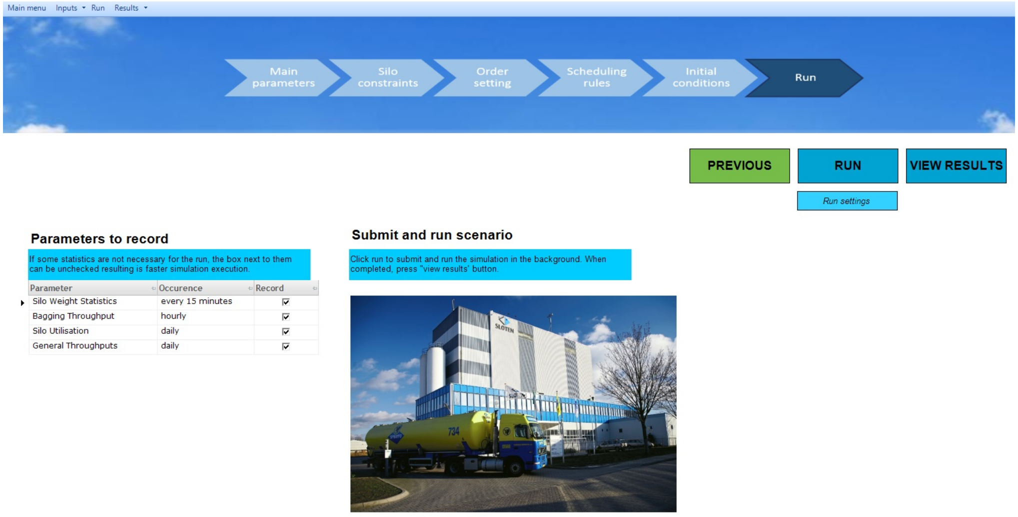

Figure D.8: SN run properties screen with possible data collection restrictions

D.2. SCENARIO RESULTS

Prepared tool in SN contains 6 tabs for results presentation on a high level, mostly including charts for convenient visual comparison between scenarios, but also having SQL queries to filter acquired data for more interesting values. It starts with a main results dashboard that has hierarchical links to 5 tabs with more detailed parameters on: mixing, orders & contamination, daily, silo and bagging statistics. Relevant dashboards contain buttons allowing to export data for processing to another tools.

The following figures included to visualise dashboard descriptions should not be connected to any scenario or each other, unless otherwise specified. There are there for demonstrative purposes only

Main results

This dashboard contains the most important information of the entire scenario divided in sections. By pressing an appropriate button more detailed window about it is displayed. Vital indicators are general throughputs and time statistics for equipment: mixer and BTH machines. Moreover, information on empty silos and silo utilisation as well as a display of timely completed orders. Finally, contamination with respect to orders and total material is given.

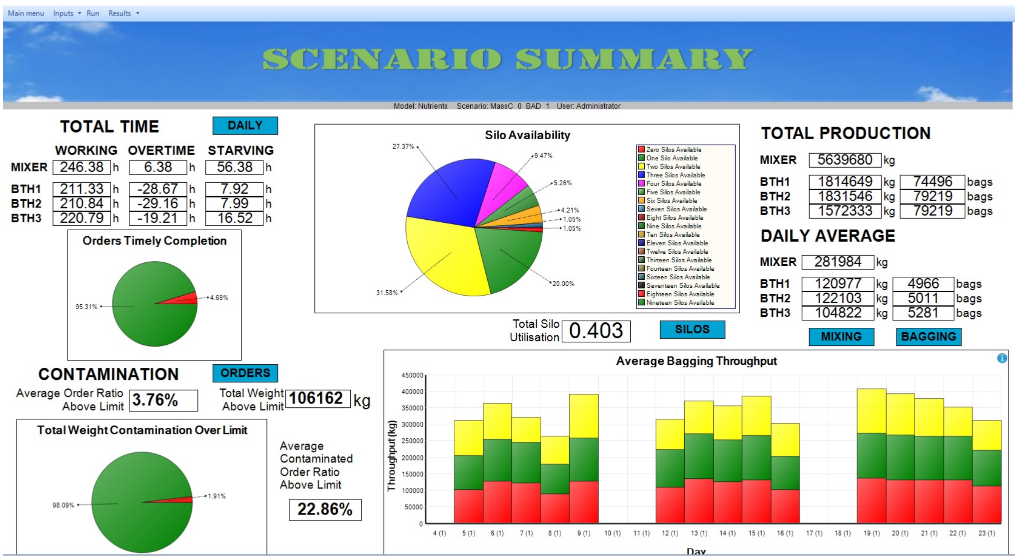

Figure D.9: Main dashboard with scenario high-level results

Mixing performance

A resource chart shows information on the starting and ending times of each order mixing, distinguishing three item categories: small bag, big bag and bulk products. It allows to see per order how long it takes to process it in the mixer and when starving times occur. Additionally item names can be displayed on the product bars to identify products of interest.

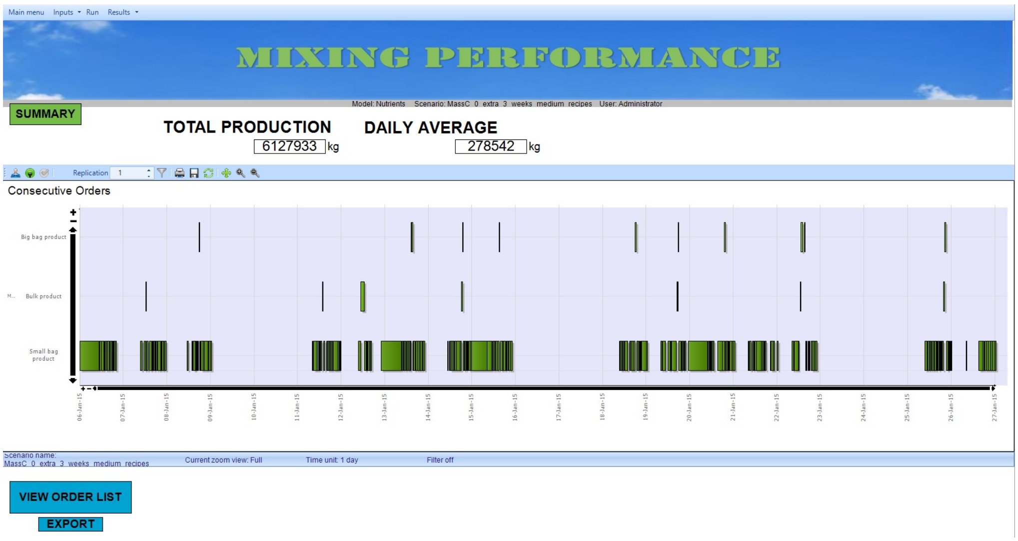

Figure D.10: Mixing performance statistics dashboard

Order & contamination parameters

This dashboard contains statistics with regards to orders as well as some average indicators on the total extent of cross-contamination. A column bar chart displays per each consecutive order how much of it is considered within (green) and how much above limits (red). Moreover a few gauges present information on the total material bagged and how much of it was over limit (average from all replications), average order ratio above limits, subset of that containing only orders with at least one bag above limits and finally total rejected bags and weight over the run period.

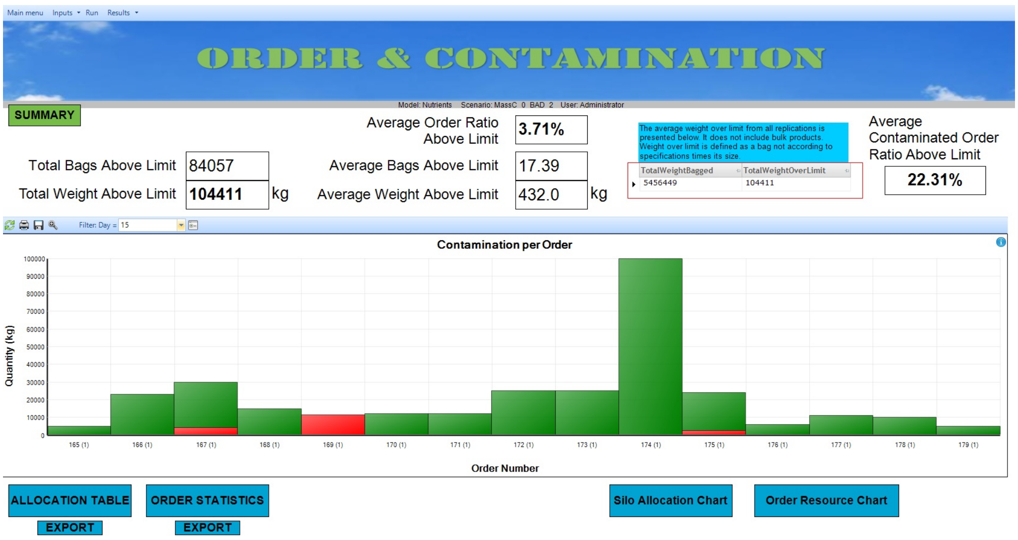

Figure D.11: Details of order contamination and statistics

Also an important feature is silo allocation chart, that is constructed when an order searches for possible destinations (flowchart presented in Figure E.9). Every time an order is prepared information on available, blocked and rejected silos is saved to provide some reasons for the silo allocation.

Daily time statistics
This dashboard presents mostly four stacked column charts for mixer and BTH1-3 machines, displaying the composition of running, starving, changeover and short stop times (as well as running late products for BTH). Added up, they show how much time is the given piece of equipment working and thus how much over- or under-time there is that day as an average of all the replications.

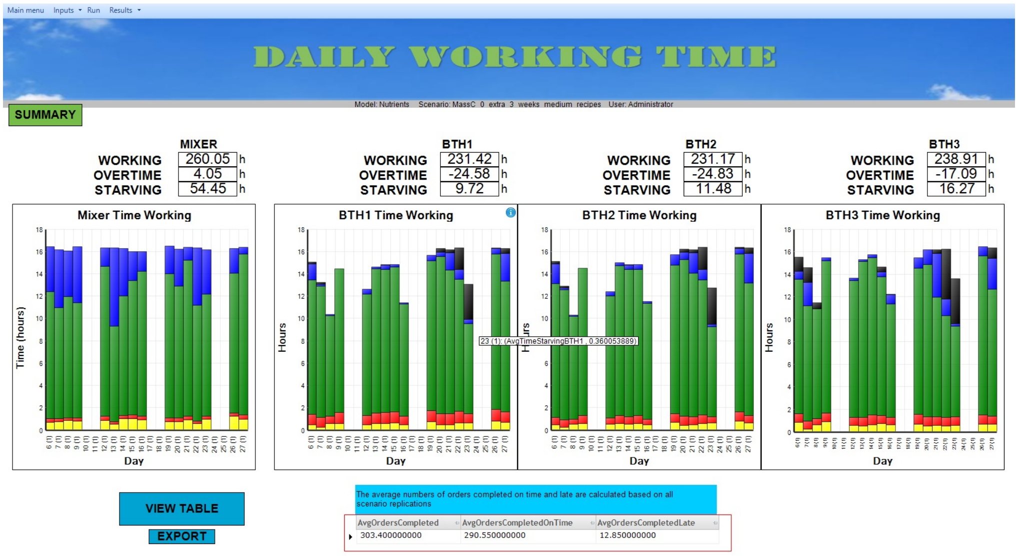

Figure D.12: Time statistics for the main equipment

On the top there are several gauges displaying the total amount of time in given category of working, overtime and starving is there in the whole run.

Silo statistics
Silo statistics aim to show the usage of silos chosen for the scenario. In general silo utilisation is defined as the average silo content weigh ratio to its capacity during a non-empty period. The figure displays such utilisation for the whole run period.

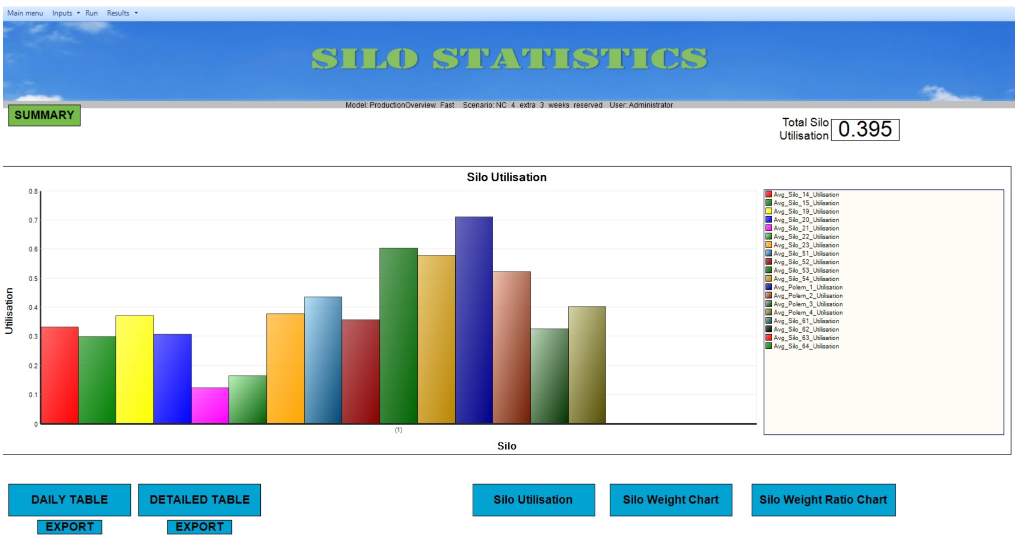

Figure D.13: Silo utilisation statistics dashboard

Further details are available for silo utilisation per given day and then silo contents charts measured in 15 minute intervals showing either the actual mass of material in the silo or its ratio to the silo capacity.

E

Model Implementation

This chapter presents several flowcharts prepared to indicate important model logic.

E.1. Order Path

Manufacturing orders are parent entities that steer the flow of product batches, their child entities. This process is shown in Figure E.1. Orders for the first day are initialised at the start of simulation run and after

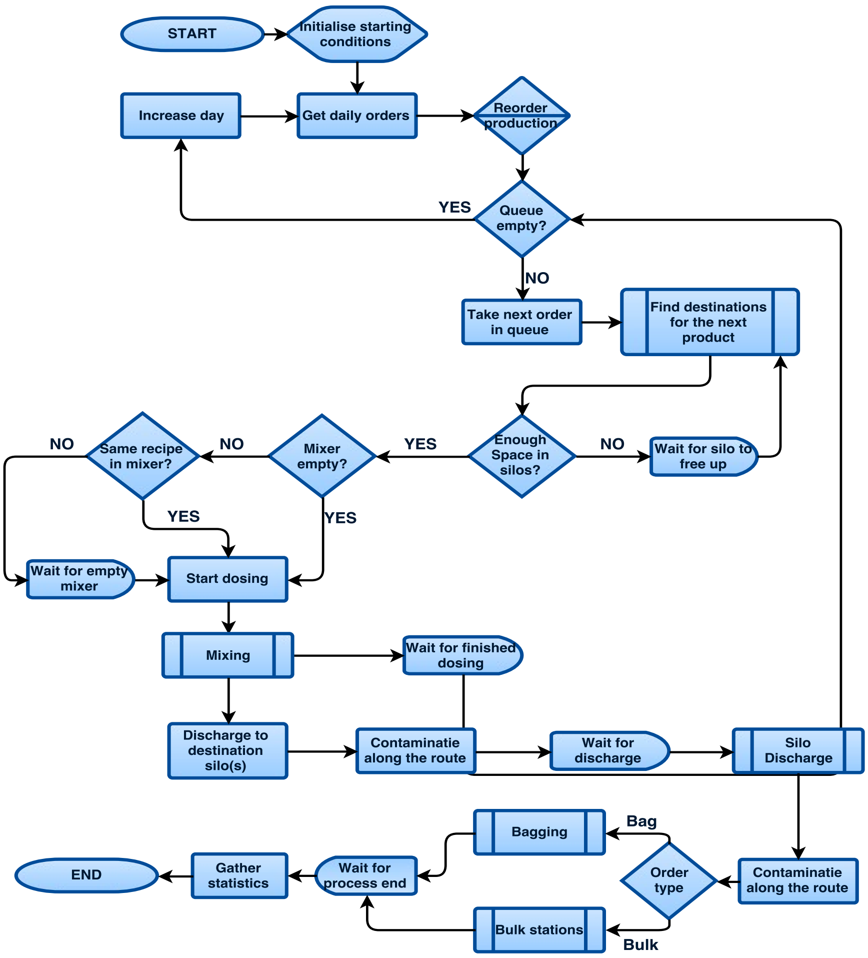

Figure E.1: A flowchart of the order sequence logic their rearrangement in accordance to the chosen scheduling rules are kept in a queue. Whenever this queue runs empty the next production day is initialised. Then, one by one orders search for possible destinations and once find sufficient space move to dosing, which commences immediately for the same recipes and after mixer changeover if the recipe is different. When the dosing is finished, another order is taken from the order daily queue.

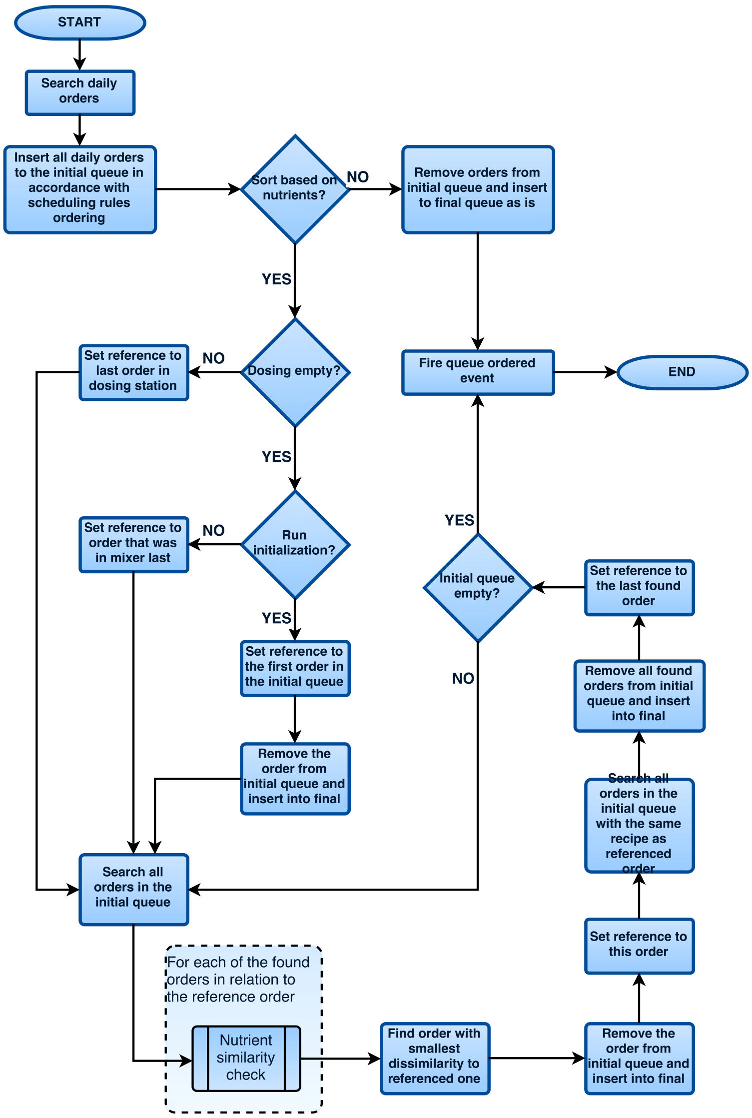

Figure E.2: A flowchart of how sequencing of daily orders is executed

Mixing takes time depending on the dosing speed and chosen destination and the cross-contamination calculation start when leaving the mixer and continue for each independent interval. As the first product reaches the chosen silo, the discharge might commence but usually the product needs to wait until a relevant system exit becomes available (or time function reaches its due date). When the mixing finishes the order entity is moved from the dosing station to the storing station awaiting next steps. From the silo product batches are sent to either bagging or bulk stations to be processed further. In case the order is split there might be order merger or the rest of the material continues later. When the whole order has been processed the order gathers final statistics and is sent to the finished orders station, where it remains till the end of the run.

The most important function in the possible daily order sequencing (flowchart shown in Figure E.2 is incrementally basing consecutive products on the least different product. This procedure starts with a reference product, which is the last product from the previous day (the last product in the mixer) or the first one from the queue in case of the model start-up. All remaining products in the queue then calculate their difference with respect to the reference product as shown in Figure E.3. All nutrients are equally important in this check and the relative difference between specified level of the reference product and the lower of higher threshold value of the investigated product is calculated.

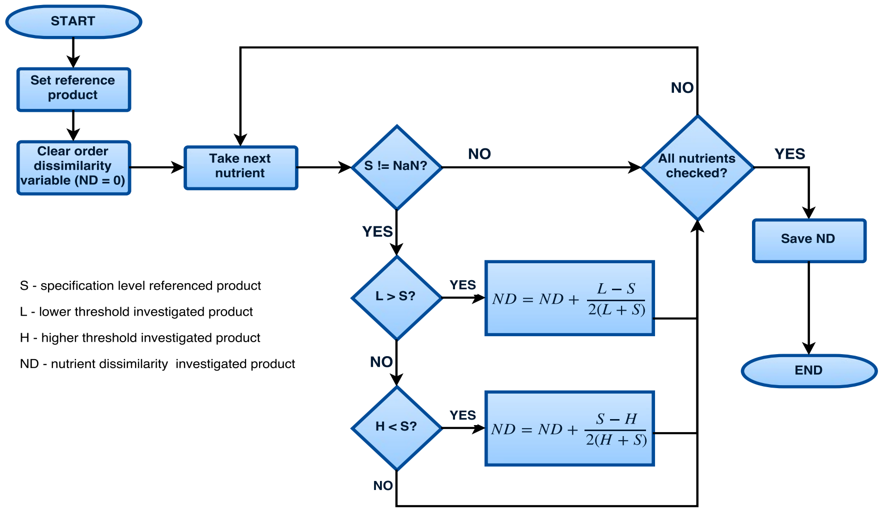

Figure E.3: A flowchart of how nutrient similarity is defined

The order with the lowest relative difference is then taken and placed next in the order mixing sequence. In case there is more than one with the same, lowest value the first one in accordance with mixing order scheduling rule (sequencing based on order parameters such as size or package size). The reference is set then to the taken product and the procedure is repeated for the set with one fewer order. The process is finished when all orders are allocated in the mixing sequence. Similar approach is taken for order allocation in silos when these are empty candidate silos. Then a nutrient similarity function is a multiplier of a silo objective function that needs to be minimised based on the current state. This way in case of multiple empty silos, depending on their last contents a preference is given based on nutrient levels on which one to choose.

E.2. ASSESSING BAG CONTENTS

In order to determine whether a packaged bag complies with specification limits for a given product a two step analysis is performed. At first, all bag contents in terms of products are gathered together, as previously the batch entities comprising it were just put together. The logic for it is shown in Figure E.4. The following step is to assess the nutrient content of a given mixture, the process of which is shown in Figure E.5. The method assumes equal spread (homogeneity) of contents in the bag as well as no sampling bias. A flowchart in Figure E.4 shows performed steps to gather together all bag contents from comprising product batches so that there is no missing or repeated data. Next to that, the process performs an important function of counting finished bags for their parent orders and signifies the end of order if all of them have been processed. To simplify the process, one by one, each of the bag child entities (batch members) are taken and its comprising product contents are added to, empty in the beginning, respective bag fields. At first original, intended recipe content is added and then, again one by one, all comprising product contaminants. For product batches, the table of contaminants is incremental and there is no removal of entries so once an empty field in the table is reached, the next product batch can be taken. The main logic is thus within two embedded for loops, where the higher level one is of the size of the number of entities and the lower level has each time the size of the number of contaminants within examined product batch. There is a significance of not ever removing product batch contents, not only to easier handling of their tables, but also to express that once a particular product was contaminated by a given other product. With quite uncertain contamination curve, the means of empirically establishing whether a particular contamination took place is added, though with a large number of entities processed one needs to know exactly what to look for in order to take advantage out of that.

Recalculation into nutrients is a sub-process for bag contents assessment, and is shown in Figure E.5. It

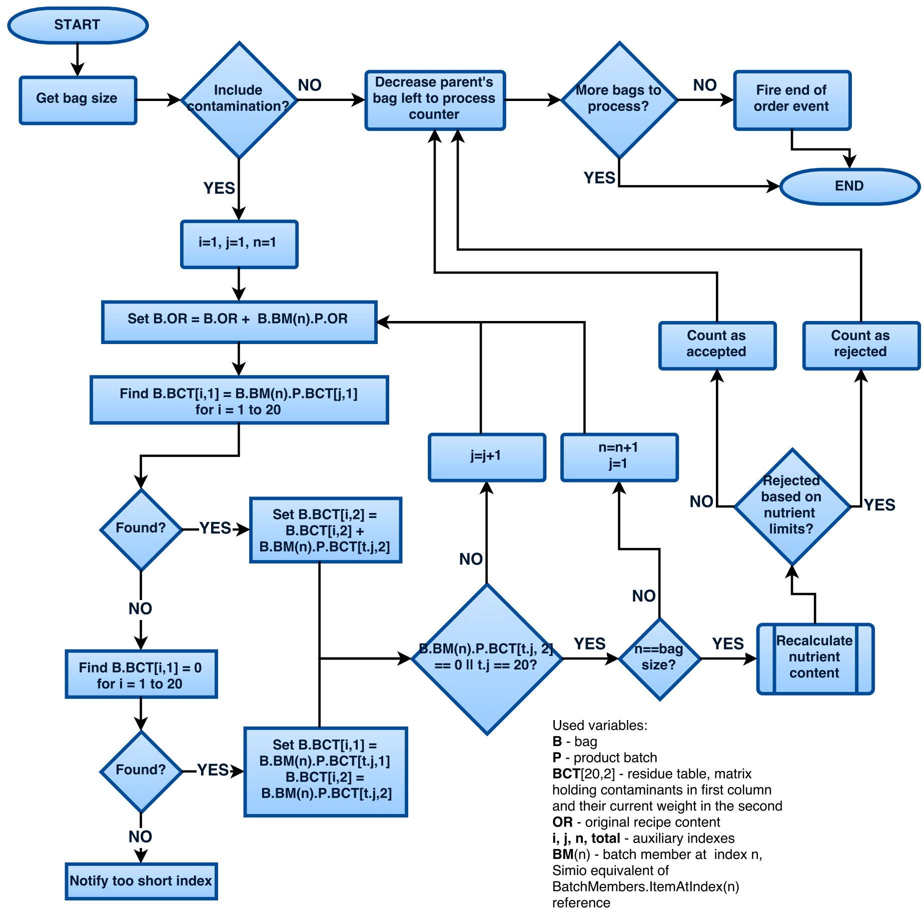

Figure E.4: A flowchart of how final bag contents are gathered

can be viewed as first a for loop for each of the 16 identified nutrients adding them up for the original recipe content, and then repeating this process for each nutrient for each of the comprising product contaminants. Thus, if the product has 12 contaminating components then including the original recipe there is a need for $16 \cdot (12+1) = 208$ calculations, just for a single bag, which is a lot of calculations.

An important feature limiting search problem is searching for specification values not in a table with all contaminants but within storage station containing all previously processed orders. Because the simulation time was limited, the build-up of orders was also constrained to manageable number of several hundred. The full table, on the other hand, has over 10 thousand entries. Once all the nutrients are added up a comparison with specification limits can be made, and is done separately for lower and higher limits for each nutrient. Once any value is considered out of specification, the bag is labelled as rejected.

E.3. SILO LOGIC

Silos are intermediary objects between the main mixer and system exits and thus take part in both silo allocation and final discharge. Their main purpose is to hold (delay) material before processing further. Since there might be material from different products in a single silo and an order is not necessarily put into a single silo the knowledge how many different products are there in and when does one finish and the next one starts is vital.

In general silo behaviour follows one big logical loop as presented in Figure E.6 and the most time is spent on waiting for discharge or material. Normally silos are initialised empty and then wait for incoming material from the mixer, which is then connected to a batch entity to save on memory and computing power. Once there is some material in the silo the discharge might commence, providing there is capacity of a relevant system exit. If not, the silo waits until it is queried for it, which is a check for possible parallel discharge

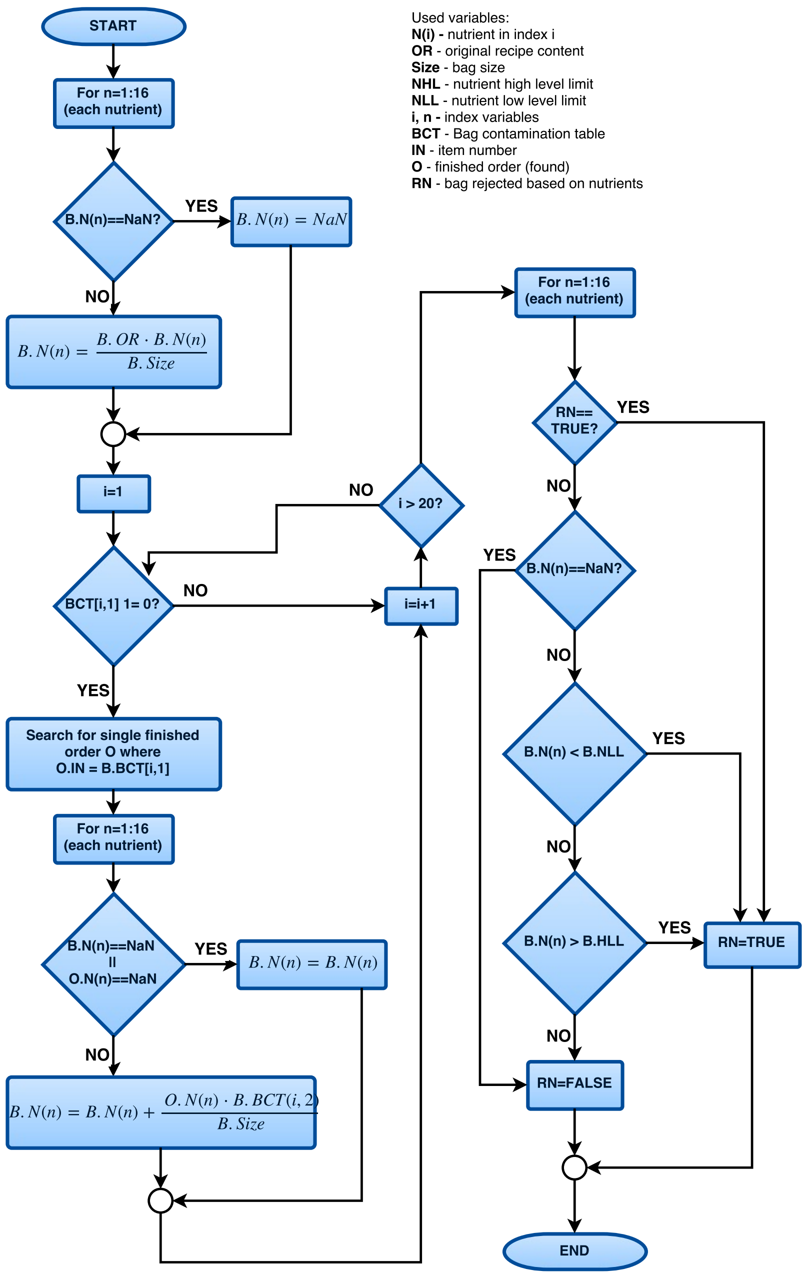

Figure E.5: A flowchart of bag contents with nutrient levels comparison

and fitting material parameters to the query. IF everything is matching the discharge commences to the appropriate destination, which might be interrupted if the buffer levels breach their high level. Discharge can be simultaneous to up to 2 small bagging machine and a single bulk station or big bag filling station.

Once the whole order in a given silo is discharged the outflow stops and references are cleared in case it runs empty or updated if there is another material in it. There might be an additional check for the same order in another silo if the order is split. Merging discharge is a process of redirecting flow from another silo to the same system exit without doing a changeover, if the route is not blocked by a parallel powder flow. Silo loop starts with a replication run and ends at the finish time.

Cross-contamination function is the central and most expensive calculation made in the model, executed for each product batch between 10 and 27 times, depending on the route taken and bases on the calculation made in section 4.4. Flowcharts for implemented functions are split into two and presented in Figures E.7 (in-

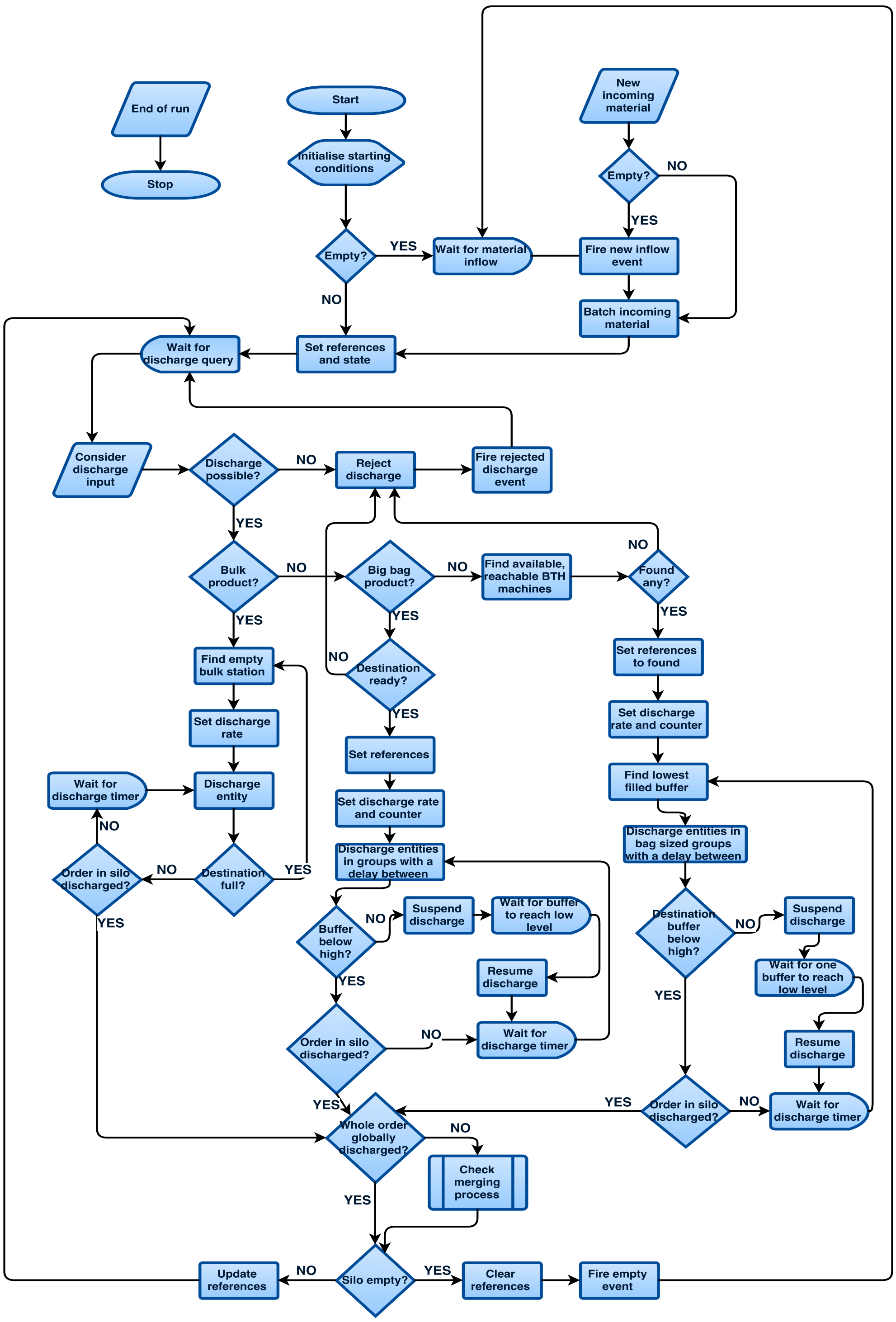

Figure E.6: A flowchart of the crucial silo logic

cluding used designations) and E.8 (also with often repeated sub-process). Simply put the process compares and shifts some of the values (quantity) in one table (product batch) to and from another table (equipment residue table) and it might be divided into 4 stages: establishing exchanged amount, updating batch original recipe content, comparing batch contamination table with equipment residue table and contaminating the batch by products in the equipment that were not previously present in the batch.

E.4. CROSS-CONTAMINATION IMPLEMENTATION

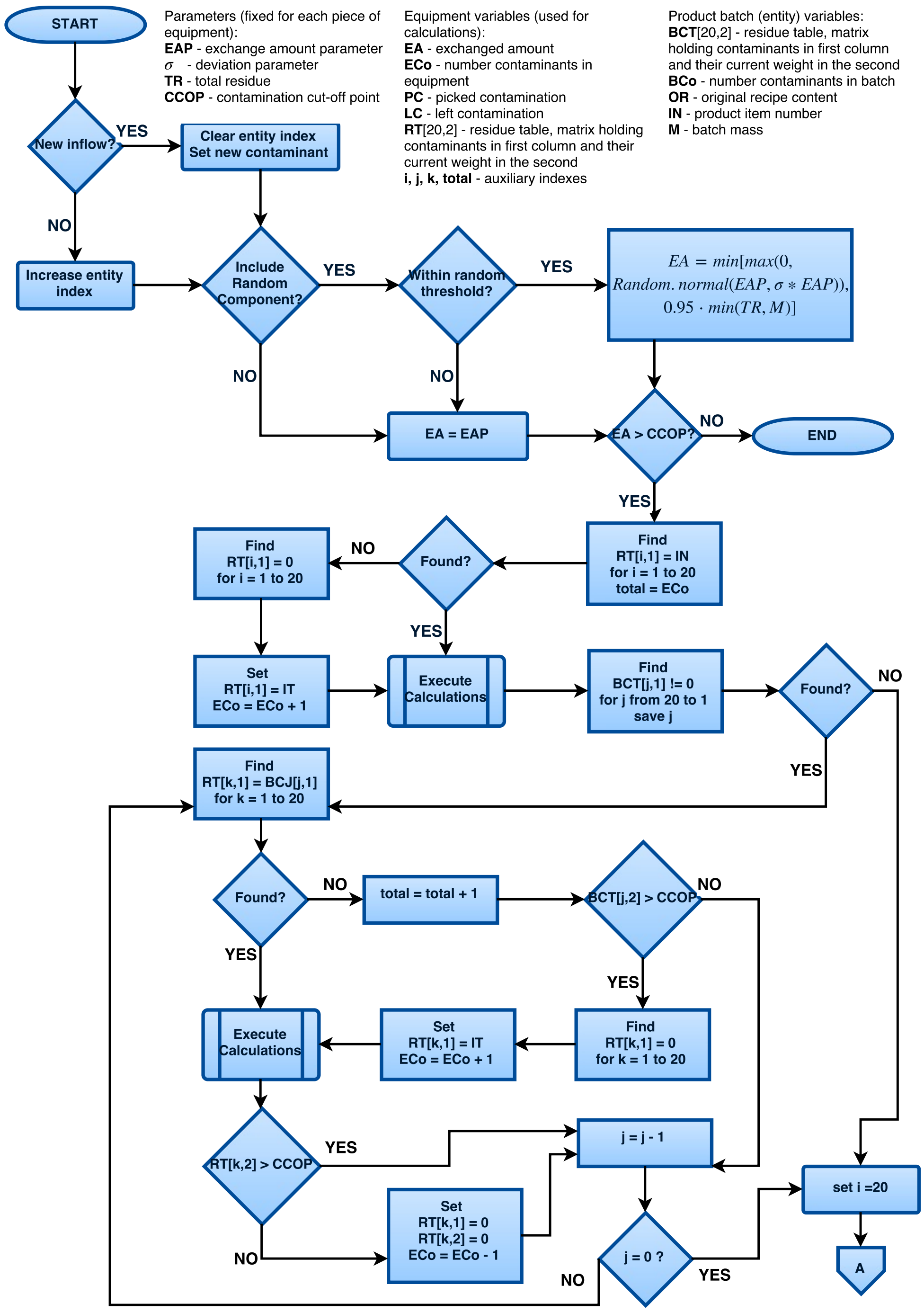

Figure E.7: A flowchart of contamination calculation implementation; Part 1 of 2

An important assumption is that once any product residue in certain equipment reaches a level below user-settable threshold level it is removed from the table and treated as 0. Once a product batch is contaminated, its presence cannot be entirely removed, so that the contamination is incremental and there are no gaps in the static table. Establishing the exchanged amount is the first step. Normally it is equal to the exchange amount parameter EAP unless it is a run with a random component, when the EA is drawn from a normal distribution of EAP with set deviation and restricted when breaches certain thresholds. Moreover,

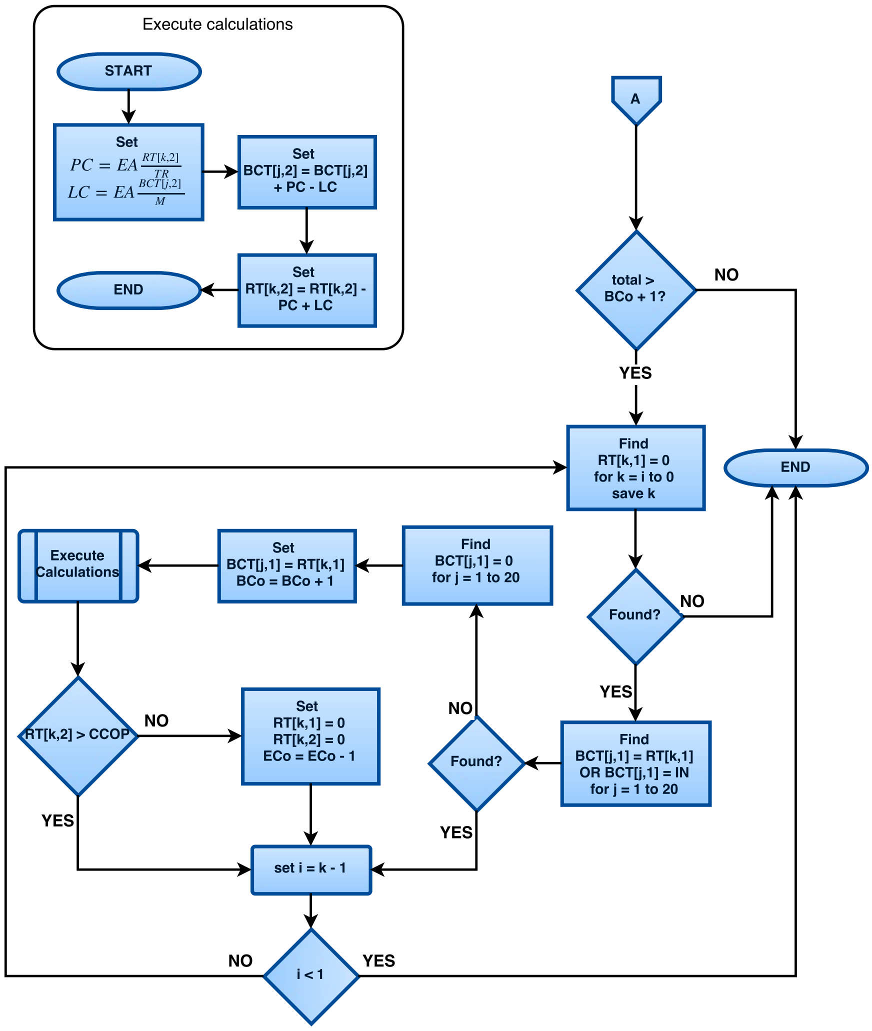

Figure E.8: A flowchart of contamination calculation implementation; Part 2 of 2

extra variables to keep track of the number of contaminants present in both equipment and product batch are introduced to save on the number of calculations. This way contaminants present in the product batch are always compared with the residue in the equipment and the search in the other way is performed only if the number of product residues in the equipment is bigger than the one in the product batch, after the initial comparison. This function (as in Figure E.8) is thus calculated infrequently, being very expensive by going through each product residue in the equipment and searching for respective product in the batch.

E.5. POSSIBLE SILO ALLOCATION FUNCTION

Another important feature of the model is allocating possible destination silos for orders before mixing, presented in Figure E.9. When dosing finishes the next order in line is taken and an attempt is made to allocate possible silos to it. First all silos that are available in a simulation run and are not reserved for another recipe are queued in a so called possible allocation queue and counted. From that queue silos with the same recipes are searched. All found are removed and either inserted into actual allocation queue is the silo fill level is below high or counted as blocked with the same recipe when the level is not below high. Moreover, silo with the same recipe might be rejected based on scheduling rules (e.g. preventing products with the same recipe but different type from being in the same storage). Afterwards, all silos that are currently holding other recipes are removed from the possible allocation queue and only empty ones remain.

The remaining empty silos are then ranked in accordance to chosen scheduling rules. In case of a run with contamination silo residue (last product in) is compared with the order being allocated based on nutrients.

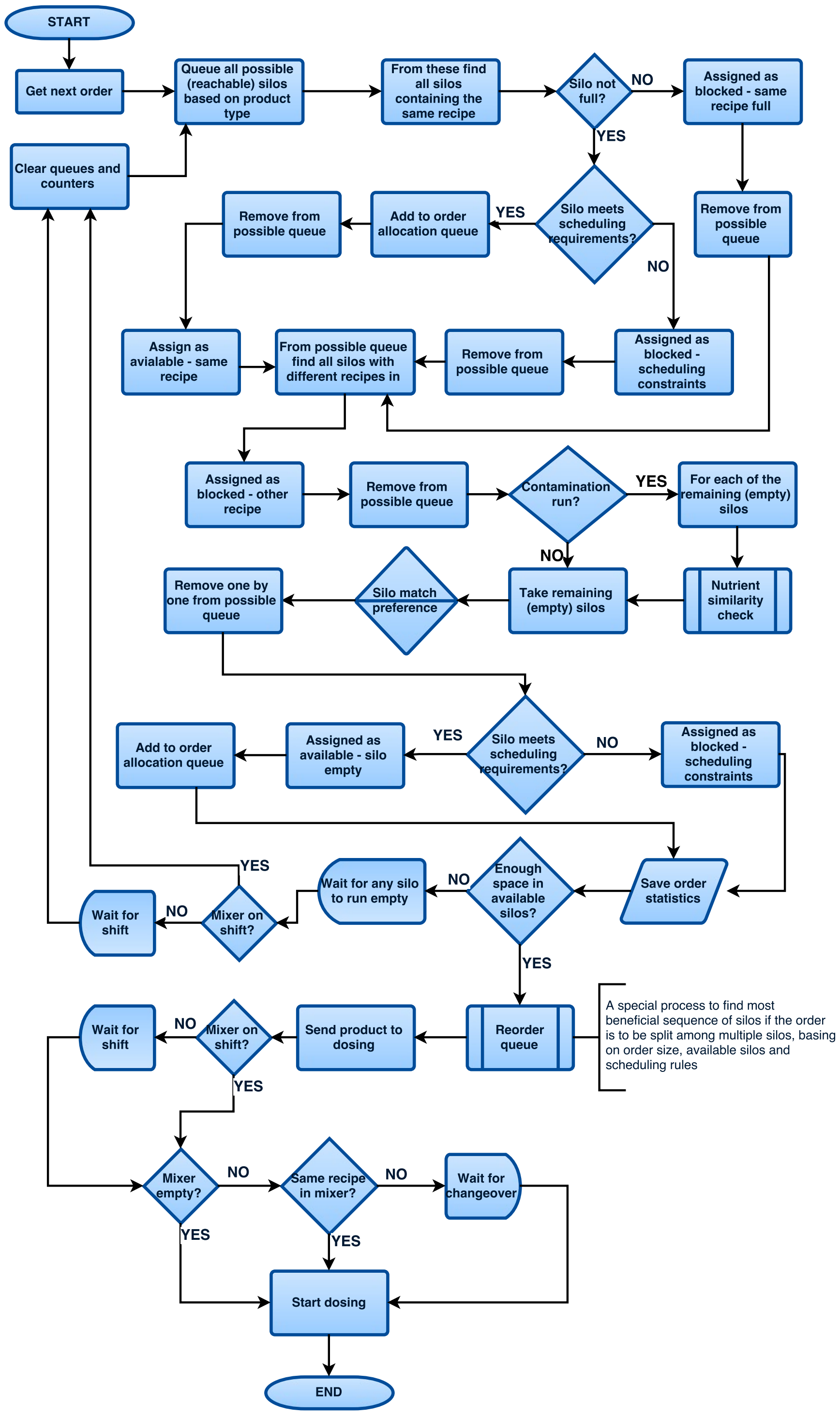

Figure E.9: A flowchart of how possible destinations are assigned to orders

Then, final order in term of scheduling rules is established and silos are one by one removed from possible allocation queue and moved to the actual allocation queue providing they meet scheduling constraints. Once all silos are processed the statistics are saved and remaining space in the silos is compared with necessary one for allocation. If that is sufficient the order allocation queue might be rearranged to find a better match in case the order is to be split (i.e. preferring discharge to parallel silos). Then the order is sent to dosing where

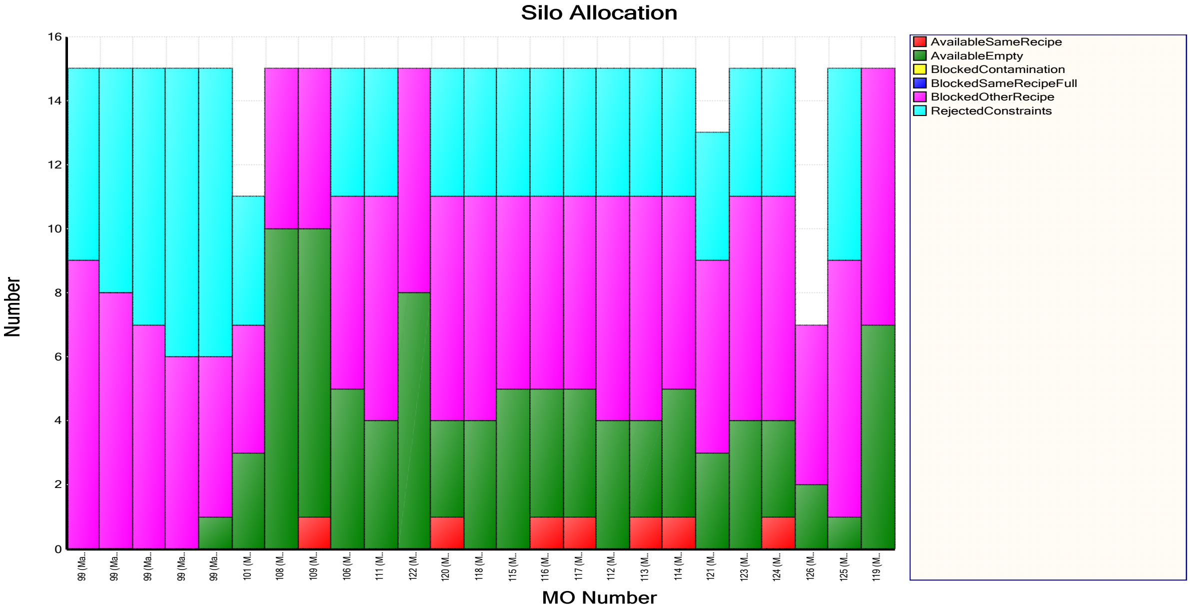

Figure E.10: An example order silo allocation chart

it awaits mixer availability and follows the procedure as described earlier in Figure E.1. When there is not enough space in the chosen silos the allocation queue is cleared and the order waits for a silo to run empty to repeat the search.

After each execution of the possible silo allocation function a data entry is made to categorise assessed silos for given order, an example of which is shows in Figure E.10. A manufacturing orders can have multiple entries if there was not enough space available to commence mixing.

E.6. Mixer Logic

The main mixer logic is closely connected to its state and especially orders currently allocated to it. Every time a new order has finished dosing, there is a process determining what to do next, more specifically whether there is enough time and capacity to process the next order or to finish for a given day. If the next order in queue is to be finished on a given day then once the mixing has ended, the statistics are saved, and new order can be processed. Logic for stopping due to time constraints for a given day is executed elsewhere.

Here, the algorithm assesses, whether there are enough resources to mix orders, that are not necessary for a given day but could be put into silos. At first, predicted ending time is checked, and if that is sufficient, an order searches for possible destinations (see Figure E.9) to determine available capacity in silos. If there is enough time and capacity the process ends without consequence. When there is enough time but not silo capacity the loop continues, waiting for capacity to become available or the end of shift. In the case when there is not enough time to finish the order on time, the shift is ended early, statistics recorded, and the next order in queue is prevented from entering dosing.

E.7. Choosing Silo to Discharge

Packaging material is a process between a silo and bagging machines, where any two machines can be chosen to bag material from a given silo. Therefore, a match has to be found between those two, while the packaging is leading by ‘pulling’ material from the silo. Figure E.12 shows how the most versatile machine BTH3 chooses a potential silo to bag from, based on scheduling rules and its internal logic. The process commences when a new product enters an empty silo, at the beginning of a shift, when a bagging machine becomes available, or when a potential discharge candidate is rejected.

The whole procedure bases on repeated searches for suitable silos (or in fact their first orders for discharge) according to scheduling rules and then checking whether discharge from them is possible and finally allocating suitable bagging machines. Checking availability comprises of parallel discharge assessment, size and restrictions for the order control as well as final machine availability check, not to commence more than

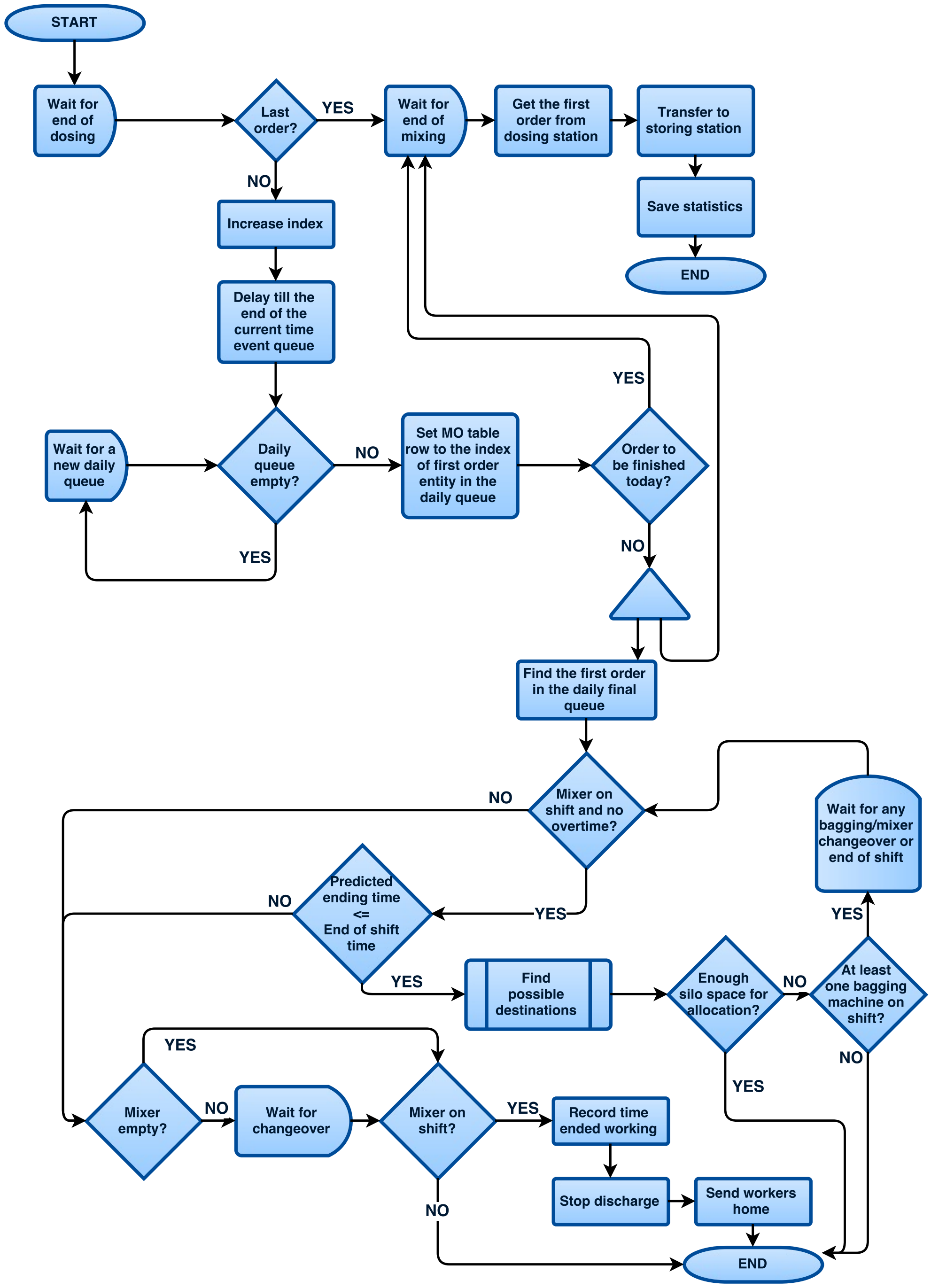

Figure E.11: A flowchart of processing logic for mixer after each order dosing finishes

one discharge to a bagging machine.

E.8. BAGGING MACHINE SHIFT END

Every time a bagging machine finishes a changeover it executes a decision process, whether there are still orders to be processed by it, and if that is possible. As the decision is based on the current state of the mixer, orders in silos and their due dates, the search is a complex one. Other processes are responsible for time

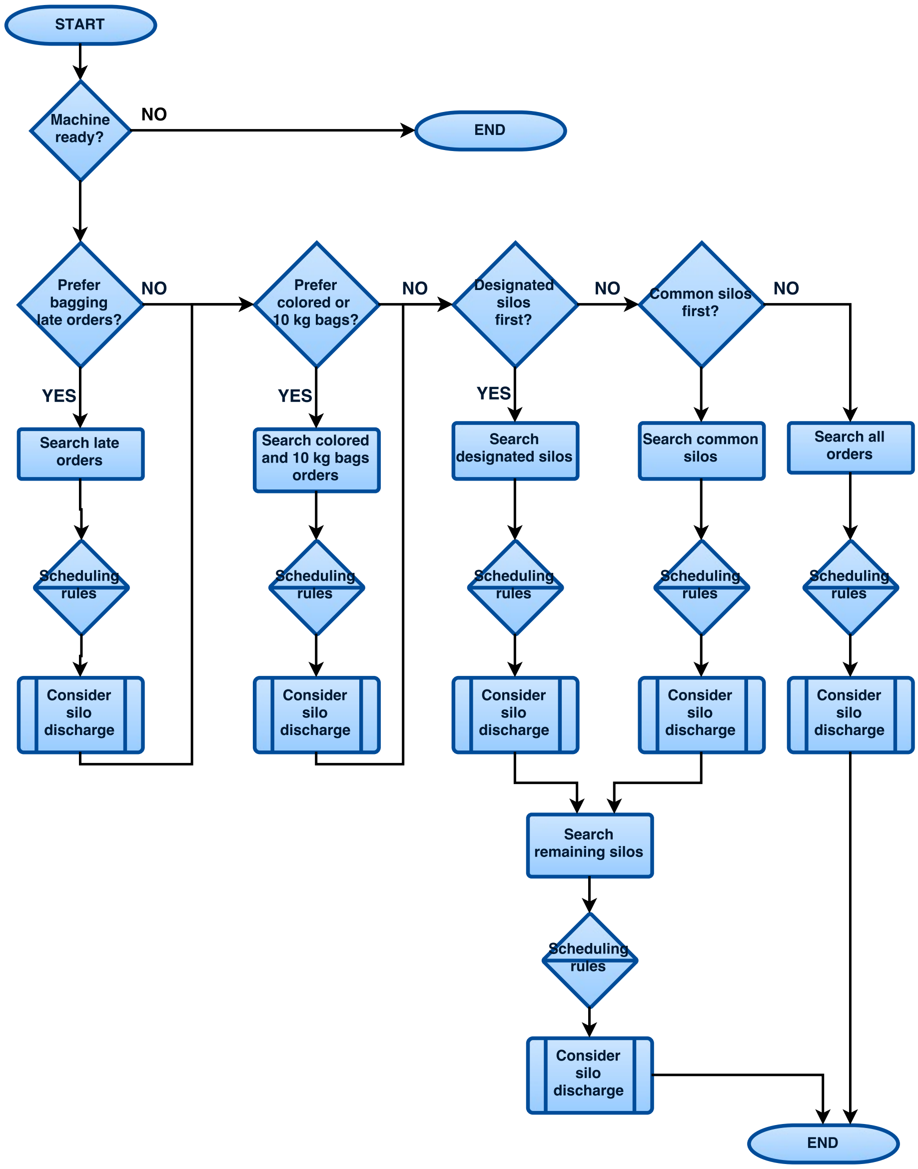

Figure E.12: A flowchart of how orders to be bagged by BTH3 machine are searched for

management. Flowchart of the process logic is shown in Figure E.13.

Here, all orders that have already been mixed and could be processed by a given machine, providing the mixer has finished mixing orders for a given day, are added to a potential queue. From these, orders that are allocated in reachable silos i.e. with a direct connection to the machine are moved to another queue, called reachable queue. Then, depending on the number of orders in the reachable queue a decision whether to continue is made.

With this method, orders that are split among multiple silos or multiple orders in a single silo are recognised and handled, and a simple predictive decision is made. Only when there is a potential reachable order that can be bagged in the future will the bagging machine stay on shift, even when the order is not immediately to be started. If it is blocked by a parallel discharge it will result in machine starving time.

The method is not optimal, it might result in unnecessary starving time of a single machine if there is one order blocked for discharge and all three available machines can process it.

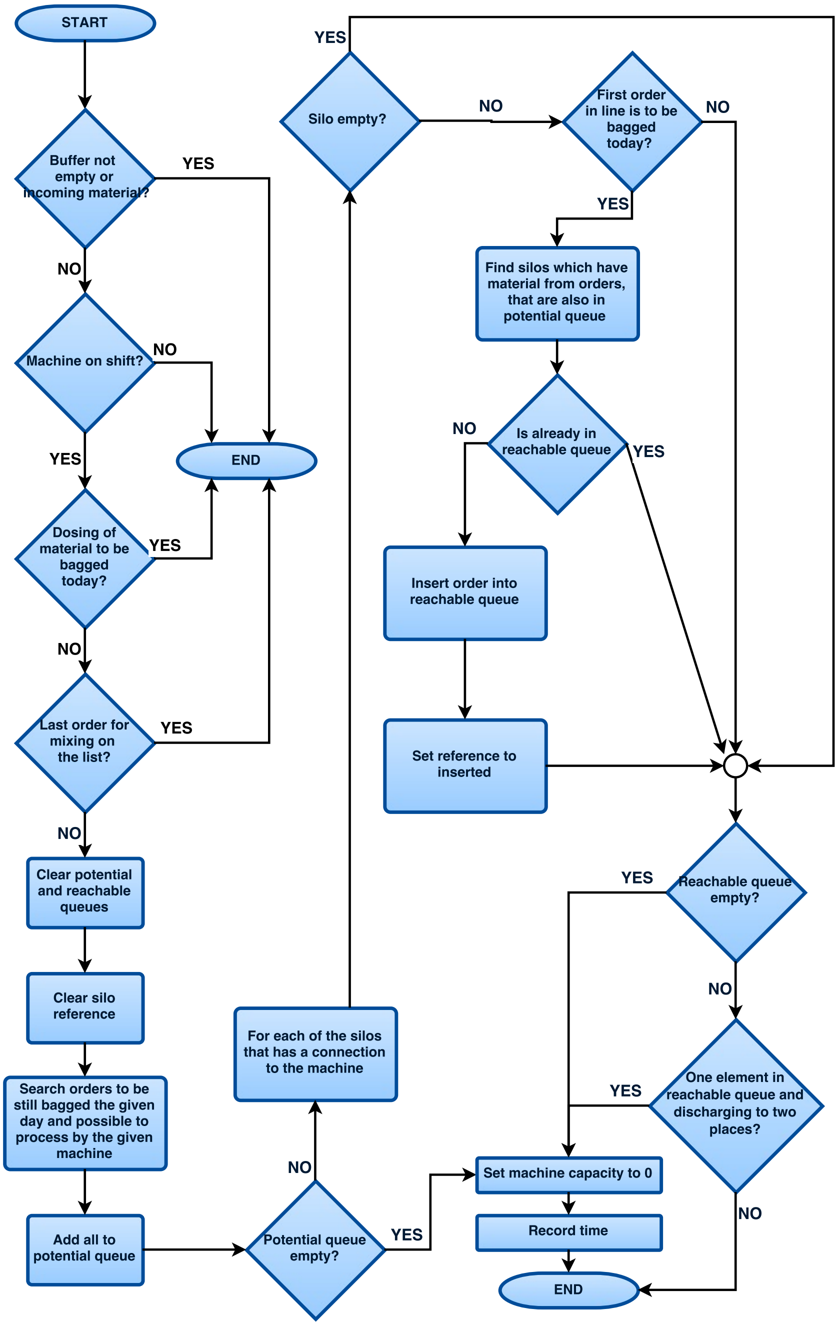

Figure E.13: A flowchart of how bagging machine decides to end early for a given day

F

Verification & Validation

F.1. Verification Tests

Below several performed verification tests are listed starting from degenerate and general logic tests in table F.1, followed by a trace test.

Carried out tests

Some degenerate tests performed are listed in table F.1.

Table F.1: List of performed general verification tests

Group	Input	Result
Dosing	Dosing speed > mixer discharge	Material in mixer increases, cyclic dosing breaks when full
	Dosing speed = mixer discharge	Roughly constant material levl in mixer
	Dosing speed < mixer discharge	Cyclic discharge breaks due to low material level
Order sequencing	Smallest orders first	Order quantity increasing in queue
	Largest packages first and join recipes	Package size decreasing in queue and same recipes together
	Nutrient sequencing	Orders shuffled, low dissimilarity and same recipes together
Initial conditions	Random product with distant due date in silo	Size and references correct, no discharge till due date
	All silos blocked for non-existing recipes	Mixing never starts
	All but one silos blocked	Material allocated to only available silo
	No orders in queue	No production
Order composition	Bulk orders only	Only silos 14-23 used, bulk stations periodic discharge when full
	Big bag orders only	Only silos 14-23 used, quick increase of WIP material
	Orders for colored products/10kg bags only	Only silos reaching BTH3 used, machines BTH1-2 idle
	Large orders only (>100 tonnes)	Orders split into multiple silos, outflow merged whene possible
Silos parameters	Silos reserved for some recipes	Reserved silos not considered for other products
	Silo discharge speed set to 1 kg/h	Extremely slow discharge
	Silo discharge speed set to 20000 tonnes/h	Extremely fast discharge until buffers full, piping not empty
	Parallel silo list set to all silos	Only single silo discharge in the system

Trace test

Trace test is based on a movement and cross-contamination of the first product batch of a random order, including logic for silo allocation and its discharge. A shortened model trace is shown below:

```
Item Name: Sprayfo geel NL 25kg
Item Number: 10041915
Recipe Number: 10040895
Recipe Name Recept 3100
Order Quantity: 24000kg
Package Size: 25kg
Due Date: 08.01.2015
Order Number: 66
Dosing speed: 50000 kg/h
Coloured product: False

Time statistics:
TimeStartedMixing 154.06402465065776 Hours
TimeEndedMixing 154.74579131731289 Hours
TimeStartedBagging 176.00702175666007 Hours
TimeEndedBagging 177.28228900885603 Hours

Silo allocation statistics:
154.06402465065776 Hours
Name Value
SilosTotal 15
SilosAvailableSameRecipe 0
SilosAvailableEmpty 1
SilosBlockedSameRecipeFull 0
SilosBlockedOtherRecipe 10
SilosRejectedConstraints 4
SilosAvailableCapacityForAllocation 65000 Kilograms
Starting dosing.
```

```
Silo AllocationQueue 1:  Silo_19
Silo chosen has big enough capacity.
No queue reordering as there is only a single silo picked.

Nutrient specification:
Contaminant Specification Lower Limit Higher Limit
Animal Fat in Fat 0 NaN 4
Ash 9 NaN 10.1
Colorant 0 NaN NaN
Copper 10 8 12
Fat 16.5 14.4 18.6
GMO 0 NaN NaN
GMO in GMO Protein 0 NaN NaN
GMO Soy Flour 0 NaN 1
Iron 100 80 120
Lactose 46.5 43.5 49.5
Probiotic 1000000 NaN NaN
Protein 21.5 18.8 24.2
Protimax 0 NaN NaN
Soyabean Protein 0 0 NaN
Vital Wheat Gluten Dry 0 NaN 1
Vitamin A 40000 36000 44000

AcceptedBagsOrder 858
AcceptedWeightOrder 21450
AcceptedOrderRatio 0.89375
RejectedBagsNutrients 102
RejectedWeightNutrients 2550
RejectedOrderRatioNutrients 0.10625
Order on time: True

Verification values:
Batch interarrival time: 0.0001 Hours
5kg / 50000 kg/h = 0.001h
Minimum dosing time: 4800 * 0.001h = 0.48h
Minimum discharge time after dosing:
3000kg / 40000kg/h = 0.075h
Dosing-->Mixer transport time: 0.001(6) hours
Mixing time: 0.41499166668038 Hours
Minimum time < Mixing time
Available silos: 15 (11 initial + 4 new)

Investigated batch: Product 346415
1. Initial
Originalrecipecontent: 5 [kg]

2. After Mixing Contamination
OriginalRecipeContent 4.8020569762106762
Contaminants:
Item Number Mass [kg]
10041865 0.0001175069627893614
10040205 0.19782551682653426

3. After the first screw conveyor
OriginalRecipeContent 2.7659848182973494
Contaminants:
Item Number Mass [kg]
10041865 0.00132106141106035
10040205 2.23269412029159

4. After the second screw conveyor
OriginalRecipeContent 0.27659848182973468
Contaminants:
Item Number Mass [kg]
10041865 0.00132106141106035
10040205 4.7206089411318839

5. After the third screw conveyor
OriginalRecipeContent 0.027659848182973484
Contaminants:
Item Number Mass [kg]
10040205 4.9694004232159124
10041865 0.00132106141106035

6. After the sixth screw conveyor
OriginalRecipeContent 0.016885977061830239
Contaminants:
Item Number Mass [kg]
Name Value
10040205 4.9801679257314717
10041865 0.00132106141106035

7. After the eigth screw conveyor
(entering silo 19)
OriginalRecipeContent 0.015562116460182749
Contaminants:
Item Number Mass [kg]
10041865 0.00132106141106035
10040205 4.5897227603541237
10040135 0.0013445461412777936
10040355 0.1986456206184527
10754455 0.0011237284007612216
10276785 0.19886749435773685

8. After the silo
OriginalRecipeContent 0.0140059048141645
Contaminants:
Item Number Mass [kg]
10041865 0.00132106141106035
10040205 4.13075048431871
10040135 0.0013445461412777936
10040355 0.178781058556607
10754455 0.00383359245582761
10276785 0.676134048043703

9. After the panumatic conveyor system
OriginalRecipeContent 0.0043660052721958519
Contaminants:
Item Number Mass [kg]
10041865 0.00132106141106035
10040205 1.2876624989213121
10040135 0.011673490401418091
10040355 1.3021951100181148
10754455 0.003833592455827609
10276785 0.34553561165688396
10038805 0.12495744039917706
10042695 0.12792395710989624
10043355 1.7989290253094348

10. After the air filter
OriginalRecipeContent 0.0031190741664567168
Contaminants:
Item Number Mass [kg]
10041865 0.00132106141106035
10040205 0.91990608922938533
10040135 0.011673490401418091
10040355 0.93028818659694135
10754455 0.003833592455827609
10276785 0.24685064096767789
10038805 0.094967654703374565
10042695 0.091576807732927257
10043355 2.7122954730286364

11. After the bagging buffer
OriginalRecipeContent 0.0029007389748047468
Contaminants:
Item Number Mass [kg]
10041865 0.00132106141106035
10040205 0.8555126629833284
10040135 0.011673490401418091
10040355 0.86516801353515549
10754455 0.003833592455827609
10276785 0.22957109609994045
10038805 0.094967654703374565
10042695 0.085389483279515108
10043355 2.8722112075185415

12. Bag contamiantion
OriginalRecipeContent 0.66430670424439575
Contaminants:
Item Number Mass [kg]
10041865 0.0060438882287918334
10040205 11.80937146779862
10040135 0.016578099923367454
10040355 3.1374302418541409
10754455 0.018826663246733256
10276785 2.4248923189217026
10038805 0.24158115955761184
10042695 0.21869821168682493
10043355 6.4882633848704536

Nutrients:
NutrientAnimalFatInFat 0
NutrientAsh 0.23915041352798244
NutrientColorant 0
NutrientCopper 21.360238935959895
NutrientFat 0.43844242480130119
NutrientGMO 0
```

```
NutrientGMOinGMOProtein 0
NutrientGMOSoyFlour 0
NutrientIron 2.657226816977583
NutrientLactose 1.235610469894576
NutrientProbiotic 520649.03791019565
NutrientProtein 0.57130376565018026
NutrientProtimax 0.0012649203173318664
NutrientSoyabeanProtein 0
NutrientVitalWheatGluten 0
NutrientVitaminA 1062.8907267910331
Bag rejected: TRUE
```

F.2. STATISTICAL TESTS

Table F.2: Accuracy of the simulated contamination curves with respect to the fitted contamination

Point	A	B	C	D	E	F	G	BAG
SS Total	1.2000	5.5072	6.7699	7.1377	13.0768	12.9861	14.7372	3.5497
SS Regression	1.0809	5.3972	6.3656	6.1235	12.9185	12.7940	14.4615	3.4512
SS Residual	0.1191	0.1101	0.4043	1.0141	0.1583	0.1921	0.2756	0.0985
R Squared	0.9008	0.9800	0.9403	0.8579	0.9879	0.9852	0.9813	0.9723
StDev	0.0109	0.0105	0.0201	0.0318	0.0126	0.0139	0.0166	0.0222

Table F.3: Goodness of fit (Kolmogorov–Smirnov test) for short stops and changeover time distributions

	Time to repair (log-normal)				Changeover (Weibull)
	BTH1	BTH2	BTH3	Mixer	BTH1-3
DN	0.185746	0.146947	0.0565757	0.06596	0.0316606
p-value	0.0	0.0	0.0000573061	0.000822343	**0.335282**
result	reject	reject	reject	reject	fail to reject

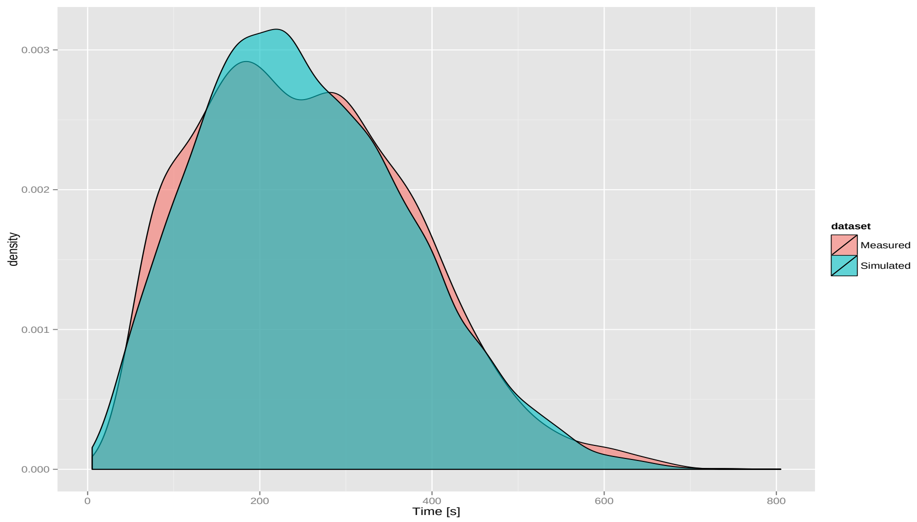

Figure F.1: Comparison between probability density function of measured and fitted distribution for bagging changeovers

Table F.4: Statistical data on obtained throughputs in the base case simulation

Machine	BTH1 [bags]	BTH2 [bags]	BTH3 [bags]	BTH1 [kg]	BTH2 [kg]	BTH3 [kg]
Average	355.32	360.11	357.72	8700.82	8813.73	7014.55
SD	17.95	15.92	18.86	512.05	484.56	1007.60
Median	359.57	363.40	362.84	8875.22	8940.43	6911.82
No measurements	300	300	300	300	300	300
Value Min	223.41	222.48	258.62	5585.15	5562.08	3201.25
Value Max	379.05	382.77	378.36	9476.19	9569.13	9198.34

G

Experiment Results

G.1. Initial Exploration Results

G.1.1. Result Tables

Table G.1: Experiment results of scenario NC_A

Scenario	**NC_A**				
KPI	Average	SD	median	no. measurements	Unit
Avg throughput bags	1073.15	41.57	1080.69	300	bags/h
Avg throughput quantity	24529.10	1400.92	24686.10	300	kg/h
Orders completed	261.00	0.00	261.00	20	-
Orders completed on time	248.85	2.76	249.00	20	-

Table G.2: Experiment results of scenario NC_B

Scenario	**NC_B**				
KPI	Average	SD	median	no. measurements	Unit
Avg throughput bags	1073.16	41.57	2080.70	300	bags/h
Avg throughput quantity	24529.1	1400.92	24686.10	300	kg/h
Orders completed	260.50	0.81	261.00	20	-
Orders completed on time	247.15	3.28	246.50	20	-

Table G.3: Experiment results of scenario NC_C

Scenario	**NC_C**				
KPI	Average	SD	median	no. measurements	Unit
Avg throughput bags	1071.31	40.65	1080.54	300	bags/h
Avg throughput quantity	24467.82	1439.16	24605.21	300	kg/h
Orders completed	260.95	0.22	261.00	20	-
Orders completed on time	248.65	2.62	249.00	20	-

Table G.4: Experiment results of scenario NC_D

Scenario	**NC_D**				
KPI	Average	SD	median	no. measurements	Unit
Avg throughput bags	1060.78	56.30	7078.38	300	bags/h
Avg throughput quantity	24209.60	1774.11	24653.46	300	kg/h
Orders completed	260.5	1.07	261.00	20	-
Orders completed on time	249.45	3.98	251.00	20	-

Table G.5: Experiment results of scenario NC_E

Scenario	**NC_E**				
KPI	Average	SD	median	no. measurements	Unit
Avg throughput bags	1071.62	44.79	1081.41	300	bags/h
Avg throughput quantity	24442.90	1490.34	24587.42	300	kg/h
Orders completed	260.85	0.48	261.00	20	-
Orders completed on time	247.85	4.90	248.00	20	-

Table G.6: Experiment results of scenario NC_F

Scenario	**NC_F**				
KPI	Average	SD	median	no. measurements	Unit
Avg throughput bags	1045.68	59.84	1064.53	300	bags/h
Avg throughput quantity	23864.88	1705.87	24242.70	300	kg/h
Orders completed	260.40	2.18	261.00	20	-
Orders completed on time	248.00	6.17	249.50	20	-

Table G.7: Experiment results of scenario NC_G

Scenario	**NC_G**				
KPI	Average	SD	median	no. measurements	Unit
Avg throughput bags	1069.78	43.29	1080.11	300	bags/h
Avg throughput quantity	24397.41	1465.65	24647.20	300	kg/h
Orders completed	260.70	0.56	261.00	20	-
Orders completed on time	250.45	4.74	252.00	20	-

Table G.8: Experiment results of scenario NC_H

Scenario	**NC_H**				
KPI	Average	SD	median	no. measurements	Unit
Avg throughput bags	1070.92	43.27	1080.63	300	bags/h
Avg throughput quantity	24433.75	1323.44	24563.2	300	kg/h
Orders completed	261.00	0.00	261.00	20	-
Orders completed on time	250.75	3.51	250.50	20	-

Table G.9: Experiment results of scenario NC_I

Scenario	**NC_I**				
KPI	Average	SD	median	no. measurements	Unit
Avg throughput bags	1077.39	28.80	1081.84	300	bags/h
Avg throughput quantity	24560.26	1323.20	24599.79	300	kg/h
Orders completed	260.95	0.22	261.00	20	-
Orders completed on time	252.50	3.27	253.50	20	-

Table G.10: Experiment results of scenario NC_J

Scenario	**NC_J**				
KPI	Average	SD	median	no. measurements	Unit
Avg throughput bags	1060.29	27.75	1063.08	300	bags/h
Avg throughput quantity	24164.30	1306.65	24256.63	300	kg/h
Orders completed	260.90	0.30	261.00	20	-
Orders completed on time	250.45	3.00	250.50	20	-

Table G.11: Experiment results of scenario NC_K

Scenario	**NC_K**				
KPI	Average	SD	median	no. measurements	Unit
Avg throughput bags	1076.46	32.79	1080.83	300	bags/h
Avg throughput quantity	24551.67	1309.24	24645.49	300	kg/h
Orders completed	261.00	0.00	261.00	20	-
Orders completed on time	251.20	3.33	252.00	20	-

Table G.12: Experiment results of scenario NC_L

Scenario	**NC_L**				
KPI	Average	SD	median	no. measurements	Unit
Avg throughput bags	1073.53	38.12	1084.20	300	bags/h
Avg throughput quantity	24471.98	1373.98	24622.98	300	kg/h
Orders completed	261.00	0.00	261.00	20	-
Orders completed on time	250.25	2.55	250.50	20	-

G.1.2. PLOTS AND FIGURES

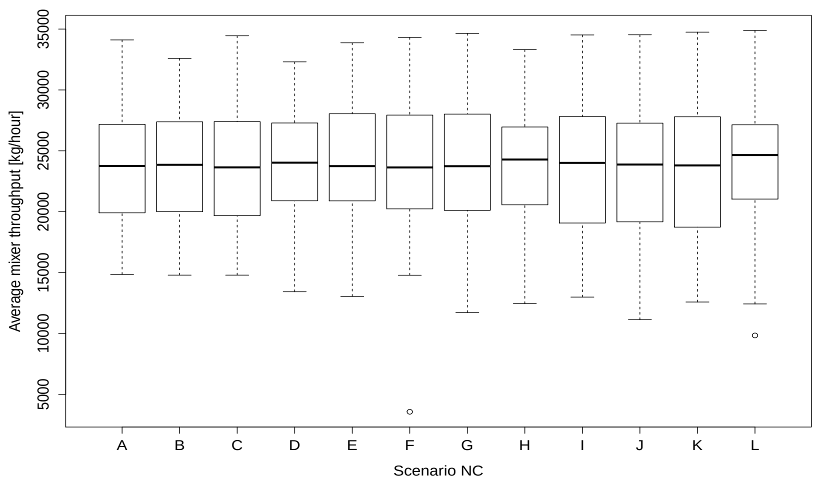

Figure G.1: A box plot for comparison of mixing throughput

G.2. CONTAMINATION INVESTIGATION RESULTS

Table G.13: Experiment results of scenario MassC_A

Scenario	**MassC_A**				
KPI	Average	SD	median	no. measurements	Unit
Avg throughput bags	1071.79	36.61	1080.72	320	bags/h
Avg throughput quantity	24699.81	1441.48	24974.09	320	kg/h
Orders completed	303.95	0.80	304.00	20	-
Orders completed on time	289.60	4.83	290.50	20	-
Avg contaminated order ratio above limit	0.1097	0.0079	0.1079	20	-
Total contamination above limits	0.01122	0.00069	0.01127	20	-

Table G.14: Experiment results of scenario MassC_B

Scenario	**MassC_B**				
KPI	Average	SD	median	no. measurements	Unit
Avg throughput bags	1068.89	37.10	1078.86	320	bags/h
Avg throughput quantity	24655.03	1417.61	24817.58	320	kg/h
Orders completed	303.75	1.22	303.00	20	-
Orders completed on time	289.15	5.53	290.50	20	-
Avg contaminated order ratio above limit	0.1062	0.0114	0.1073	20	-
Total contamination above limits	0.01102	0.00076	0.01086	20	-

Table G.15: Experiment results of scenario MassC_C

Scenario	**MassC_C**				
KPI	Average	SD	median	no. measurements	Unit
Avg throughput bags	1064.18	59.44	1082.05	320	bags/h
Avg throughput quantity	24531.18	1779.36	24882.07	320	kg/h
Orders completed	303.40	2.48	304.00	20	-
Orders completed on time	290.55	4.09	291.00	20	-
Avg contaminated order ratio above limit	0.1908	0.0135	0.1904	20	-
Total contamination above limits	0.01685	0.00062	0.01687	20	-

Table G.16: Experiment results of scenario MassC_D

Scenario	**MassC_D**				
KPI	Average	SD	median	no. measurements	Unit
Avg throughput bags	1055.26	102.63	1081.36	320	bags/h
Avg throughput quantity	24398.01	2623.48	24917.00	320	kg/h
Orders completed	300.00	12.84	304.00	20	-
Orders completed on time	282.50	21.76	290.00	20	-
Avg contaminated order ratio above limit	0.1880	0.0092	0.1881	20	-
Total contamination above limits	0.01684	0.00090	0.01684	20	-

Table G.17: Experiment results of scenario MassC_E

Scenario	**MassC_E**				
KPI	Average	SD	median	no. measurements	Unit
Avg throughput bags	1069.26	49.08	1082.72	320	bags/h
Avg throughput quantity	24650.07	1671.28	24976.83	320	kg/h
Orders completed	303.90	2.19	305.00	20	-
Orders completed on time	291.05	3.57	291.50	20	-
Avg contaminated order ratio above limit	0.1856	0.0138	0.1827	20	-
Total contamination above limits	0.01667	0.00100	0.01669	20	-

Table G.18: Experiment results of scenario MixC_A

Scenario	**MixC_A**				
KPI	Average	SD	median	no. measurements	Unit
Avg throughput bags	1067.01	39.68	1078.43	320	bags/h
Avg throughput quantity	24616.74	1547.02	24737.83	320	kg/h
Orders completed	303.05	2.38	304.00	20	-
Orders completed on time	289.35	4.67	290.50	20	-
Avg contaminated order ratio above limit	0.0479	0.0022	0.0485	20	-
Total contamination above limits	0.00549	0.00024	0.00554	20	-

G.3. ADDITIONAL SILOS

Table G.19: Experiment results of scenario MassC_F

Scenario	**MassC_F**				
KPI	Average	SD	median	no. measurements	Unit
Avg throughput bags	1063.53	40.26	1075.30	320	bags/h
Avg throughput quantity	24506.67	1428.42	24679.23	320	kg/h
Orders completed	303.75	1.18	304.00	20	-
Orders completed on time	289.75	3.46	290.00	20	-
Avg contaminated order ratio above limit	0.1190	0.0107	0.1209	20	-
Total contamination above limits	0.01023	0.00065	0.01027	20	-

Table G.20: Experiment results of scenario MassC_G

Scenario	**MassC_G**				
KPI	Average	SD	median	no. measurements	Unit
Avg throughput bags	1073.21	33.76	1080.03	320	bags/h
Avg throughput quantity	24681.34	1357.57	24755.60	320	kg/h
Orders completed	304.90	0.44	305.00	20	-
Orders completed on time	294.15	4.34	295.50	20	-
Avg contaminated order ratio above limit	0.1056	0.0104	0.1046	20	-
Total contamination above limits	0.00926	0.00073	0.00918	20	-

Table G.21: Experiment results of scenario MassC_H

Scenario	**MassC_H**				
KPI	Average	SD	median	no. measurements	Unit
Avg throughput bags	1072.62	40.51	1085.16	320	bags/h
Avg throughput quantity	24724.48	1307.10	24938.18	320	kg/h
Orders completed	304.30	1.27	305.00	20	-
Orders completed on time	292.85	3.09	293.00	20	-
Avg contaminated order ratio above limit	0.0997	0.0089	0.0980	20	-
Total contamination above limits	0.00899	0.00061	0.00897	20	-

Table G.22: Experiment results of scenario MassC_I

Scenario	**MassC_I**				
KPI	Average	SD	median	no. measurements	Unit
Avg throughput bags	1075.13	34.46	1083.68	320	bags/h
Avg throughput quantity	24761.09	1449.19	24914.85	320	kg/h
Orders completed	303.75	1.37	304.00	20	-
Orders completed on time	292.90	3.99	293.50	20	-
Avg contaminated order ratio above limit	0.0867	0.0090	0.0851	20	-
Total contamination above limits	0.00867	0.00062	0.00861	20	-

Table G.23: Experiment results of scenario MassC_J

Scenario	**MassC_J**				
KPI	Average	SD	median	no. measurements	Unit
Avg throughput bags	1079.11	30.47	1084.61	320	bags/h
Avg throughput quantity	24873.79	1278.97	24913.92	320	kg/h
Orders completed	304.25	1.26	305.00	20	-
Orders completed on time	293.65	3.64	294.00	20	-
Avg contaminated order ratio above limit	0.0868	0.0063	0.0864	20	-
Total contamination above limits	0.00789	0.00049	0.00779	20	-

Table G.24: Experiment results of scenario MassC_K

Scenario	**MassC_K**				
KPI	Average	SD	median	no. measurements	Unit
Avg throughput bags	1076.93	37.23	1085.96	320	bags/h
Avg throughput quantity	24806.59	1336.02	24871.01	320	kg/h
Orders completed	304.35	0.96	305.00	20	-
Orders completed on time	293.45	2.50	293.50	20	-
Avg contaminated order ratio above limit	0.0920	0.0085	0.0909	20	-
Total contamination above limits	0.00817	0.00049	0.00825	20	-

Table G.25: Experiment results of scenario MassC_L

Scenario	**MassC_L**				
KPI	Average	SD	median	no. measurements	Unit
Avg throughput bags	1083.68	27.52	1087.86	320	bags/h
Avg throughput quantity	24984.12	1298.89	25099.30	320	kg/h
Orders completed	304.40	1.24	305.00	20	-
Orders completed on time	295.75	2.72	0.50	20	-
Avg contaminated order ratio above limit	0.1000	0.0077	0.0986	20	-
Total contamination above limits	0.00872	0.00057	0.00881	20	-

Table G.26: Experiment results of scenario MassC_M

Scenario	**MassC_M**				
KPI	Average	SD	median	no. measurements	Unit
Avg throughput bags	1084.26	24.38	1087.53	320	bags/h
Avg throughput quantity	25016.20	1289.66	25042.21	320	kg/h
Orders completed	304.55	0.50	305.00	20	-
Orders completed on time	295.60	2.33	296.00	20	-
Avg contaminated order ratio above limit	0.1091	0.0085	0.1081	20	-
Total contamination above limits	0.00930	0.00062	0.00916	20	-

Table G.27: Experiment results of scenario MassC_N

Scenario	**MassC_N**				
KPI	Average	SD	median	no. measurements	Unit
Avg throughput bags	1073.13	37.31	1082.88	320	bags/h
Avg throughput quantity	24689.41	1475.05	24776.34	320	kg/h
Orders completed	302.40	2.75	303.50	20	-
Orders completed on time	291.90	2.83	291.50	20	-
Avg contaminated order ratio above limit	0.0997	0.0089	0.0980	20	-
Total contamination above limits	0.00762	0.00052	0.00761	20	-

Table G.28: Experiment results of scenario MassC_O

Scenario	**MassC_O**				
KPI	Average	SD	median	no. measurements	Unit
Avg throughput bags	1076.73	36.27	1082.85	320	bags/h
Avg throughput quantity	24752.60	1275.93	24734.79	320	kg/h
Orders completed	303.90	1.04	304.00	20	-
Orders completed on time	291.75	4.76	292.50	20	-
Avg contaminated order ratio above limit	0.0875	0.0100	0.0852	20	-
Total contamination above limits	0.00793	0.00057	0.00794	20	-

Table G.29: Experiment results of scenario MassC_P

Scenario	**MassC_P**				
KPI	Average	SD	median	no. measurements	Unit
Avg throughput bags	1077.18	30.04	1082.63	320	bags/h
Avg throughput quantity	24778.73	1287.48	24873.11	320	kg/h
Orders completed	303.45	1.50	304.00	20	-
Orders completed on time	292.70	3.74	294.00	20	-
Avg contaminated order ratio above limit	0.0842	0.0085	0.0811	20	-
Total contamination above limits	0.00784	0.00049	0.00768	20	-

Table G.30: Experiment results of scenario MassC_R

Scenario	**MassC_R**				
KPI	Average	SD	median	no. measurements	Unit
Avg throughput bags	1076.67	35.86	1085.14	320	bags
Avg throughput quantity	24830.89	1355.78	24985.24	320	kg
Orders completed	304.10	1.37	305.00	20	-
Orders completed on time	293.75	4.77	294.00	20	-
Avg contaminated order ratio above limit	0.0834	0.0041	0.0831	20	-
Total contamination above limits	0.00806	0.00032	0.00809	20	-

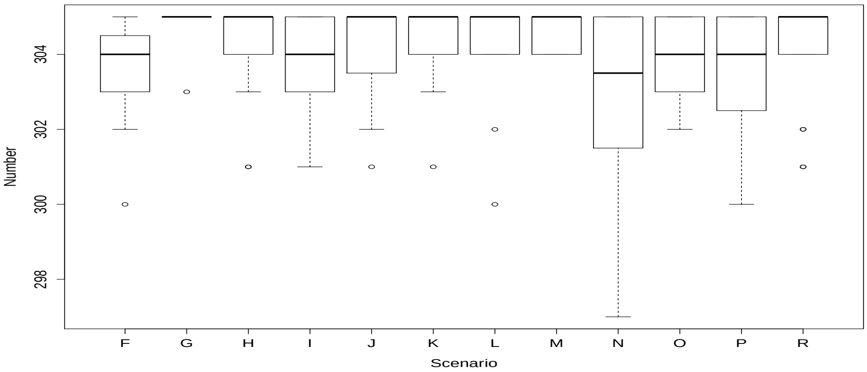

Figure G.2: A box plot comparing the number of completed orders within the simulation run per scenario

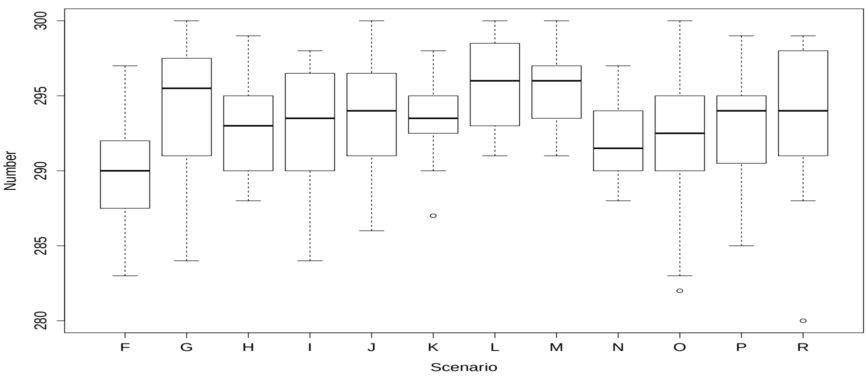

Figure G.3: A box plot comparing the number of completed orders on time within the simulation run per scenario

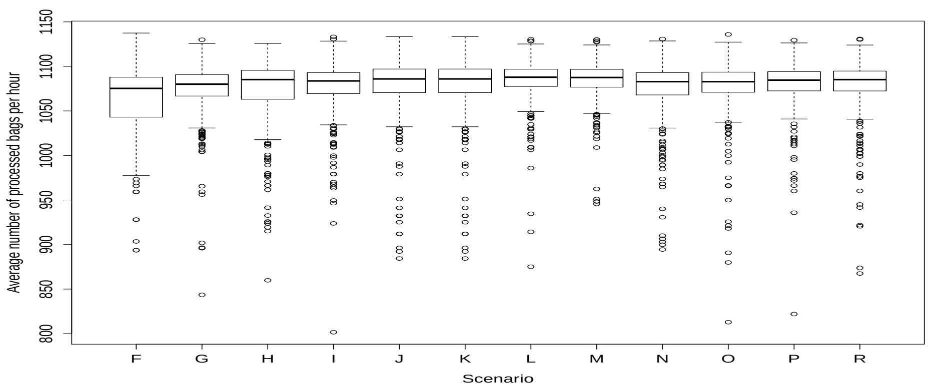

Figure G.4: A box plot comparing the average bagging throughput in silo number/size sensitivity analysis

G.4. SCHEDULING RULES INVESTIGATION

Table G.31: Experiment results of scenario Scheduling_A

Scenario	**Scheduling_A**				
KPI	Average	SD	median	no. measurements	Unit
Avg throughput bags	1066.60	40.71	1078.26	320	bags/h
Avg throughput quantity	24528.63	1498.91	24678.77	320	kg/h
Orders completed	301.40	1.53	301.00	20	-
Orders completed on time	286.60	3.35	286.50	20	-
Avg contaminated order ratio above limit	0.0888	0.0070	0.0901	20	-
Total contamination above limits	0.00774	0.00067	0.00762	20	-

Table G.32: Experiment results of scenario Scheduling_B

Scenario	**Scheduling_B**				
KPI	Average	SD	median	no. measurements	Unit
Avg throughput bags	1064.49	42.73	1076.60	320	bags/h
Avg throughput quantity	24483.95	1469.78	24565.54	320	kg/h
Orders completed	301.60	1.39	301.00	20	-
Orders completed on time	287.60	3.02	288.00	20	-
Avg contaminated order ratio above limit	0.0930	0.0097	0.0935	20	-
Total contamination above limits	0.00787	0.00072	0.00782	20	-

Table G.33: Experiment results of scenario Scheduling_C

Scenario	**Scheduling_C**				
KPI	Average	SD	median	no. measurements	Unit
Avg throughput bags	1078.70	29.31	1083.41	320	bags/h
Avg throughput quantity	24882.86	1461.94	25060.82	320	kg/h
Orders completed	304.25	0.83	304.00	20	-
Orders completed on time	293.60	3.38	295.00	20	-
Avg contaminated order ratio above limit	0.0915	0.0068	0.0912	20	-
Total contamination above limits	0.00850	0.00052	0.00841	20	-

Table G.34: Experiment results of scenario Scheduling_D

Scenario	**Scheduling_D**				
KPI	Average	SD	median	no. measurements	Unit
Avg throughput bags	1053.06	88.08	1081.49	320	bags/h
Avg throughput quantity	24235.70	2436.75	24873.95	320	kg/h
Orders completed	300.45	5.15	303.00	20	-
Orders completed on time	277.00	15.22	282.50	20	-
Avg contaminated order ratio above limit	0.0919	0.0116	0.0919	20	-
Total contamination above limits	0.00846	0.00077	0.00835	20	-

Table G.35: Experiment results of scenario Scheduling_E

Scenario	**Scheduling_E**				
KPI	Average	SD	median	no. measurements	Unit
Avg throughput bags	1056.60	78.49	1083.57	320	bags/h
Avg throughput quantity	24402.81	2242.66	25031.50	320	kg/h
Orders completed	300.15	3.40	300.00	20	-
Orders completed on time	272.90	11.53	276.50	20	-
Avg contaminated order ratio above limit	0.0865	0.0079	0.0869	20	-
Total contamination above limits	0.00932	0.00049	0.00932	20	-

Table G.36: Experiment results of scenario Scheduling_F

Scenario	**Scheduling_F**				
KPI	Average	SD	median	no. measurements	Unit
Avg throughput bags	1069.88	43.65	1081.77	320	bags/h
Avg throughput quantity	24593.86	1542.45	24797.85	320	kg/h
Orders completed	304.10	0.94	304.00	20	-
Orders completed on time	290.30	5.74	292.00	20	-
Avg contaminated order ratio above limit	0.0917	0.0068	0.0906	20	-
Total contamination above limits	0.00873	0.00063	0.00856	20	-

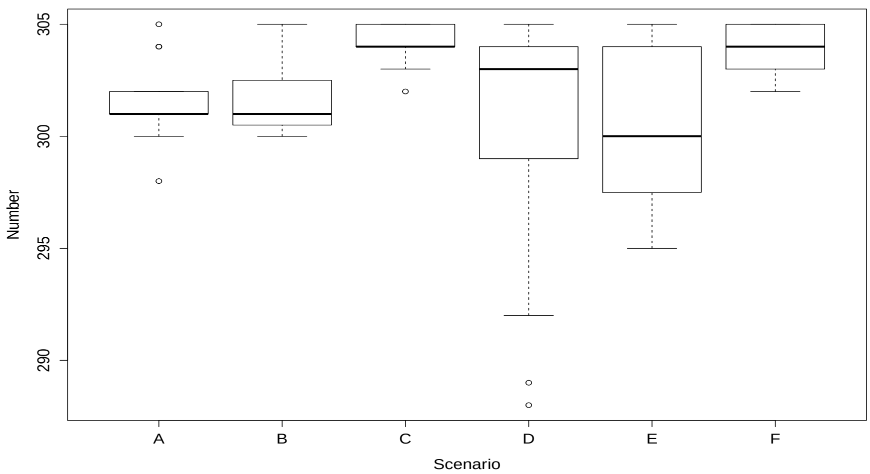

Figure G.5: A box plot comparing the number of completed orders within the simulation run per scenario

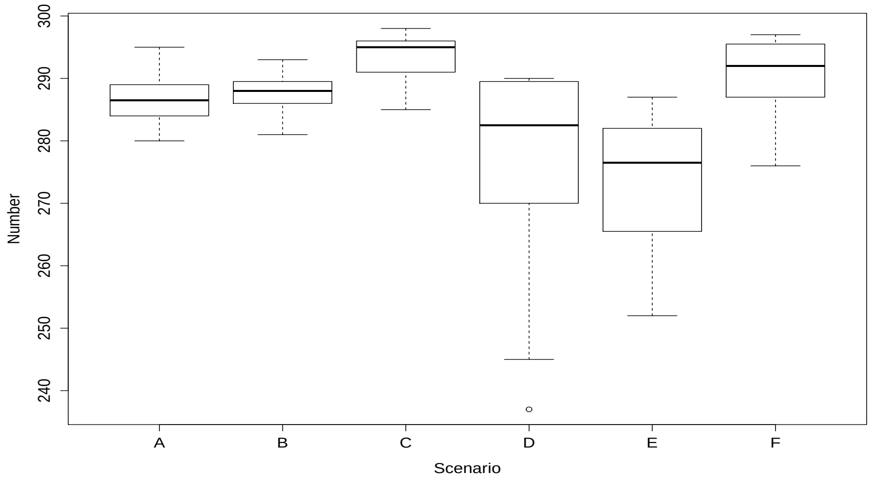

Figure G.6: A box plot comparing the number of completed orders on time within the simulation run per scenario

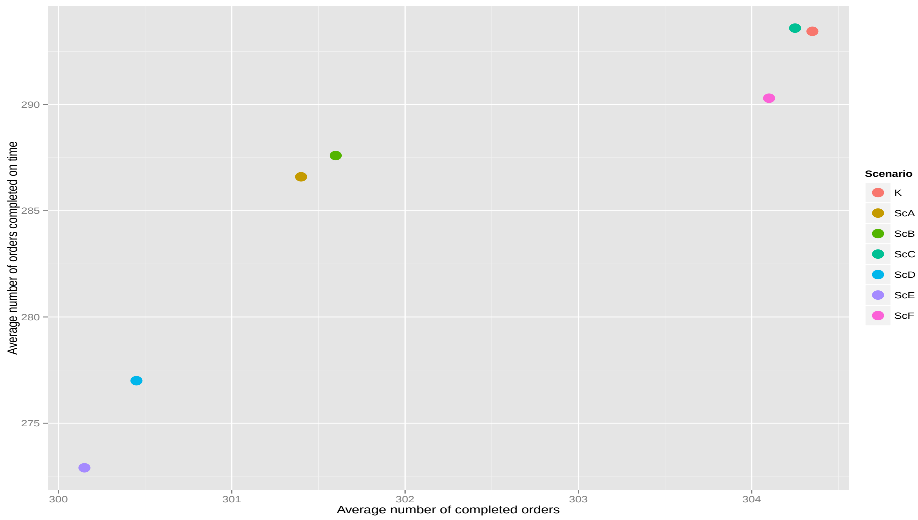

Figure G.7: A scatter plot displaying average results of orders completed on time as a function of the total number of completed orders

G.5. RANDOM COMPONENT INVESTIGATION

This section contains additional experiments performed for the investigation, which are not directly relevant to answering the research questions from section 1.3 on page 4 but are nevertheless explored to increase the knowledge about some possible effects of certain interventions.

Table G.37: Random components chosen for analysis

Scenario	σ	Nutrient-based silo allocation
Random_C	0.5	YES
Random_D	0.5	NO
Random_E	0.5	YES
Random_F	0.5	YES
Random_G	0.5	NO

Chosen values σ for the random component as well as whether nutrient-based silo allocation was performed are shown in table G.37. It is firstly desired to assess whether the random component or its size has any impact on the total contamination, and then, whether nutrient-based silo allocation has considerable influence when there are more silos as in investigation from section 6.4.2. It is an attempt to determine if a recreation of peaks and valleys as observed for the results of the contamination measurements (Figure 5.2 on page 36) has a noticeable effect on production performance. Silo input parameters are placed into table G.38.

Table G.38: Silo parameters for all experiments with random component for cross-contamination calculations

Silo Number	51	52	53	54	61	62	63	64
Capacity [kg]	42000	32000	32000	22000	0	0	0	0

The dispatching rules set for this part of the investigation are put into table G.39

Table G.39: Dispatching rules fixed for scenarios with random component for cross-contamination

Mixing order	Silo match	BTH1-2 silo pref.	BTH3 silo pref.	BTH1-2 dispatch	BTH3 dispatch
Smallest order	Best size fit	All	All	Biggest Order	Smallest remaining material

Then, there are variations made to the values of the scheduling alternatives as shown in table G.40, creating essentially four groups of scheduling rules.

Table G.40: Scheduling rules chosen for scenarios including the random component

Scenario	1	2	3	4	5	6	7	8	9	10	11
Random_A	YES	YES	YES	YES	YES	YES	NO	YES	NO	YES	NO
Random_B	YES	YES	YES	YES	YES	YES	NO	YES	NO	YES	NO
Random_C	YES	YES	NO	NO	NO	YES	NO	YES	NO	YES	NO
Random_D	YES	YES	NO	NO	NO	YES	NO	YES	NO	YES	NO
Random_E	YES	YES	NO	NO	NO	NO	NO	YES	NO	YES	NO
Random_F	YES	YES	YES	NO	NO	YES	NO	YES	NO	YES	NO
Random_G	YES	YES	YES	NO	NO	YES	NO	YES	NO	YES	NO
MixC_B	YES	YES	YES	YES	YES	YES	NO	YES	NO	YES	NO

To sum up, all the performed additional scenarios with a random component have $\sigma = 0.5$ fixed. Scenario Random_C has fewer constraints on scheduling in comparison to Random_A, where avoidance of splitting is not forced as well as division of orders with the same recipe but a different type (scheduling alternatives 3–5). Scenario Random_D has the exact same set of input parameters as Random_C, with an exception of nutrient-based silo allocation, which is suppressed. Similarly, scenario Random_E looks at the impact of preemptions, the exclusion of which is the only difference with experiment Random_C.
Then, scenario Random_F differs from Random_C again by a single parameter - avoidance of small order splitting among multiple silos (scheduling alternative 3). This, is then also checked against the impact of nutrient-based silo allocation, which concludes the prepared set.

G.5.1. EXPERIMENT RESULTS

Table G.41: Experiment results of scenario Random_C

Scenario	**Random_C**				
KPI	Average	SD	median	no. measurements	Unit
Avg throughput bags	1080.44	30.01	1085.94	320	bags/h
Avg throughput quantity	24917.05	1402.32	25067.18	320	kg/h
Orders completed	304.40	0.66	304.50	20	-
Orders completed on time	293.35	3.32	294.50	20	-
Avg contaminated order ratio above limit	0.08719	0.00675	0.08515	20	-
Total contamination above limits	0.0080	0.0006	0.0079	20	-

Table G.42: Experiment results of scenario Random_D

Scenario	**Random_D**				
KPI	Average	SD	median	no. measurements	Unit
Avg throughput bags	1081.08	23.39	1083.40	320	bags/h
Avg throughput quantity	24924.59	1358.07	25120.96	320	kg/h
Orders completed	304.50	0.74	305.00	20	-
Orders completed on time	295.10	4.62	296.50	20	-
Avg contaminated order ratio above limit	0.08595	0.00795	0.08660	20	-
Total contamination above limits	0.0079	0.0006	0.0078	20	-

Table G.43: Experiment results of scenario Random_E

Scenario	**Random_E**				
KPI	Average	SD	median	no. measurements	Unit
Avg throughput bags	1075.62	38.68	1083.98	320	bags/h
Avg throughput quantity	24830.48	1502.97	25069.75	320	kg/h
Orders completed	303.75	1.70	304.00	20	-
Orders completed on time	290.00	5.04	289.00	20	-
Avg contaminated order ratio above limit	0.08533	0.00681	0.08496	20	-
Total contamination above limits	0.0080	0.0006	0.0082	20	-

Table G.44: Experiment results of scenario Random_F

Scenario	**Random_F**				
KPI	Average	SD	median	no. measurements	Unit
Avg throughput bags	1075.96	35.66	1084.05	320	bags/h
Avg throughput quantity	24787.01	1458.89	24943.80	320	kg/h
Orders completed	304.05	1.07	304.00	20	-
Orders completed on time	293.20	3.52	293.00	20	-
Avg contaminated order ratio above limit	0.08544	0.00679	0.08656	20	-
Total contamination above limits	0.0078	0.0007	0.0077	20	-

Table G.45: Experiment results of scenario Random_G

Scenario	**Random_G**				
KPI	Average	SD	median	no. measurements	Unit
Avg throughput bags	1073.67	36.52	1084.01	320	bags/h
Avg throughput quantity	24723.48	1522.69	24873.41	320	kg/h
Orders completed	304.45	0.74	305.00	20	-
Orders completed on time	295.05	3.17	295.50	20	-
Avg contaminated order ratio above limit	0.08706	0.00775	0.08427	20	-
Total contamination above limits	0.0081	0.0008	0.0081	20	-

Figure G.8 contains a scatter plot of total contamination as a function of the average bagging throughput, distinguished by scenarios (RaA is an equivalent of Random_A etc.).

Additionally, a scatter plot displaying relation of orders completed in set simulation time to orders finished on their due date is shown in Figure G.9. Scenarios Random_A and Random_B overlay each other.

Finally, another scatter plot, in Figure G.10, displaying total contamination as a function of the average contamination in polluted orders. Polluted orders are those, which have at least one bag considered out of specifications.

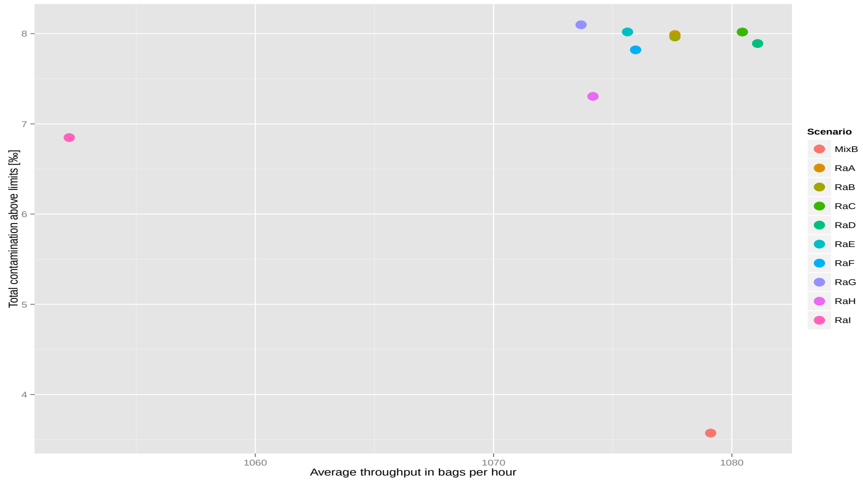

Figure G.8: A scatter plot displaying average results for contamination with respect to achieved throughput, for analysis with random component

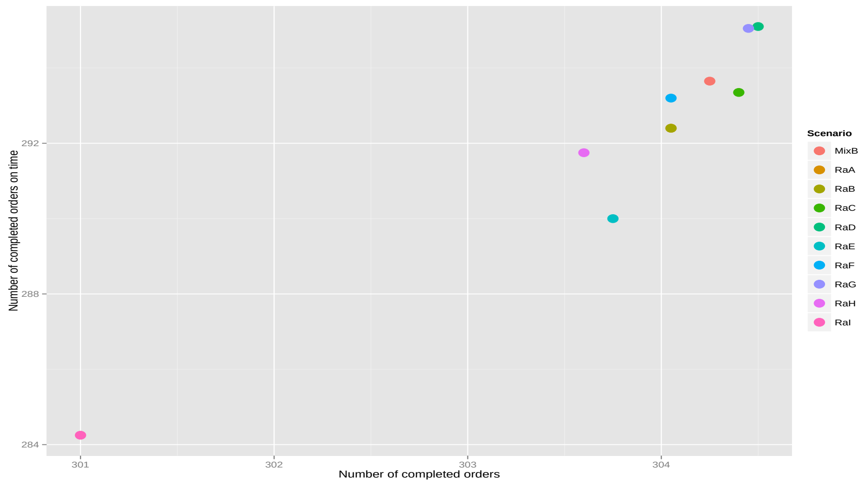

Figure G.9: A scatter plot displaying average number of orders completed on time as a function of total number of completed orders

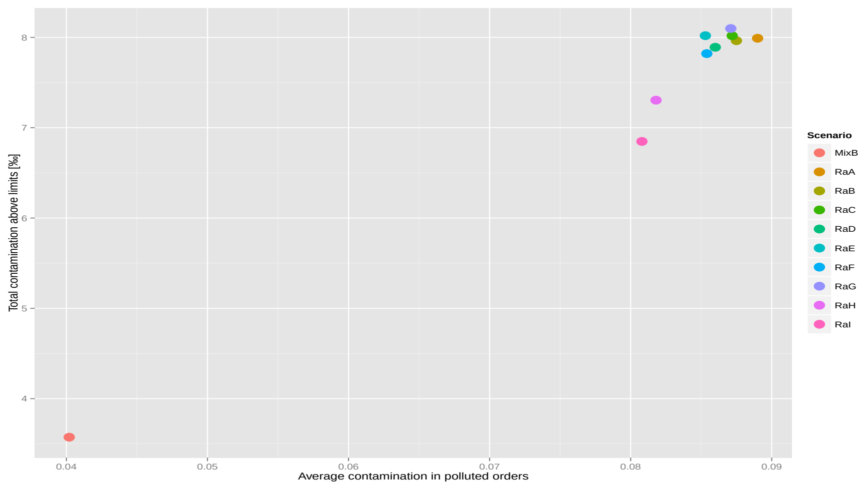

Figure G.10: A scatter plot displaying average contamination in polluted order against total contamination

H

Output Analysis

This chapter contains statistical data analysing the experiment results included in chapter G.

H.1. Initial Sensitivity Analysis

First of all the impact of changing discharge rates on order completion is investigated. As not all runs manage to complete all orders the performance indicator is orders completed on time, being the difference between orders ended and orders ended late. Thus Scenario NC_A is compared with NC_B and NC_C, then NC_E with equivalent and so on. For reserved silos two-sided analysis is made and when varying discharge speed one-sided as there is expectation that higher discharge speed results in more orders completes on time. Only alternative hypothesis H_1 is specified in the result tables (see tables H.1, H.2 and H.3 on the following page). In two cases it is expected, with 95% confidence, that lower than nominal silo discharge results in fewer completed orders on time. Moreover, also in two cases reserving silos the means significantly differ and when comparing scenarios NC_E and NC_G it might be concluded that higher discharge speed than nominal has a positive effect of the number of orders completed on time.

Then, the influence of the increasing number of silos involved on order completion is investigated. Results of t-tests are put into tables H.4, H.5 and H.6 on the next page). They show, that there is no apparent difference in timely order completion between 0 and 2 additional silos. But having 4 extra silos is better than having 0 (p-value = 0.0002423) or having 2 (p-value = 0.0005541) for standard discharge rate. Having 4 additional silos and higher discharge speed is also significantly better than adding none or two.

Moreover, similar analysis is done for mixer and bagging throughputs. As only the bagging is expected to vary more significantly at first a box plot comparing average mixing throughputs is shown in Figure G.1. Values are indeed very similar and no further tests of means are made. Also, no following tests for different scenario set of mixing throughput are made. Distinction between bagging machines is done further in the report when assessing different scheduling rules and not general throughputs. As the intent is to determine whether adding additional silos and changing silo discharge speeds has an effect on the average throughput.

T-test results are put into tables H.7, H.8, H.9 and H.10 on page 133. First of all, they all consistently show (with 95% confidence) that lower discharge speed results in smaller average bagging throughput. Consequently, increased discharge speed has no effect on bagging speed and thus it can be concluded that the nominal discharge speed of 20 t/h is set correctly in order not to hinder performance.

Moreover, having two additional silos has no positive effect on bagging throughput, but having four might. Although there is no significant increase of throughput between 0 and 4 additional silos (p-value of 0.07403), the one sided test between NC_E and NC_I rejects the null hypothesis, concluding with 95% confidence that there is an increase in throughput going from 2 to 4 silos. Nevertheless, scenario NC_I has the biggest average bagging throughput and lower standard deviation. From analysis of production performance, without including cross-contamination calculations can be concluded that silo discharge speed of 20 t/h is needed and increasing it further to 22 t/h (and boosting discharge to big bag station to 15 t/h) will not increase performance.

Table H.1: Comparison of impact of different discharge speeds on order completion for no additional silos

Hypothesis	n	mean	SD	var equal	t	df	p	95% confidence interval
H_1 :NC_A>NC_B	40	248.00	3.11	TRUE	1.7736	38	**0.04207**	0.08404611: Inf
H_1 :NC_A<NC_C	40	248.75	2.66	TRUE	0.23506	38	0.5923	-Inf: 1.634496
H_1 :NC_A!=NC_D	40	249.15	3.39	TRUE	-0.55414	38	0.5827	-2.791932: 1.591932

Table H.2: Comparison of impact of different discharge speeds on order completion for 2 additional silos

Hypothesis	n	mean	SD	var equal	t	df	p	95% confidence interval
H_1 :NC_E>NC_F	40	247.93	5.50	TRUE	-0.085102	38	0.5337	-3.12164: Inf
H_1 :NC_E<NC_G	40	249.15	4.94	TRUE	-1.7051	38	**0.04817**	-Inf: -0.02926495
H_1 :NC_E!=NC_H	40	249.30	4.46	TRUE	-2.1516	38	**0.03784**	-5.628489: -0.171511

Table H.3: Comparison of impact of different discharge speeds on order completion for 4 additional silos

Hypothesis	n	mean	SD	var equal	t	df	p	95% confidence interval
H_1 :NC_I>NC_J	40	251.47	3.27	TRUE	2.0665	38	**0.02282**	0.3775205: Inf
H_1 :NC_I<NC_K	40	251.85	3.32	TRUE	1.2452	38	0.8897	-Inf: 3.060188
H_1 :NC_I!=NC_L	40	251.38	3.11	TRUE	2.4264	38	**0.0201**	0.3727977: 4.1272023

Table H.4: Comparison of impact of 0 to 2 additional silos on order completion

Hypothesis	n	mean	SD	var equal	t	df	p	95% confidence interval
H_1 :NC_A<NC_E	40	248.35	3.96	FALSE	0.79509	29.935	0.7836	-Inf: 3.134814
H_1 :NC_A<NC_G	40	249.65	3.91	FALSE	-1.3047	30.542	0.1009	-Inf: 0.4802682

Table H.5: Comparison of impact of 0 to 4 additional silos on order completion

Hypothesis	n	mean	SD	var equal	t	df	p	95% confidence interval
H_1 :NC_A<NC_I	40	250.68	3.51	TRUE	-3.8166	38	**0.0002423**	-Inf: -2.037638
H_1 :NC_A<NC_K	40	250.03	3.25	TRUE	-2.4288	38	**0.009995**	-Inf: -0.7187276

Table H.6: Comparison of impact of 2 to 4 additional silos on order completion

Hypothesis	n	mean	SD	var equal	t	df	p	95% confidence interval
H_1 :NC_E<NC_I	40	250.18	4.74	TRUE	-3.5296	38	**0.0005541**	-Inf: -2.42885
H_1 :NC_E<NC_K	40	249.53	4.47	TRUE	-2.5271	38	**0.007891**	-Inf: -1.115085

Table H.7: Comparison of impact of silo discharge and reservation on bagging throughput with no additional silos

Hypothesis	n	mean	SD	t	df	p	95% confidence interval
H_1 :NC_A>NC_B	600	1062.63	42.38	6.2773	597.56	**3.312e-10**	15.53185: Inf
H_1 :NC_A<NC_C	600	1072.23	41.16	0.54843	597.7	0.7082	-Inf: 7.383496
H_1 :NC_A!=NC_D	600	1066.97	49.91	3.0572	550.32	**0.002342**	4.423463: 20.323430

Table H.8: Comparison of impact of silo discharge and reservation on bagging throughput with 2 additional silos

Hypothesis	n	mean	SD	t	df	p	95% confidence interval
H_1 :NC_E>NC_F	600	1058.65	54.47	6.0044	554	**1.739e-09**	18.83294: Inf
H_1 :NC_E<NC_G	600	1070.7	44.09	0.51549	597.31	0.6968	-Inf: 7.79169
H_1 :NC_E!=NC_H	600	1071.28	44.08	0.19671	597.29	0.8441	-6.364977: 7.781979

Table H.9: Comparison of impact of silo discharge and reservation on bagging throughput with 4 additional silos

Hypothesis	n	mean	SD	t	df	p	95% confidence interval
H_1 :NC_I>NC_J	600	1068.84	29.57	7.3952	597.17	**2.4e-13**	13.29432: Inf
H_1 :NC_I<NC_K	600	1076.93	30.89	0.36823	588.22	0.6436	-Inf: 5.087692
H_1 :NC_I!=NC_L	600	1075.46	33.87	1.3966	556.46	0.1631	-1.568617: 9.287001

Table H.10: Comparison of silo discharge speed and number of extra silos impact on bagging throughputs

Hypothesis	n	mean	SD	t	df	p	95% confidence interval
H_1 :NC_A<NC_E	600	1072.39	43.25	0.43074	594.7	0.6666	-Inf: 7.344177
H_1 :NC_A<NC_I	600	1075.27	35.85	-1.4486	532.33	0.07403	-Inf: 0.5825061
H_1 :NC_A<NC_K	600	1074.81	37.51	-1.0801	567.24	0.1403	-Inf: 1.737458
H_1 :NC_E<NC_I	600	1074.51	37.80	-1.8699	510.18	**0.03103**	-Inf: -0.6840012

H.2. CROSS-CONTAMINATION INVESTIGATION

Table H.11: Comparison of impact of order sequencing and nutrient-based silo allocation on total cross-contamination

Hypothesis	n	mean	SD	var equal	t	df	p	95% conf. interval
H_1 :MassC_A<MassC_B	40	0.01112	0.00074	TRUE	0.8324	38	0.7948	-Inf: 0.00059
H_1 :MassC_A<MassC_C	40	0.01403	0.00293	TRUE	-26.45	38	**<2.2e-16**	-Inf: -0.00527
H_1 :MassC_A<MassC_E	40	0.01394	0.00290	TRUE	-21.57	38	**<2.2e-16**	-Inf: -0.00518
H_1 :MassC_A>Mix_A	40	0.00835	0.00295	FALSE	34.142	23.4	**<2.2e-16**	0.00544: Inf
H_1 :MassC_C<MassC_D	40	0.01684	0.01394	TRUE	0.0281	38	0.5111	-Inf: 0.00043
H_1 :MassC_C<MassC_E	40	0.01676	0.00835	FALSE	0.6643	31.6	0.7443	-Inf: 0.00064
H_1 :MassC_C>Mix_A	40	0.01117	0.00078	FALSE	74.672	24.5	**<2.2e-16**	0.01110: Inf
H_1 :MassC_E>Mix_A	40	0.01108	0.00570	FALSE	47.208	21.1	**<2.2e-16**	0.01077: Inf

H.3. LAYOUT INTERVENTIONS INVESTIGATION

Table H.12: Comparison of impact of additional silos on order completion

Hypothesis	n	mean	SD	var equal	t	df	p	95% conf. interval
H_1 :MassC_G>MassC_F	40	291.95	4.56	TRUE	3.455	38	**0.0006841**	2.252911: Inf
H_1 :MassC_H>MassC_F	40	291.30	3.67	TRUE	2.9132	38	**0.002981**	1.305929: Inf
H_1 :MassC_I>MassC_F	40	291.32	4.10	TRUE	2.6005	38	**0.006594**	1.107811: Inf
H_1 :MassC_J>MassC_I	40	293.27	3.88	TRUE	0.6058	38	0.2741	-1.337114: Inf
H_1 :MassC_K>MassC_J	40	293.55	3.16	TRUE	-0.1975	38	0.5778	-1.906899: Inf
H_1 :MassC_L>MassC_K	40	294.60	2.89	TRUE	2.715	38	**0.004956**	0.8717751: Inf
H_1 :MassC_M>MassC_L	40	295.68	2.57	TRUE	-0.1826	38	0.5719	-1.535288: Inf
H_1 :MassC_N>MassC_L	40	293.82	3.42	TRUE	-4.2795	38	0.9999	-5.366743: Inf
H_1 :MassC_M>MassC_N	40	293.75	3.22	TRUE	4.4009	38	**4.226e-05**	2.282552: Inf
H_1 :MassC_O>MassC_K	40	292.60	3.95	FALSE	-1.3776	28.7	0.9105	-3.797477: Inf
H_1 :MassC_L>MassC_O	40	293.75	4.42	FALSE	3.1793	30.2	**0.0017**	1.865045: Inf
H_1 :MassC_P>MassC_K	40	293.07	3.25	TRUE	-0.7263	38	0.764	-2.490852: Inf
H_1 :MassC_O>MassC_P	40	292.23	4.36	TRUE	-0.6836	38	0.7508	-3.293081: Inf
H_1 :MassC_R>MassC_I	40	293.32	4.47	TRUE	0.5958	38	0.2774	-1.555461: Inf
H_1 :MassC_K>MassC_R	40	293.60	3.86	FALSE	-0.2427	28.7	0.595	-2.401188: Inf

Table H.13: Comparison of impact of additional silos on total contamination

Hypothesis	n	mean	SD	var equal	t	df	p	95% conf. interval
H_1 :MassC_G<MassC_F	40	0.00975	0.00085	TRUE	-4.325	38	**5.329e-05**	-Inf: -0.00059
H_1 :MassC_H<MassC_F	40	0.00961	0.00089	TRUE	-6.071	38	**2.275e-07**	-Inf: -0.00089
H_1 :MassC_I<MassC_F	40	0.00945	0.00102	TRUE	-7.585	38	**2.014e-09**	-Inf: -0.00121
H_1 :MassC_J<MassC_I	40	0.00828	0.00069	TRUE	-4.329	38	**5.251e-05**	-Inf: -0.00048
H_1 :MassC_K<MassC_J	40	0.00803	0.00052	TRUE	1.764	38	0.9572	-Inf: 0.00055
H_1 :MassC_L<MassC_K	40	0.00845	0.00061	TRUE	3.175	38	0.9985	-Inf: 0.00084
H_1 :MassC_M<MassC_L	40	0.00901	0.00067	TRUE	2.958	38	0.9973	-Inf: 0.00090
H_1 :MassC_N<MassC_L	40	0.00817	0.00079	TRUE	-6.173	38	**1.647e-07**	-Inf: -0.00080
H_1 :MassC_M<MassC_N	40	0.00846	0.00103	TRUE	9.002	38	1	-Inf: 0.00198
H_1 :MassC_O<MassC_K	40	0.00805	0.00055	TRUE	-1.398	38	0.08511	-Inf: 4.99e-05
H_1 :MassC_L<MassC_O	40	0.00833	0.00071	TRUE	4.260	38	0.9999	-Inf: 0.00111
H_1 :MassC_P<MassC_K	40	0.00801	0.00052	TRUE	-2.051	38	**0.0236**	-Inf: -5.82e-05
H_1 :MassC_O<MassC_P	40	0.00789	0.00054	TRUE	0.491	38	0.6867	-Inf: 0.00038
H_1 :MassC_R<MassC_I	40	0.00837	0.00059	FALSE	-3.820	28.6	**0.00033**	-Inf: -0.00034
H_1 :MassC_K<MassC_R	40	0.00812	0.00042	TRUE	0.801	38	0.786	-Inf: 0.00034

Table H.14: Comparison of impact of additional silos on the average throughput

Hypothesis	n	mean	SD	t	df	p	95% conf. interval
H_1 :MassC_G>MassC_F	640	1068.37	37.49	3.2889	619.152	**0.0005315**	4.828893: Inf
H_1 :MassC_H>MassC_F	640	1068.08	40.68	2.8426	637.975	**0.002309**	3.822827:Inf
H_1 :MassC_I>MassC_F	640	1069.33	37.95	3.9084	623.146	**5.155e-05**	6.708968: Inf
H_1 :MassC_J>MassC_I	640	1076.03	35.91	0.6341	634.22	0.26317	-2.877708: Inf
H_1 :MassC_K>MassC_J	640	1076.93	37.26	0	638	0.5	-4.855933: Inf
H_1 :MassC_L>MassC_K	640	1080.3	32.93	2.6019	587.403	**0.004752**	2.473952: Inf
H_1 :MassC_M>MassC_L	640	1083.97	26.02	0.2844	628.911	0.3881	-2.805336: Inf
H_1 :MassC_N>MassC_L	640	1078.4	33.22	-4.0613	586.819	1	-14.8164: Inf
H_1 :MassC_M>MassC_N	640	1078.7	32.03	4.4589	549.507	**4.997e-06**	7.014838: Inf
H_1 :MassC_O>MassC_K	640	1076.83	36.78	-0.0692	637.562	0.5276	-4.994947: Inf
H_1 :MassC_L>MassC_O	640	1080.2	32.4	2.725	594.847	**0.003309**	2.746652: Inf
H_1 :MassC_P>MassC_K	640	1078.02	34.06	0.8073	613.98	0.2099	-2.262811: Inf
H_1 :MassC_O>MassC_P	640	1077.92	33.54	-0.8959	619.572	0.8147	-6.744498: Inf
H_1 :MassC_R>MassC_I	640	1075.9	35.2	0.5526	636.995	0.2904	-3.047902: Inf
H_1 :MassC_K>MassC_R	640	1076.8	36.58	0.0907	637.099	0.4639	-4.504707: Inf

H.4. RANDOM COMPONENT

Table H.15: Comparison of impact of random component on the average throughput

Hypothesis	n	mean	SD	t	df	p	95% conf. interval
H_1 :Ra_A<MassC_J	640	1077.27	37.86	0.2261	637.366	0.5894	-Inf: 5.611756
H_1 :Ra_B<MassC_J	640	1077.27	37.86	0.2261	637.366	0.5894	-Inf: 5.611756
H_1 :MixC_B!=MassC_J	640	1078.02	34.06	0.8073	613.98	0.4198	-3.115306: 7.464032

Table H.16: Comparison of impact of random component on the total contamination

Hypothesis	n	mean	SD	var equal	t	df	p	95% conf. interval
H_1 :Ra_A!=MassC_J	40	0.00794	0.00057	TRUE	0.553	38	0.5835	-0.00027: 0.00047
H_1 :Ra_B!=MassC_J	40	0.00793	0.00056	TRUE	0.4082	38	0.685	-0.00029: 0.00044
H_1 :Ra_A!=Ra_B	40	0.00798	0.00062	TRUE	0.1359	38	0.8926	-0.00038: 0.00043
H_1 :MixC_B!=MassC_J	40	0.00573	0.00222	FALSE	-37.379	21.1	**<2.2e-16**	-0.00456: -0.00408

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