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Investigating inspection strategies and inspection room capacity with a discrete-event simulation model

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Abstract

Quality control (QC) methods are important for organizations in managing the quality of their products. Operations of the incoming materials inspection are utilizing these methods.

In this thesis, a system of incoming materials inspection is modeled with a discrete-event simulation model. The developed model is used to investigate resourcing decisions and different inspection strategies. Two different datasets are used: a generated dataset and a case company's dataset.

With the case company's data, the model's time parameters are first configured after which the whole model is validated against the actual data. The results of the validation phase indicate that the model skips 11% more lots compared to the actual data, and some of the actual figures from the data are not fitting into the empirical intervals of the model results. Still, the model can be used to compare different inspection strategies and resourcing decisions.

The results with both datasets indicate that using the Skip-lot Sampling Plan-2 (SkSP-2) or Inspection strategy A leads to more inspections and higher detect rate on average compared to Inspection strategy B. With the case company's dataset, a lot is found defective in around 5% of the inspections with all the compared inspection strategies. Sensitivity analysis with the case company's data indicates that the small changes in the fault rates have some impact on the results. Decision-makers in the case company can use these results as supporting information to guide their decisions regarding resourcing and inspection strategies.

Keywords Discrete-event simulation, Quality control, Skip-lot sampling, Resource planning, Inspection strategy, Incoming materials inspection

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Tekijä Petteri Koskiahde

Työn nimi Mallinnus tarkastusstrategioista ja tarkastushuoneen kapasiteetista tapahtumapohjaisen simulointimallin avulla

Koulutusohjelma Matematiikka ja Operaatiotutkimus

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Tiivistelmä

Laadunvalvonnan menetelmät ovat tärkeitä organisaatioille, jotta ne voivat hallita tuotteidensa laatua. Saapuvien materiaalien tarkastus hyödyntää näitä menetelmiä.

Tässä työssä saapuvien materiaalien tarkastuksen systeemiä mallinnetaan tapahtumapohjaisen simulointimallin avulla. Kehitettyä mallia käytetään tutkimaan resursoinnin päätöksiä ja tarkastusstrategioita. Mallia tutkitaan kahdella eri tietolähteellä: itse luodulla tietolähteellä sekä tarkastelun kohteena olevan yrityksen tietolähteellä.

Kun mallia tutkitaan tarkastelun kohteena olevan yrityksen tietolähteellä, ensin aikaparametrit konfiguroidaan, jonka jälkeen malli validoidaan vertaamalla tuloksia historialliseen tietoon. Validointivaiheen tulokset osoittavat, että malli ohittaa 11% enemmän eriä verrattuna todelliseen tietoon. Lisäksi osa todellisista luvuista ei sisälly mallin tuottamiin empiirisiin intervalleihin. Mallia voidaan kuitenkin käyttää tarkastusstrategioiden sekä resursoinnin päätöksien vertailuun.

Tulokset molempien tietolähteiden kanssa osoittavat että Skip-lot Sampling Plan-2 (SkSP-2) tarkastusstrategian tai Tarkastusstrategia A:n käyttö johtaa suurempiin tarkastusmääriin sekä suurempaan virheiden havaitsemisosuuteen verrattuna Tarkastusstrategia B:n käyttöön. Tarkastelun kohteena olevan yrityksen tietolähteen kanssa kaikki vertaillut strategiat löytävät noin 5% tarkastuksista erän, joka sisältää vikaantuneita kappaleita. Mallin herkkyysanalyysin perusteella pienet muutokset virheiden suhteellisissa osuuksissa vaikuttavat hieman lopputuloksiin. Päätöksentekijät tarkastelun kohteena olevassa yrityksessä voivat käyttää mallin tuloksia päätöksenteon tukena resursointiin ja tarkastusstrategioihin liittyvissä päätöksissä.

Avainsanat Tapahtumapohjainen simulointi, Laadunvalvonta, Erien ohitukseen perustuva otanta, Resurssisuunnittelu, Tarkastusstrategia, Saapuvien materiaalien tarkastus

Preface

My journey in the university has been full of unforgettable memories. At the beginning of my studies, I couldn't have known what these amazing years at Aalto University would teach and bring to me. Meeting and studying with so many kind and intellectual people, making new friendships, doing volunteer work in student associations, and spending an exchange semester at the University of Limerick made a permanent impact to my way of thinking. I'm so grateful for everything I experienced during this journey.

I want to thank Assistant Professor Philine Schiewe for guidance and help with this thesis. I want to thank my advisor Iiro, who has helped me throughout this master's thesis project. I also want to thank everyone at the case company who has helped me with the thesis. Furthermore, I want to thank my family, partner, and friends who have always been there for me. Lastly, I want to thank everyone who I have met along the way.

June 18, 2026

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Statement of using artificial intelligence

Artificial intelligence tools have been used in this thesis to support the process including but not limited to coding, searching sources of information, and writing. In writing, AI-based tools have been used, for example, to find grammar errors, to help with LaTeX-syntax, and to make the text flow smoother. All the decisions are author's own. The author is responsible for all the possible errors.

Contents

Abbreviations

ERP	Enterprise Resource Planning
EDW	Enterprise Data Warehouse
QC	Quality Control
SPC	Statistical Process Control
DES	Discrete-Event Simulation
QAB	Quality Assurance Buffer
ISO	International Organization for Standardization
ASQ	American Society for Quality
AQL	Acceptable Quality Level
LQL	Limiting Quality Level
SSP	Single Sampling Plan
DSP	Double Sampling Plan
SkSP-2	Skip-lot Sampling Plan-2
UD	Usage Decision

1 Introduction

Organizations use quality management methods to track and improve the quality of their products and services. One of the important areas in quality management is quality control (QC). This refers to the methods for ensuring quality stays at the desired level (American Society for Quality, 2026). One way of controlling the quality of products is inspecting them. Generally, these inspections can be performed at any stage of production from incoming materials to final products. By inspecting incoming materials before they are sent to the later stages of assembly, manufacturing companies can prevent issues arising from non-conforming materials. Detecting failures early decreases the amount of rework to be done and increases the quality of final products. Thus, manufacturing companies are interested in detecting failures early.

A central aspect regarding these inspections is their cost. If there were unlimited money available, every single incoming material could be inspected thoroughly to avoid defects. However, inspecting 100% of the units is not feasible due to limited resources. On the other hand, companies could neglect these inspections and reduce inspection costs to zero while absorbing all the costs caused by defective materials. This may be a reasonable strategy if the cost of inspections exceeds the cost of defects in final products. However, in reality, the decision of how much to inspect is somewhere between the two extremes and also involves other factors that can be considered. This decision is also guided by the company's business strategy and the emphasis it places on quality control.

An inspection strategy is a guideline determining whether the next unit or batch is inspected or not. In order to plan the inspections, companies need to select an inspection strategy that suits their needs and investigate how many resources are needed to execute the selected strategy. This selection and determination of resources go hand in hand and also include consideration of how many defective units can be found with the use of the chosen strategy.

Making a well-informed decision on the inspection strategy and resources is not an easy task in a complex manufacturing environment. Companies have various possibilities to investigate the problem at hand from heuristic capacity calculations to advanced modeling techniques, such as linear programming or discrete-event simulation models. In this thesis, a model to tackle this problem is developed in collaboration with a company, later on referred to as the case company.

In this thesis, an inspection room in the case company's facility is modeled as a discrete-event system. In these systems, the state of the system develops through events, such as a material arriving, a resource becoming available, and an inspection ending. A discrete-event simulation model is developed to test different inspection strategies for the incoming materials and to investigate how many resources their execution requires. The model mimics the actual inspection room operation and executes selected inspection strategies. With the help of the model, decision-makers can investigate how well different inspection strategies find defective lots in the incoming materials and how much they burden the resources of the inspection room.

The thesis is structured as follows: In Section 2, material inspections and discrete-event simulation applications are investigated based on the literature. In Section 3, the concrete problem at hand is described, and the developed model is presented. In Section 4, the results with both the generated data and the case company's data are presented. Additionally, the validation of the model with the case company's dataset and sensitivity analysis are performed. In Section 5, the limitations of the results are discussed, and possible future developments are described. In Section 6, the study is concluded and summarized.

2 Literature review and background

In a large corporation, there may be a great number of materials that are not made internally. Many materials are sourced from suppliers which poses a quality risk. Since the materials are not made internally, the quality cannot be directly influenced. Lee and Li (2018) studied the supplier quality management from three different perspectives. They highlight that on a broad level, the quality of incoming materials could be improved in the following ways: Investing in the supplier, giving incentives regarding the quality, or inspecting the products. In this thesis, the focus is on the inspections of the incoming materials. The main problem, as also stated by (Dodge and Romig, 1929), is to determine how much to inspect the materials. Inspecting every unit of material is not always economically feasible, especially when the inspection is destructive. On the other hand, inspecting nothing can lead to detecting too many defects in the assembly phase.

2.1 Statistical quality control

Statistical quality control methods are used for tracking and improving quality based on statistics. Three major areas in the statistical methods of quality control are identified in (Montgomery, 2012): Statistical process control (SPC), design of experiments and acceptance sampling.

Statistical process control introduces the concept of control charts. In a control chart, a quality characteristic of the products, e.g. average height of pipes, is monitored against the time or sample number. If the defined characteristic gets out of the statistically determined limits, it suggests that some uncommon variation is present in the process.

Design of experiments is a method of gathering information about the relationships between the controllable process input variables and the desired quality characteristics of the product. By changing the process input variables, the experiments provide information about the behavior of the quality characteristics which can be used to determine the optimal input variables.

The last major area of the statistical quality control methods is acceptance sampling which is examined in this thesis. The acceptance sampling methods are related to inspecting the products, and they are used for deciding whether to accept or reject a lot or a batch of products based on inspecting a sample. The inspections can be performed in many different phases of the process, but usually they are done when the materials arrive to the process (incoming materials inspection) or for the final products (outgoing materials inspection). In this thesis, the focus is on the incoming materials inspection.

Montgomery (2012) describes the utilization of these methods described above for the organizations. At first, there is not much information about the quality, which leads to the use of acceptance sampling and inspections. Then the organizations start to learn the importance of improving processes and start to use SPC and experimental designs while lowering the utilization of acceptance sampling.

2.2 Acceptance sampling

Acceptance sampling methods fall between inspecting 100% of the units and accepting every unit without inspection. Instead of inspecting every unit in a lot, only a sample is inspected, and a usage decision for the lot is made based on that. A usage decision is a decision whether the whole lot can be used in the production. The main driver for utilizing acceptance sampling is the inspection cost since the less time is spend inspecting the materials the more the resources can be utilized elsewhere. Montgomery (2012) highlights that the sample taken must be random. If it contains biases, the acceptance sampling methods do not guarantee protection against the poor-quality lots.

Dodge and Romig (1929) study sampling inspections and introduce economically feasible single sampling method for inspections. Rather than inspecting all the units in the incoming lots, they develop a sampling plan in which a lot is accepted or rejected based on a sample, but the customer risk tolerance of defective units is still satisfied. The procedure of the single sampling plan (SSP) is outlined below.

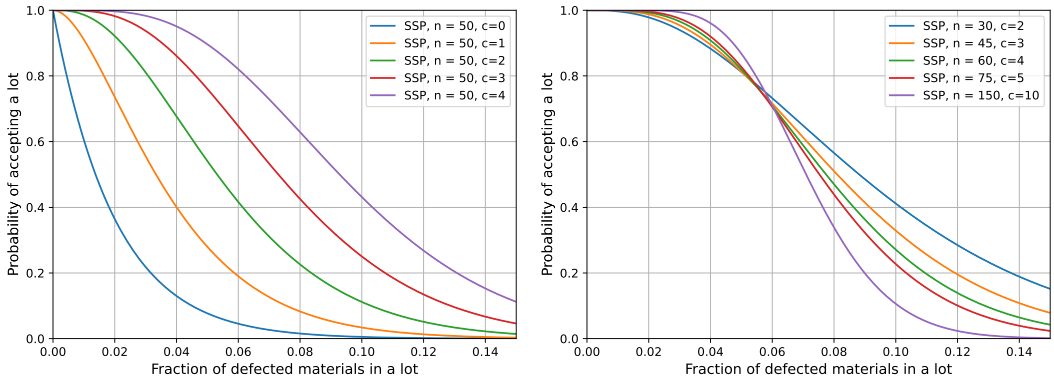
1. Take a random sample of n units from the lot. Inspect it.
2. If the number of defective units is at most the acceptance number c, the lot is accepted.
3. If the number of defective units is more than c, the lot is completely inspected.

In their work, they imply that the utilization of probability theory does not guarantee the quality. If all the units need to be conforming, complete inspections should be taken.

The SSP can be analyzed with a probabilistic approach. The probability of accepting a lot under SSP with n and c can be derived with the binomial distribution:

$$P_a = \sum_{d=0}^{c} \binom{n}{d} p^d (1-p)^{n-d}, \tag{1}$$

where p represents the probability of a defect in the lot and d the number of defects found in the sample (Montgomery, 2012). To describe the risks of the inspection plan, operating-characteristic curves (OC curves) are developed. These curves provide information about the probability of accepting a lot with a given quality of the lot. Each curve represents one combination of sample size n and acceptance number c of a sampling plan. In Figure 1a, single sampling plans with sample size $n = 50$ and varying acceptance number c can be seen. As the acceptance number decreases, the probability of accepting a lot with a certain fraction of defects also decreases. In Figure 1b, single sampling plans with different sample sizes are presented. The acceptance number is set to be proportional to the sample size. The higher the sample size, the steeper the curve. The ideal OC curve is obtained when every unit is inspected and inspections are error free. Then the curve would look like a step function. But as noted in (Montgomery, 2012), this is not possible in the scenarios happening in reality.



(a) Single sampling plan with sample size $n = 50$ and varying acceptance number c

(b) Single sampling plan with the increase of sample size n with acceptance number c being $\frac{1}{15}$ of n

Figure 1: OC curves for SSPs

The OC curves are providing important information for consumers and suppliers. According to (Montgomery, 2012), suppliers may be interested in a point indicating which fraction of defective materials in a lot leads to accepting the lot with 95% of the time. On the other hand, consumer would be interested in the point indicating which fraction of defective materials in a lot leads to accepting the lot 5% of the time.

Dodge and Romig (1941) expand their work with sampling plans by studying single and double sampling plans. Double sampling differs from single sampling by allowing a second sample of size n_2 to be taken in addition to first sample n_1 in certain situations. There exist two acceptance numbers c_1 and c_2 corresponding to these samples. Let n_{d_1} be the number of defects in the sample 1 and n_{d_2} be the number of defects in the sample 2. The procedure is the following:

1. Take a sample of n_1.
2. If $n_{d_1} \leq c_1$, the lot is accepted.
3. If $n_{d_1} > c_2$, the whole lot is inspected.
4. If $c_1 < n_{d_1} \leq c_2$, the second sample n_2 is taken from the lot.
5. If $n_{d_1} + n_{d_2} \leq c_2$, the lot is accepted.
6. Otherwise the whole lot is inspected.

After the double sampling process, all the non-conforming units are repaired or replaced by conforming units.

Dodge (1943) develop a sampling method CSP-1 for continuous production flow of units. Whereas previously introduced sampling plans are mainly used for production, where the materials are coming into inspection in lots, this method is developed for the materials that are coming in as units. The method starts by inspecting every incoming unit, but after i number of consecutive accepted units only a fraction f of units are inspected and the remaining 1-f are skipped. If some of the units inspected in this skipping phase are found defective, the plan returns to 100% inspection until i number of consecutive accepted units are found. All the defective units found by this sampling plan are repaired or replaced with non-defective unit. This plan is a baseline for the skip-lot sampling plans discussed in Section 2.3.

2.3 Skip-lot sampling

Skip-lot sampling is an application of using a continuous sampling plan for lots instead of units. Therefore, only a portion of lots is inspected. The inspection of a lot is based on a sample. Dodge (1955) introduce the skip-lot sampling plan SkSP-1, which is based on the continuous sampling plan CSP-1. In (Dodge, 1955), SkSP-1 is applied to incoming raw materials that arrive in lots and have characteristics that require testing. Perry (1973) develop this method further and allow the use of a reference sampling plan. This method is named SkSP-2 and follows the procedure below:

1. Inspect every lot according to the reference sampling plan until i consecutive lots are accepted.
2. Then move to the skip-lot phase, where only a fraction f of the lots are inspected.
3. When a lot is rejected during the skip-lot phase, return to step 1.

This plan leads to a decreased number of inspections when the quality of the lots is good.

When the skipping phase is included, P_a is not as trivial to compute. Perry (1973) present a Markov-chain based method to determine $P_a(f,i)$. In this method, the states of the plan are interpreted as Markov chain states. With the transition matrix, the method provides the following equation for determining the probability of accepting a lot:

$$P_a(f,i) = \frac{fP + (1-f)P^i}{f + (1-f)P^i}, \tag{2}$$

where P is the probability of acceptance in the reference sampling plan. In Figure 2, operating-characteristic curves for different sampling plans are presented. The simple sampling plan has the sample size $n = 20$ and the acceptance number $c = 1$. SkSP-2-plans have SSP with $n = 20$ and $c = 1$ as the reference plan, $f = \frac{1}{4}$ and $i \in \{4, 10\}$. Due to skipping lots, it is apparent that using SkSP-2 sampling plan leads to higher probability of accepting lots with certain quality compared to SSP.

In order for an organization to select a sampling plan, they should determine two parameters, Acceptable Quality Level (AQL) and Limiting Quality Level (LQL). AQL is a level of defectives in a lot which is still acceptable with high probability, $1-\alpha$. LQL is a level of defectives in a lot that should be rejected very often with probability β. When these parameters and their probabilities are determined, the OC-curve used

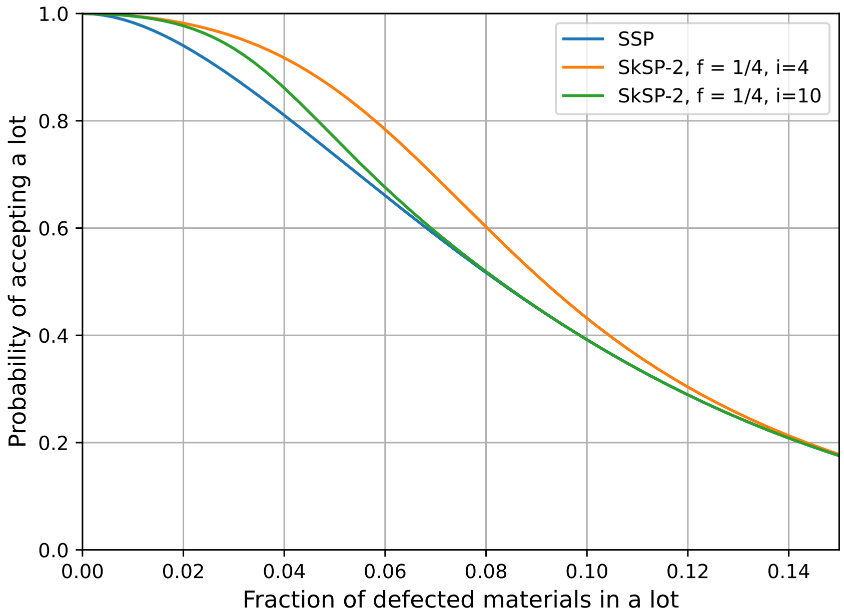


Figure 2: OC-curves for SSP, SkSP-2 with $i = 4$ and $f = \frac{1}{4}$, and SkSP-2 with $i = 10$ and $f = \frac{1}{4}$ (Perry, 1973)

will be the one satisfying two-point problem (Montgomery, 2012),

$$1 - \alpha = \sum_{d=0}^{c} \binom{n}{d} \mathrm{AQL}^{d} (1 - \mathrm{AQL})^{n-d} \tag{3}$$

$$\beta = \sum_{d=0}^{c} \binom{n}{d} \mathrm{LQL}^{d} (1 - \mathrm{LQL})^{n-d}, \tag{4}$$

where c is the acceptance number, and d is the number of defects in the sample.

Balamurali and Subramani (2012) study SkSP-2 with double sampling plan as a reference plan, SkDSP-2. They use the two-point problem (3)-(4) to find the optimal parameters for the plan. In the paper, a table for $\alpha = 5\%$ and $\beta = 10\%$ is given, so the reader can determine the plan by selecting values for AQL and LQL. They also compare the SkDSP-2 to SSP and DSP and show that SkDSP-2 provides the best protection for the supplier of the lots out of these strategies.

There also exist many other skip-lot sampling plans. Burton and Bernard (1983) develop skip-lot sampling plans further and include switching rules for the sampling plans. The main idea is to create a program that can react well to the changing quality of the products. They divide the procedure of skip-lot sampling into three states: lot-by-lot sampling (state 1), skip-lot sampling (state 2) and skip-lot sampling interruption (state 3). The biggest change compared to SkSP-2 by (Perry, 1973) is that instead of switching right away back from state 2 to state 1, there is a possibility to move to a temporary skip-lot interruption state. From that state, it is possible to either disqualify the product and jump back to state 1 or requalify the product and continue with skip-lot sampling. The methodology in the paper is at its base similar to the skip-lot procedure in (International Organization for Standardization, 2005), covered in more detail in Section 2.5.2.

Balamurali and Subramani (2010) study the economics of SkSP-3. This plan introduces an additional state after a lot is rejected during the skipping phase. The state does not change immediately to lot-by-lot inspection, rather the next k lots are inspected. If no lots are rejected in those k consecutive lots, the skipping state is continued. But if a lot is rejected at that state, the plan returns to the state of lot-by-lot inspection until i consecutive lots are accepted. For lots with quite good quality level (e.g. 0.03-0.07 fraction of defects in a lot), using SkSP-3 leads to higher probability of acceptance than using specific SkSP-2 or SSP.

Balamurali et al. (2014) study skip-lot sampling with resampling, SkSP-R. If a lot is rejected during a skipping phase, and at least k inspected lots during the skipping phase have been accepted consecutively, the state does not change to the normal lot-by-lot inspection. Rather, there is a resampling state, where the next lot is inspected according to the reference plan. If the usage decision is positive, the skip-lot sampling is continued. However, if the lot is not accepted, resampling is done m times and if the lot is not accepted on the (m-1)st resampling, then the state is changed to the normal lot-by-lot inspection. Otherwise, the skip-lot sampling is continued. Their results indicate that the SkSP-R plan is useful when the quality of lots is good.

Hsu (1977) study the economics of skip-lot sampling and develop a cost model for a destructive testing scenario. In the model, production costs, inspection costs, and penalty costs are considered. From the economic point of view, the skip-lot sampling may be more feasible than the lot-by-lot sampling as less lots are destroyed in the inspection.

2.4 Skip-lot sampling strategies used in the thesis

The inspection strategies used in this thesis are based on skip-lot sampling. In this section, three different inspection strategies are presented. In these strategies, an inspection means an inspection of a sample, not the whole lot.

2.4.1 SkSP-2 inspection strategy

The inspection strategy SkSP-2 presented in Table 1 is based on (Perry, 1973). The strategy consists of two states, lot-by-lot inspection (State 1), and skip-lot inspection (State 2).

State	Description
State 1	Inspect every incoming lot until i consecutive lots are accepted. Then move to State 2.
State 2	Inspect the first lot. If the lot is accepted, skip the next $\frac{1}{f} - 1$ lots and perform State 2 again. Otherwise, move to State 1.

Table 1: Description of the SkSP-2 inspection strategy

The difference between the SkSP-2 strategy used in this thesis and the one presented in the literature is the deterministic skipping order. In the literature, a randomly sampled fraction f of the lots are inspected in State 2, whereas in the strategy used in this thesis, the first lot is inspected and the rest of the lots in the cycle are skipped. This provides better explainability for the modeling.

2.4.2 Inspection strategy A

The first of the case company's inspection strategies investigated in this thesis is Inspection strategy A presented in Table 2.

State	Description
State 1	Inspect every lot. When a certain number of consecutive lots are accepted, move to State 2. If a lot is rejected, move to Interruption 1.
State 2	Inspect only a certain share of the lots. When a certain number of consecutive inspected lots are accepted, move to State 3. If a lot is rejected, move to Interruption 2.
State 3	Inspect only a certain share of the lots. When a certain number of consecutive inspected lots are accepted, move to State 4. If a lot is rejected, move to Interruption 3.
State 4	Inspect only a certain share of the lots. Stay in the state until a lot is rejected. If a lot is rejected, move to Interruption 3.
Interruption 1	Perform an additional inspection procedure. Move to State 1.
Interruption 2	Perform an additional inspection procedure. Move to State 2.
Interruption 3	Perform an additional inspection procedure. Move to State 3.

Table 2: Description of Inspection strategy A

The idea of Inspection strategy A is to reduce the number of inspections gradually when the quality of the lots is good. It has multiple skipping phases, whereas SkSP-2 by (Perry, 1973) has only one.

2.4.3 Inspection strategy B

The second of the case company's inspection strategies investigated in this thesis is Inspection strategy B, presented in Table 3.

State	Description
State 1	Inspect a fraction of lots. In a case of rejection of the lot, move to Interruption. After a certain series of events, move to State 2.
State 2	Inspect a fraction of lots. In a case of rejection of the lot, move to Interruption.
Interruption	Perform an additional inspection procedure. Move to State 1.

Table 3: Description of Inspection strategy B

Inspection strategy B is formed by two skipping states: State 1 that is the first skipping state of the strategy and State 2 that is the second skipping state. As the strategy contains only skipping states, it is planned to use for lots that have demonstrated very good quality in the past. If a lot is rejected in State 2, the strategy cannot return to the same state, rather it needs to first go through Interruption and State 1 before returning back to State 2.

2.5 Standards for acceptance sampling

In many industries, e.g. manufacturing and pharmaceuticals, it is common to make processes follow standards. These standards contain requirements and guidelines how to make a process that produces consistent and good quality outputs.

A process can be audited by authors and awarded with a certification if it fulfills the standard's requirements. This not only signals the customer about the quality of the products but also ensures that the company has the right tools to monitor and improve the quality.

2.5.1 Military Standard 105D

Military Standard 105D was published in 1963 by the Department of Defence in the US. It gives guidance on how the acceptance sampling should be conducted. (Department of Defence, 1963)

In the standard, there are many acceptance sampling related definitions and tables for single, double, and multiple sampling plans with tightened, normal, and reduced inspections. Also, a distinction is made between defects and defectives. Unit of product has a defect if it does not satisfy some of the requirements. There can be many defects in one unit of the product, and the unit is labeled as defective by the most severe defect (Critical, Major, or Minor).

2.5.2 ISO2859-3:2005(E)

In 2005, the International Organization for Standardization published standard ISO2859-3:2005(E), which deals with skip-lot sampling procedures. The standard requires that before using skip-lot sampling, both the supplier and the product need to be qualified for the skip-lot sampling. (International Organization for Standardization, 2005)

The requirements for the supplier are split into three parts. The supplier needs to have documentation of their quality assurance processes, their system needs to be able to capture changes in the quality levels and they must not have made any changes that could lead to a decreased quality level.

The requirements for the product qualification are more detailed, and they can be found from the standard in detail. To mention a few, the standard requires a stable design from the product to qualify for the skip-lot sampling procedure. The product cannot have any critical non-conformities, and the defined Average Quality Limit (AQL) has to exceed a certain threshold. Also, the AQL level quality must have been maintained over a certain period.

The procedure for skip-lot sampling by ISO2859-3:2005(E) is shown in Figure 3. As can be seen, the procedure involves three states: lot-by-lot sampling, skip-lot sampling, and interruption of skip-lot sampling. When the requirements for the supplier and the product are fulfilled, the inspection strategy can move from lot-by-lot sampling in State 1 to skip-lot sampling in State 2. As long as the qualifications are fulfilled or the quality score is not set to zero, the inspections are made with skipping lots. If the quality score is reset to zero, the state is changed to the skip-lot sampling interruption in State 3. If the requalification is given, the skip-lot inspection can be continued but otherwise the state of the inspection strategy returns to lot-by-lot inspection in State 1. This procedure differs from the approaches covered earlier in Section 2 by the fact that the decisions on inspection frequencies and the transition between states are made by updating the quality score. More details of this process can be found in (International Organization for Standardization, 2005).

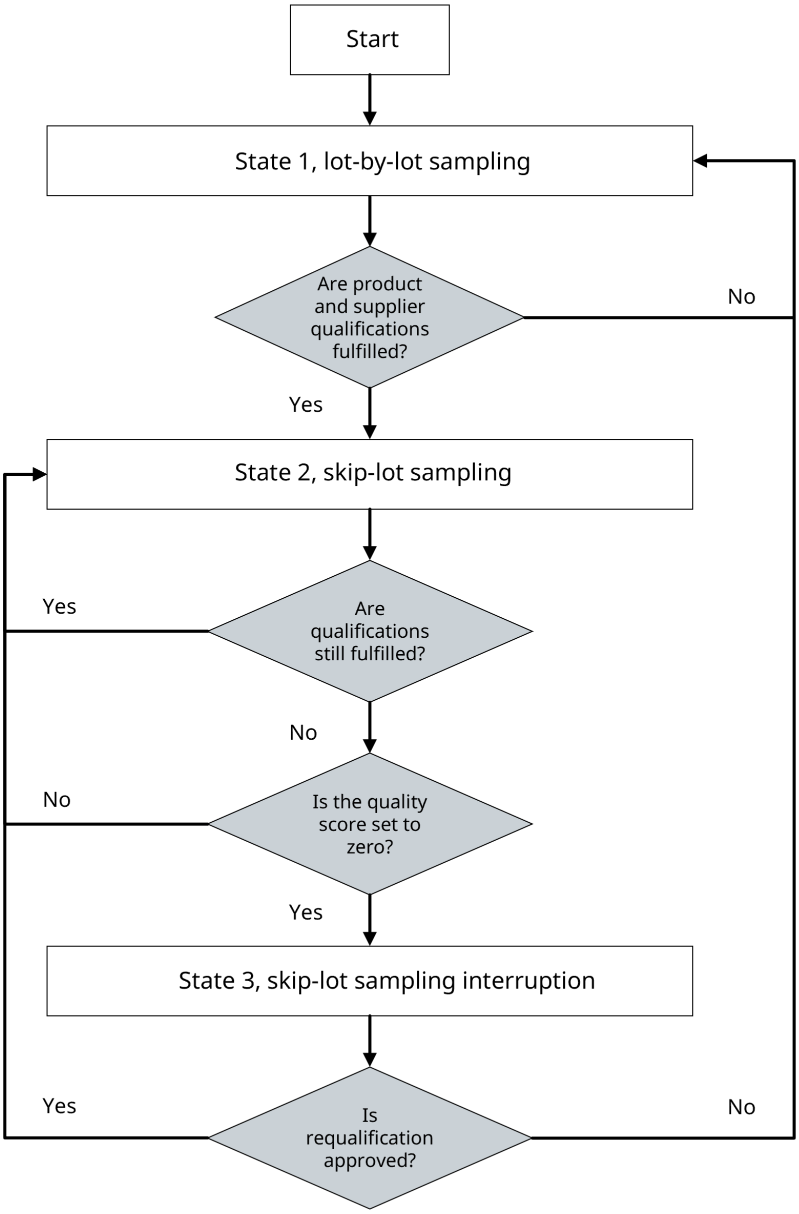


Figure 3: Outline of the skip-lot sampling procedure by ISO2859-3:2005(E) standard (International Organization for Standardization, 2005)

2.6 Discrete-event simulations in modeling systems

The previous subsections of Section 2 consider acceptance sampling methods and standards. One important factor relating to the inspection of incoming materials is the inspection resources needed to execute the inspection strategies. Even though there are a lot of different standards and methods available, an organization may not be able to utilize them if they lack sufficient inspection resources. Therefore, the required inspection capacity must be investigated.

With the acceptance sampling methods, the average total inspection per lot can be calculated with statistics, e.g. (Montgomery, 2012). However, this metric considers the number of inspections, but not necessarily the capacity needed to perform the inspections. For example, inspecting different materials may take different time. Furthermore, there may be limitations which resources can be used for a certain inspection task. Thus, a model that can account for the different constraints and characteristics of the system is required to model the inspection capacity in a complex environment.

This kind of capacity and resource problems are widely investigated with operations research models. Key requirement in developing an operations research model is understanding the restrictions of the system and its capacity. Decision-makers are interested in questions such as how to allocate resources and how much benefits can be achieved by modifying certain processes or investing in equipment. Questions like this can be answered with a variety of operations research methods, such as mathematical optimization (Saaty et al., 2003; Abdulbaki et al., 2017) and discrete-event simulation (Bedoya-Valencia and Kirac, 2016; Freiberg and Scholz, 2015) of which the latter is used in this thesis.

There are many approaches for modeling a system. Law (2015) divide these approaches in a tree presented in Figure 4. As illustrated, one can either study the

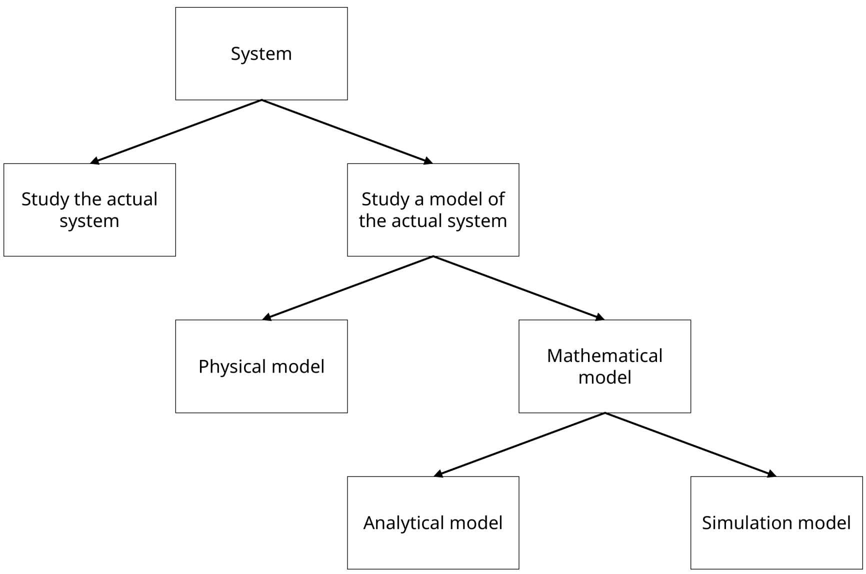


Figure 4: Different approaches to modeling a system by (Law, 2015)

system directly, e.g. changing something in the system and observing the consequences, or study the system with a model. The model can be either a physical model, e.g. the same system as a miniature, or it can be a mathematical model. In some situations, the interactions in the system are very complex and there is not a possibility to derive analytical solutions to the system behavior. Simulation is a modeling technique that allows system analysis without the analytical solutions by changing the mathematical input for the model and studying how the output of the system behaves. Discrete-event simulations belong to this group of mathematical models.

2.6.1 Discrete-event simulations

The system can be either discrete or continuous. The state of the discrete system is changing only in discrete points in time whereas the state of the continuous system may be changing continuously. For example, an ice-cream shop can be modeled as a discrete system, where its state is updated when a new customer arrives or the current one is served. An example of modeling a system as a continuous system is a boat in the lake. Its state is updating continuously depending on the state equations that describe its movement.

Discrete-event simulation is a modeling technique, where the state variables of the system are changing in distinct points in time (Law, 2015). According to Fishman (2001), every discrete-event system inherits at least following seven concepts: Work, resources, buffers, routing, scheduling, sequencing, and performance. Work is the unit that is served in the system, e.g. an item inspected in the inspection room. Resources are the devices or machines with which the work is done. Buffers are the places where the work is waiting for servicing. Every unit has a routing which tells what kind of processes and operations are needed to perform for it in the system. For example, a routing could be the specified steps in manufacturing that are needed to be done for the unit. Scheduling describes when the work can be done, e.g. there may not be work done in the evenings. Sequencing tells in which order the items are handled in the system. Performance references to metrics that describe the system behavior, e.g. throughput time.

System can be either an open- or a closed-loop system. In an open-loop system, the system state is not impacting the input whereas in closed-loop system, the state has an impact to the input. In Figure 5, single and multiple route open-loop systems and single route closed-loop system are presented. All systems have inputs as arrivals and outputs as departures. Buffer is a place where the work is waiting to be processed. Server is the facility that does the work. Arrows are describing the flow of the system. In open-loop systems, the arrows are directing from arrivals to departures whereas in closed-loop system, there is so-called feedback loop from a server to a buffer. In b), there are two different routes for a work to be processed. Parameter q determines the division proportions of the work. In general, modeling very complex phenomena can be done by using the same fundamental building blocks as in Figure 5.

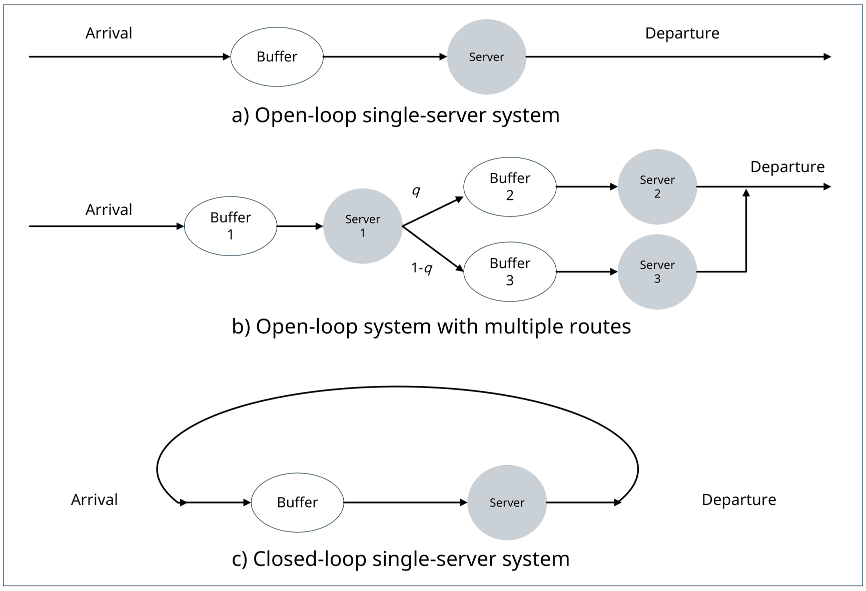


Figure 5: Open- and closed-loop diagram examples by (Fishman, 2001)

2.6.2 Applications of DES models

Discrete-event simulation models allow the modeling of various metrics of a complex system across different scenarios. As done also by (Rau et al., 2013; Rajendran et al., 2015), the simulations are run to test different scenarios in this thesis. Rau et al. (2013) create a discrete-event simulation (DES) model of a physical therapy clinic in Taiwan aiming to support decision-making in strategic capacity planning. By using the model, they recognize possible improvement actions, such as grouping therapists together as pools. They tracked key metrics, such as waiting time and the number of patients. The study highlights that modeling the operations with a DES model provides a possibility to seek improvement actions and test different scenarios. Rajendran et al. (2015) analyze the operation of ports with mathematical models. They develop an integer linear programming (ILP) model, but due to computational complexity, they also create a discrete-event simulation model. They create different scenarios of the operations (e.g. different priorities for ship types or port resource allocation) and track the waiting time of the ships and the utilization of the access channels. Similarly to this thesis, the utilization of resources is one of the key metrics investigated.

When using a discrete-event simulation modeling approach, data related factors are important. The model should reflect the reality in order to use it for supporting the decision-making. Zhu et al. (2012) study the operation of an intensive care unit (ICU) with a discrete-event simulation model. The model uses operational data and is validated in two phases: discussing with experts and comparing the output against the actual data. They also mention that the use of the operational data may not necessarily reflect the operations in the future, which they tackle by adjusting the data to the future growth. Famiglietti et al. (2017) study radiation treatment center's operations with a discrete-event simulation software. They gather data from multiple sources for the research and manage to create a valid simulation model of the center. They mention that if the model is not correctly describing the operations of the treatment center, the results regarding the changes made are not reliable. Abd Suki et al. (2016) conduct a case study, where they investigate quality related factors for a circuit board manufacturing company by a discrete-event simulation model. They present a framework for building a DES model in three phases from defining the project to developing and experimenting the simulation model to analysing the results. Similarly to (Zhu et al., 2012), they also mention that the simulation output should be matched to the theoretical output. The approach in this thesis follows this same principle, as the number of inspections and skips made by the model are matched against the historical quantities.

Quality related factors can be investigated with DES models (Famiglietti et al., 2017; Abd Suki et al., 2016). As quality can be improved by e.g. improving processes, DES models can bring important insights for decision-makers of the impact of the possible changes in the inspection process. The approach in this thesis connects a DES model of the incoming materials inspection to different skip-lot sampling procedures.

3 Research methods

To model the incoming materials inspections, there needs to be an understanding of the system around this operation. In this section, the background information, the inspection room, and the inspection process are first described. Based on this information, a DES model of the system is developed and presented.

3.1 Background

Some of the information considering the processes and flows of the incoming materials, inspection room, and quality was gathered by interviewing employees in the inspection room and talking with the case company's quality-related staff. These sessions were mostly done together with a senior employee. The interviews and sessions were conducted as informal discussions and notes were taken. No strict structure was forced to these sessions.

The case company has a logistic center very close to one of its factories. This logistic center has high volumes of incoming materials, and its operations are crucial when it comes to the manufacturing being on time. There are several parallel processes going on in the logistic center, and one of these processes is the inspection of the incoming materials.

The materials come to the inspection in lots. A lot is a collection of units of a material from a certain supplier. An inspection is a measurement of geometrical shapes of the material. Also, it can involve measuring the roughness of the material's surface or cleanliness of the material. A material is defective if any of its characteristics does not fulfill the specified requirements.

Category	Description
100%	Every unit of a material belonging to this category is inspected.
Periodical (Sample-based)	Only samples of the materials are inspected. The decision of whether to inspect an inspection lot is directed by an inspection strategy.
Initial inspection	When a new material is introduced, every unit is inspected to ensure quality.
Notification-based inspection	Inspections done due to fault notifications or errors found at some manufacturing phase.
Exempt material	Materials that do not belong to any of the categories above.

Table 4: Inspection categories of materials

Not every unit of incoming materials is inspected. As the volume of incoming materials is high, inspecting everything would be infeasible due to the limited time and inspection resources. The different inspection categories are presented in Table 4, and generally every material arriving to the logistics center falls into one of the categories.

Category 100% contains materials that are always inspected regardless of the circumstances. The materials in this category are not inspected in the inspection room.

The materials belonging to the sample-based inspection category are inspected in the inspection room. These inspections are based on a sample and controlled by an inspection strategy. The objective of this process is to confirm the supplier's ability to maintain a good quality for its products.

Initial inspections are so-called validation inspections. These inspections require more resources than the periodical ones, since inspecting materials the first couple of times requires more focus on the inspections. Also, if the material is new, a measurement program needs to be created whereas in the periodical inspections the program is already available. In this category, all the units in the lot are inspected unless the number of units is too high.

Notification-based inspections burden the inspection room. These inspections are performed if some issue is found in the assembly phase and the same issue is likely to be found from other units of the material or if a supplier notifies about a specific issue in the material. When this kind of notification is received, the specified materials in the storage are directed to the inspection room and inspected.

In the interview of the inspectors, it was mentioned that some employees working in the assembly are bypassing the official processes and asking straight from the inspectors to do measurements relating to the issue they have found. These requests require inspection capacity but may not be recorded in the systems.

3.1.1 Problem description

The sample-based inspection strategies and the required inspection capacity have not been investigated comprehensively. The objective is to produce information of how well specific inspection strategies find defective lots and how changing the number of inspection resources or the inspection strategy impacts the queue for the inspection room, the inspection resource utilization, and the number of inspections. These questions are answered with a DES model of the system formed by the incoming materials inspection process.

3.1.2 Inspection room setup

The center of the inspection process is the inspection room itself. Physically in front of the inspection room, there is a quality assurance buffer (QAB) for inspection lots to wait for the inspection. Outside the inspection room, there also exists so-called block stock, where the inspection lots with a negative usage decision are directed.

In the inspection room, there is a three-level trolley to which the soon-to-be inspected lots are directed. The bottom two rows of this trolley are for incoming, not yet inspected, lots and the top row is for outgoing inspected lots.

There are three digital measurement machines and two joint-rod machines which are called "Devices" and "Romers" respectively in this thesis. There are also manual tools which are used for different measurements taken by hand. Devices can measure objects of different sizes. One of the Devices can measure only the smallest materials, another can measure small and middle-sized materials, and the last one can also measure large-sized materials. Still, some of the materials are too big or shaped in a way that they cannot be measured with these devices. Romers are joint-rod devices, and they can be used to measure objects with different shapes and sizes. Almost every material can be inspected with Romers. The third way of inspecting materials is manual inspection. By these inspections, it is meant that the qualities of the material are measured with hand-used devices. This category is large and has many different measurement devices.

3.1.3 Inspection process

Materials arrive to the logistic center in purchase orders. When the unpacking starts, the materials are first registered to the ERP system. At the same time, an inspection lot or lots are automatically created from the purchase order items, and the system decides which lots are inspected. Each material-supplier combination has an inspection strategy that it obeys. If the strategy is in a state of inspection, the inspection lot is directed to QAB in front of the inspection room to wait for the inspection. Otherwise, the inspection lot is directed to the storage.

There exists a working queue of the inspection lots. In that queue, the inspection lots are listed in criticality order that reflects the urgency of the inspection. This list behaves as a priority guideline for the inspectors.

A sample from the inspection lot is called from the buffer outside the room to the trolley inside the inspection room. When the sample is taken from the trolley, it is first unpacked. Then inspector sets up the measurement environment and performs the measurements. In a case of using Device or Romer, an inspection program is run whereas in a case of using the manual tools, the inspector measures the needed features. If the measured feature values are inside the tolerance values, the next item is taken from the sample and inspected until every item in the sample is inspected. If some of the critical tolerances are not fulfilled, the measurement is done again to make sure the item is non-conforming.

The measurement time is dependent on the material. Some materials are more efficient to inspect than others. If the measured feature value of the material is not in the tolerance, the inspection takes more time as this non-conformance needs to be confirmed. In general, sample-based inspections are faster to perform than initial inspections as the inspection programs are already available, and the inspectors have measured many similar items before.

After the measurement of the sample is done, a usage decision for the inspection lot is given. A positive usage decision is given by the inspector if all the units in the sample are conforming whereas a negative usage decision is given if at least one of the units in the sample is non-conforming. If the decision is positive, the sample and the corresponding inspection lot is directed to the storage or the factory depending on the urgency. If the usage decision is negative, the whole inspection lot is directed to the block stock from which the lot is scrapped or sent back to the supplier. In a situation with time pressure, the whole lot can be inspected, and the conforming materials can be sent to the factory. Also, if some rare material is in question, a partner company can be used to repair the non-conforming unit.

In the interviews, it was stated that the stakeholders inside the company require higher share of inspections done by Devices or Romers. The explanation for this need is likely relating to the measurement reports Devices and Romers produce. For some stakeholders, it is easier to trust and refer an inspection report where the measurement is done by a machine instead of a human.

3.2 Discrete-event simulation model of the system

This section presents a discrete-event simulation model reflecting the system of the inspection room and process presented in Sections 3.1.2 and 3.1.3. There are some simplifications made to ensure the model is explainable. This DES model is developed by using a discrete-event simulation framework SimPy in Python (Team SimPy, 2026).

The inspection process is modeled as an open-loop system with multiple routes. The inspection machines (Romers, Devices and Manuals) are the resources, and the working unit is an individual lot. The model is considering lots belonging to either sample-based inspection category or initial inspection category. The process for each individual lot is described in Section 3.2.1, the model parameters in Section 3.2.2, the performance measures in Section 3.2.3, and the input data in Section 3.2.4.

3.2.1 Inspection process in the model

The inspection process in the model from the perspective of one lot is described in Figure 6. This process is conceptual, and the exact implementation in the code may differ in some parts. In the beginning of each simulation, the model starts the inspection process for every incoming inspection lot at the same time on t_{start} but in the arrival date order. First, a lot waits for the arrival date. When the arrival date is reached, a lot that belongs to the sample-based inspection category proceeds to wait for an arbitrary starting slot resource. After the start slot is received, the decision of whether to inspect or skip the lot is made based on the material-supplier combination's inspection strategy. If a lot belongs to the initial inspection category, it is directly moved to wait for a feasible inspection resource. This is done, as all the lots belonging to the initial inspection category are inspected, meaning that these lots do not follow any inspection strategy and do not need an arbitrary starting slot.

If the state of the inspection strategy indicates a skip, no inspection is done and an automatic positive usage decision is given to the lot. If it is weekend, the model waits until the week starts to give the usage decision. Then, the corresponding inspection strategy is updated, and the results are collected. At the same time, the starting slot of the material-supplier combination is returned for the combination's next lots.

If the state of the inspection strategy indicates an inspection, the lot is inspected. This starts by waiting for a feasible inspection resource from the inspection room.

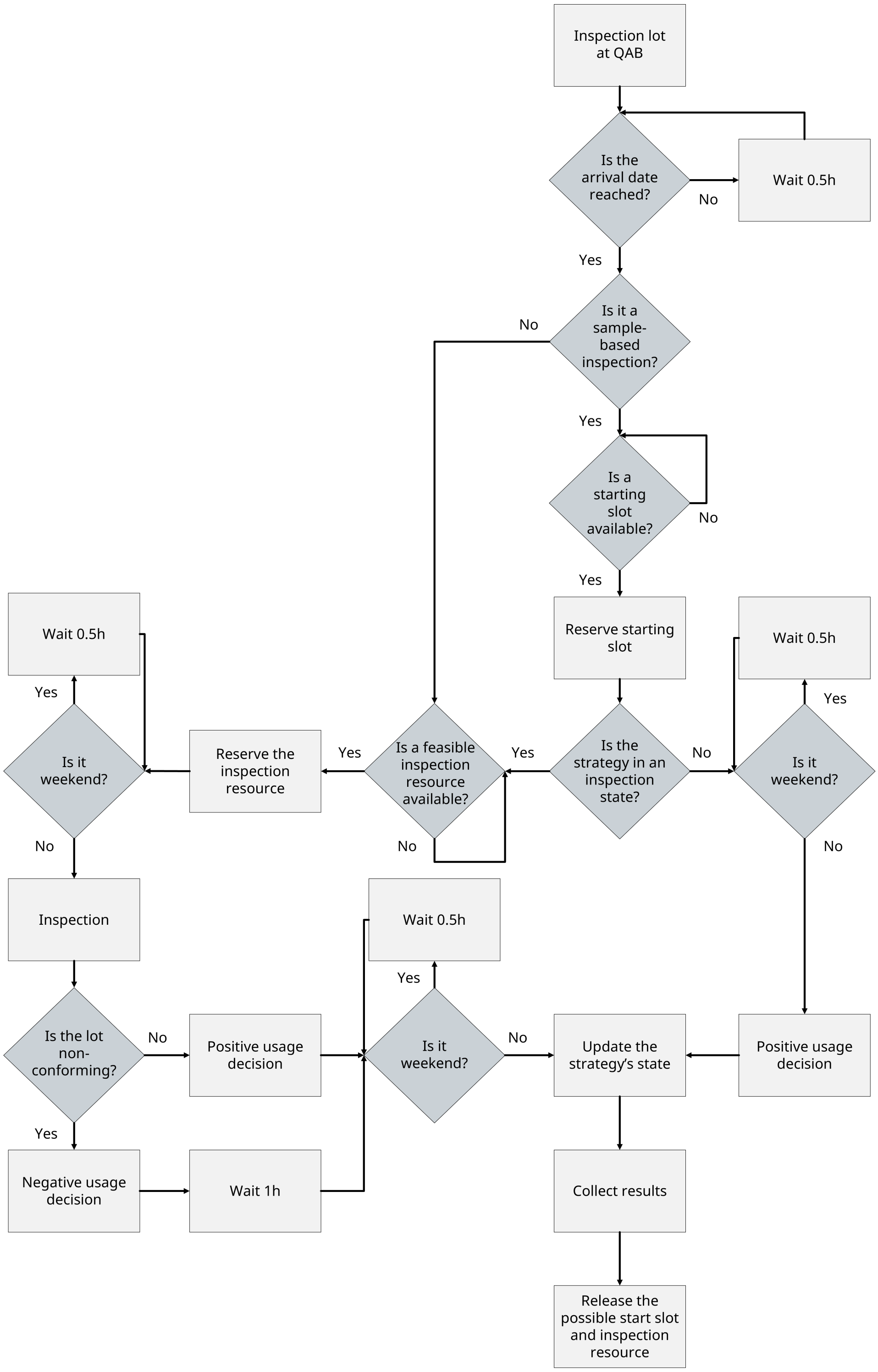


Figure 6: Conceptual process diagram of the inspection process in the used DES model

Each lot has information on which resource it can be inspected. When a feasible inspection resource becomes available, the lot reserves the resource. Then, the model ensures it is not weekend and starts the inspection. The inspection time is dependent on the sample size determined from the lot size. The weekend time is not included in the inspection time. After the inspection a usage decision is given. Each incoming lot contains only either defective units or not defective units, as it is assumed that all the units in the incoming lot are produced under the same conditions. Thus, the defective lots are formed due to a systematic error in the process producing the units in the incoming lots.

If the lot contains only defective units, a negative usage decision is given, whereas a positive usage decision is given to the lots containing only not defective units. Whether or not the lot contains defects depends on the data used. There are no inspection errors present in the model, so if a sample from a lot containing defects is inspected, the usage decision is negative.

When giving a negative usage decision, one hour is added to the inspection time to simulate that it takes some time to confirm the defective result. After the negative usage decision and the additional waiting time, it is still verified that it is not a weekend. For a positive usage decision, this waiting time is not needed, and it is made sure that there is no weekend. Then, the corresponding inspection strategy is updated based on the current state and the usage decision, the lot-specific results are collected, and the starting slot and the inspection resource are released. If the lot belongs to the initial inspection category, no inspection strategy is updated, and no starting slot is released as there is not any strategy or starting slot for these lots.

Updating the state of the inspection strategy is dependent on the usage decision and the strategy itself. The strategies used are described in Section 2.4. For example, let a lot have a material-supplier combination that follows Inspection strategy A. If a negative usage decision is given (the lot is rejected), and the strategy is in State 3, the strategy is updated so that the next state is Interruption 3.

The importance of the arbitrary starting slot for each material-supplier combination belonging to the sample-based inspection category needs to be highlighted. There is only one starting slot resource available for each of the material-supplier combinations. This leads to inspecting only one lot of a certain material-supplier combination at a time. This is mandatory, as overlapping inspection of the lots from the same combination may lead to some unwanted behavior of the inspection strategy. For example, let there be a material-supplier combination in a state of inspecting every lot, and one more positive usage decision qualifies it to a skip-lot phase. If there are no restrictions on how many lots of the same combination can be inspected at the same time, while inspecting the next lot, another lot from the combination may enter for the inspection. If the first inspected lot gets a positive usage decision, the next lot should be skipped. However, as there is already a lot from the combination under inspection, it is not skipped. Thus, it is important that only one lot of the same material-supplier combination is inspected at the same time.

3.2.2 Model parameters

In the DES model presented above, the inspection room is described with resources. The inspection of a lot is performed completely with one resource. This resource can be either Device, Romer or a manual resource called Manual. The number of Devices and Romers are marked with parameters r_d and r_r. The number of manual inspection resources is marked with parameter r_m. Thus, $r_\mathrm{d} + r_\mathrm{r} + r_\mathrm{m}$ inspections can be performed at the same time.

The simulation starting date is controlled with the parameter t_start. This parameter is the date when the simulation starts processing the inspection lots. As there is no work done during weekends, the model is configured not to allow inspections to start or end on weekends. Also, the weekend time is not included in the inspection times. The working hours per day is controlled with parameter w_h. The number of simulations is marked with n_sim.

An important part for the inspection operation is the time it takes. To make the model not only simple and explainable but also reliable, two different inspection operations are distinguished, the initial inspection and the sample-based inspection.

For setting up the inspection of the lot, 0.5 h is reserved. Thus, the total inspection time is:

$$T_\text{total inspection} = 0.5 + n \cdot t_\mathrm{unit}, \tag{5}$$

where n is the sample size taken from the lot and $t_\mathrm{unit} \in \{T_\mathrm{i}, T_\mathrm{s}\}$ depending on whether the lot belongs to the initial or sample-based inspection category. The sample size n is dependent on the lot size N, but the exact rules are not presented in this thesis. The indicative rules for determining n for the lots belonging to the sample-based inspection category are presented in Table 5.

Lot size N	Sample size n
Small lots	1-3
Medium sized lots	4-7
Large lots	8-10

Table 5: Indicative sample size for the lots belonging to the sample-based inspection category

For the lots belonging to the initial inspection category, the sample size is determined differently. For smaller lots, every unit is inspected. However, after the lot size exceeds a certain threshold, only a specific number of units is inspected.

Every material-supplier combination in the sample-based inspection category has an inspection strategy. In the model, there is a parameter that specifies which inspection strategy is used. The lots belonging to the initial inspection category are not directed by an inspection strategy rather all the lots in that category are inspected.

3.2.3 Model performance measures

To compare the simulation runs with different parameters, the simulation output needs to be measured. In this thesis, the queue for the inspection room, the usage decisions given per date and the utilization of inspection resources are investigated. Furthermore, throughout the simulations the detection rate, the inspection efficiency, the number of inspections, and the last usage decision date are measured.

The queue for the inspection room is a performance metric measuring how many lots are waiting for the inspection. In this model, it is calculated for each date at the last half an hour of the workday. For example, the queue for the day 5 with $w_{\mathrm{h}} = 8$ is calculated at the time 47.5h, and the length of the queue is determined by counting how many lots that have already arrived to the QAB have not yet started the inspection at that time. The average queue at a specific date is the average value of this metric at this date across the simulations.

The usage decisions given per date measures the output of the inspection room. It is the number of given usage decisions that are given based on the inspection result at a specific date. Thus, the usage decisions that are given automatically from the skipped lots are not included in this metric. The average number of usage decisions at a specific date is the average value of this metric at this date across the simulations.

The utilization metric is calculated for each working day by dividing the sum of the hours that the resources are used by the sum of the available resource hours. For example, let there be one Romer, one Device and one Manual and $w_{\mathrm{h}} = 8$. If the Romer is used 7 hours in one day and the other resources are used 5 hours in that same day, then the utilization for the resources in that day is $\frac{17}{24} \approx 0.71$. The average utilization at a specific date is the average value of this metric at this date across the simulations.

In general, there are two reasons for the utilization to be below 1. First, if there are just not enough incoming lots for the inspection room's resources, then there is a possibility for idle time. Second, if all of the lots in the queue belong to the sample-based inspection category and are from the material-supplier combinations for which there currently is some lot under inspection in the inspection room, then there may be idle time. Resources are not utilized on the weekends, as there is no work done then. When calculating the average utilization during a time interval, weekends are not included.

The detect rate is calculated for each simulation as

$$\text{Detect rate} = \frac{\text{Number of negative usage decisions}}{\text{Number of defects in the data}}.$$

This metric describes which share of the defects in the data are found. As there are no inspection errors present in the model, and each lot contains either only defective units or not defective units, inspecting every lot leads to the detect rate of 1.

The inspection efficiency is calculated for each simulation as

$$\text{Inspection efficiency} = \frac{\text{Number of negative usage decisions}}{\text{Number of inspections}}.$$

This efficiency metric measures which share of the inspections end up finding defects. The metric is not reliable in the extreme situation where all the lots and units are defective, as the efficiency will be 1 regardless of the strategy. However, in common situations, it measures the strategy's ability to focus on inspecting the suppliers with poor quality.

The number of inspections is the number of inspected lots. The last usage decision date is calculated separately for each simulation. The median last usage decision date is the median of these dates.

Some of the metrics are also reported with 90% empirical intervals. This interval is the range in which 90% of the simulation metric values fall.

3.2.4 Model input data

The input data for the model consists of incoming inspection lots, and each row in the data is relating to a certain inspection lot. The features of the input data are described in Table 6.

Column	Description
Material key	Unique identifier for material
Supplier key	Unique identifier for supplier
Inspection category	Whether the inspection lot belongs to the sample-based or initial inspection category
Number of units in the lot	How many units there are in the lot
Arrival date	When does the lot become available for inspection
Defective lot	Whether or not all the units in the lot are defective
Inspection resources	What resources can be used to inspect the lot (Device/Romer/Manual)

Table 6: Description of the model input data

The material and supplier key features determine the material-supplier combination of the lot. Each combination obeys its own inspection strategy. The inspection category is either sample-based inspection or initial inspection category, and this category determines the unit inspection time parameter. The number of units in the lot together with the inspection category are used to determine the sample size. The arrival date information is used to determine when the lot becomes available for the inspection. This date is deterministic, in other words, no arrival rate is used. The defective lot feature tells if the units in the lot contain defects or not. In one lot, every unit is either defective or not defective. The inspection resources feature determines the resources that can be used for inspecting the lot.

4 Results

In this section, the model is run with two different datasets. First, to investigate the basic dynamics of the developed discrete-event simulation model, the model is run with a generated dataset. Then, the model is configured and validated with the case company's dataset after which results and sensitivity analysis are presented.

4.1 Results with generated data

The generated dataset contains in total 2000 lots of 10 different materials from 5 different suppliers. Thus, there are 50 unique material-supplier combinations, leading to each of the combinations having 40 lots. Each lot contains either 10 or 60 units of the material. The materials 1 to 5 can be inspected with Romers and Devices, the materials 6, 7, and 8 with only Romers, and the materials 9 and 10 with Romers, Devices, and Manuals. All the lots belong to the sample-based inspection category.

	Supplier 1	Supplier 2	Supplier 3	Supplier 4	Supplier 5
Material 1	4/40	2/40	14/40	18/40	18/40
Material 2	1/40	2/40	10/40	20/40	17/40
Material 3	1/40	2/40	15/40	18/40	16/40
Material 4	1/40	0/40	18/40	16/40	15/40
Material 5	4/40	1/40	17/40	21/40	13/40
Material 6	3/40	1/40	11/40	15/40	14/40
Material 7	2/40	2/40	12/40	13/40	20/40
Material 8	2/40	1/40	20/40	18/40	13/40
Material 9	3/40	4/40	22/40	18/40	9/40
Material 10	1/40	1/40	15/40	14/40	17/40
Fault rate	0.055	0.040	0.385	0.428	0.380

Table 7: Number of faulty lots in the generated dataset with respect to the total number of combination's lots

The number of defective lots in the dataset with respect to the total number of the material-supplier combination's lots can be seen in Table 7. As can be seen, the suppliers 3, 4, and 5 have more faults on average (fault rates 0.39, 0.43, and 0.38 respectively) than the suppliers 1 and 2 (fault rates 0.06 and 0.04 respectively), indicating worse quality of the suppliers 3, 4, and 5. Overall, the fault rate in the dataset is approximately 0.26. In Figure 7, the number of arriving lots per date can be seen. The arrivals of the of the lots are distributed randomly across the weekdays in March and April 2025.

The number of Romers r_{r}, Devices r_{d}, and Manuals r_{m} are set to 2. The working hours per day w_{h} is set to 8. The simulation starting date t_{start} is set to 1st March 2025. The number of simulations n_{sim} is set to 100. The inspection time per lot is dependent

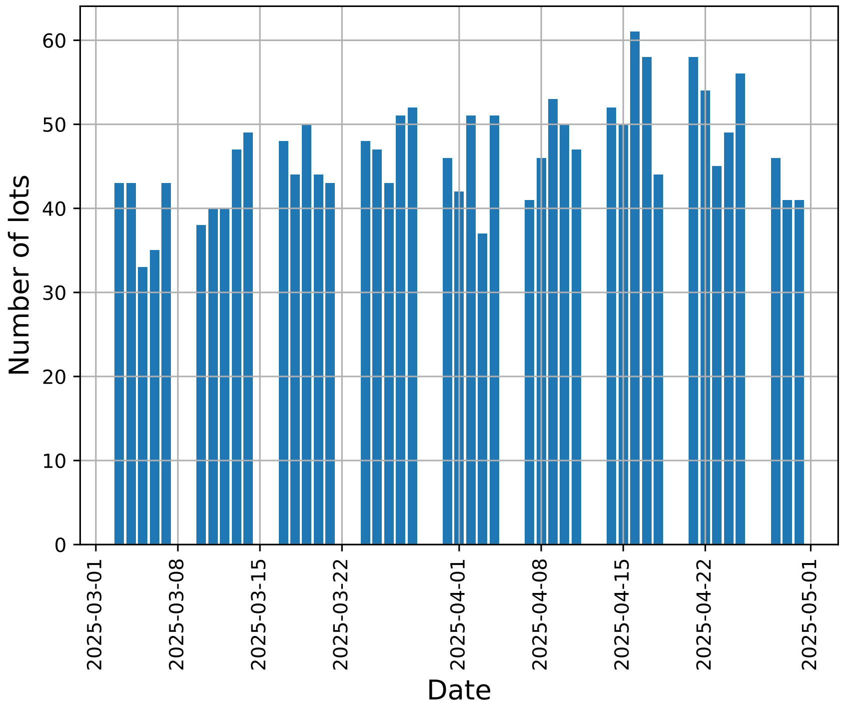


Figure 7: Arriving lots per date in the generated dataset

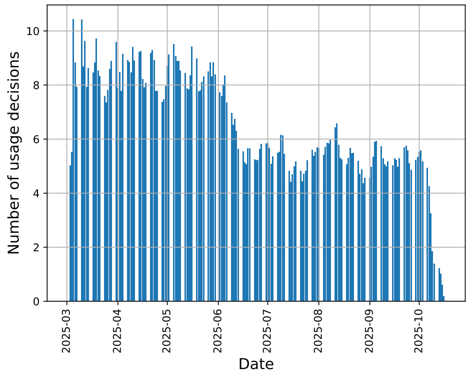
on the sample size, which can be determined from the lot size based on Table 5. The unit time for a sample-based inspection is sampled from the distribution:

$$T_s = \begin{cases} 1, \text{ with } p = 0.8 \\ 1.5, \text{ with } p = 0.2 \end{cases} \tag{6}$$

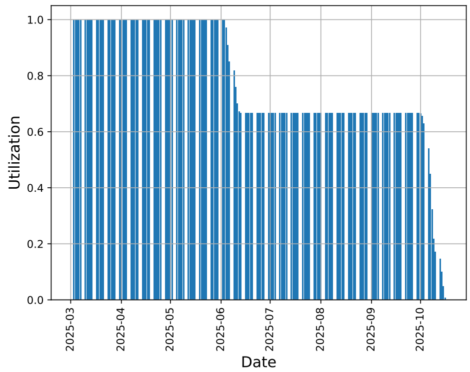
The inspection strategy used is SkSP-2 with $i = 3$ and $f = \frac{1}{5}$. The reference plan is a single sampling plan with acceptance number $c = 0$ and sample size n determined from Table 5. Each of the strategies is starting at State 1.

The results with these parameters can be seen in Figure 8, where the average usage decisions per date is shown in Figure 8a, the average resource utilization per date is shown in Figure 8b, and the number of lots waiting for the inspection is shown as average, and five different runs of the simulations are shown in Figure 8c. According to the model results, the queue of the lots waiting for the inspection increases until there are no longer new lots arriving. This means that the input for the inspection room is higher than the output in this time interval, and the current resources are not enough for stabilizing the queue. The queue exceeds 1200 lots at its longest, as seen in Figure 8c. The queue starts to decrease at the beginning of May, which is the same time as there are no longer new lots arriving. Also, the differences between the simulation runs with respect to the queue seem to be small with these input parameters.

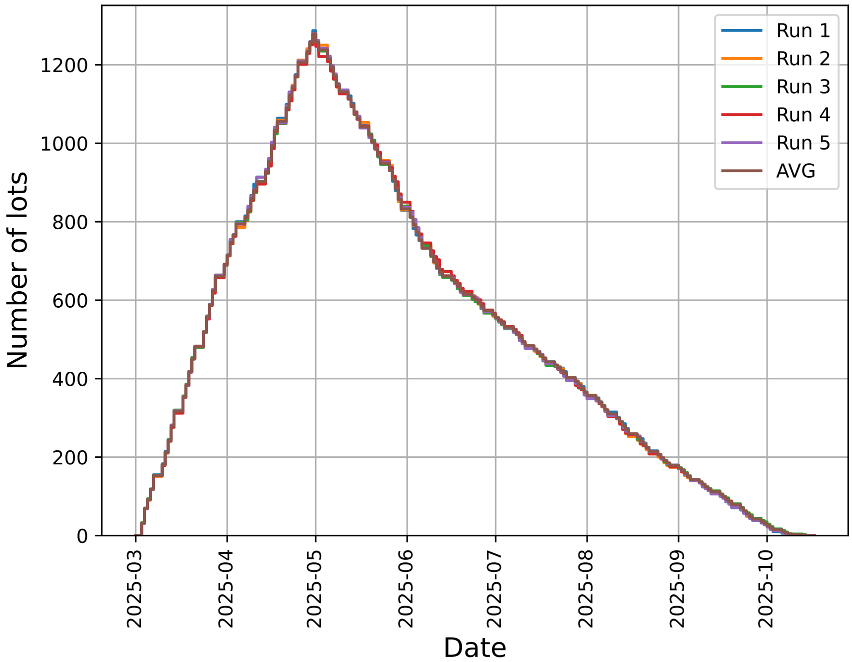
In Figures 8a and 8b, the number of usage decisions per date and the utilization per date drop before July. At the first glance, this may look odd as the model should utilize all the available resources. The reason for this sudden drop comes from the



(a) Number of usage decisions per date



(b) Resource utilization per date



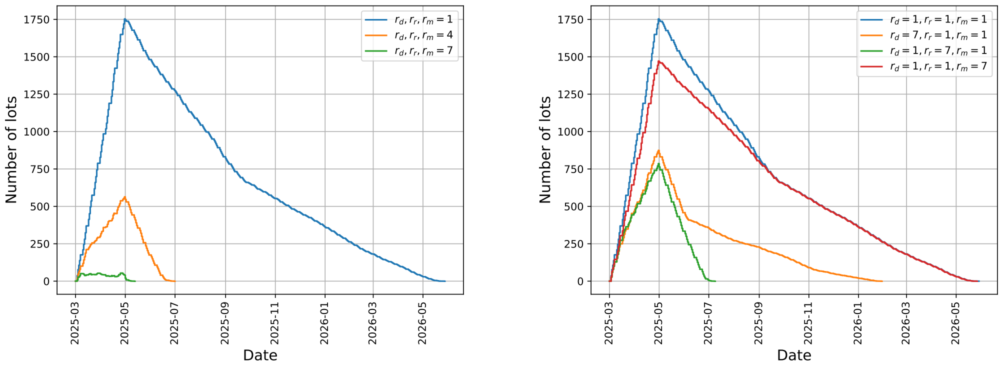
(c) Lots waiting for a usage decision

Figure 8: Performance measures of the inspection room with SkSP-2 inspection strategy with $i = 3$ and $f = \frac{1}{5}$

data. Only the materials 9 and 10 can be processed manually, and after processing all the lots containing these materials, there is no need for the manual resources. Thus, only $\frac{2}{3}$ of the resources are utilized later on.

4.1.1 Varying inspection resources

To investigate how the inspection room capacity behaves with changing the number of resources, the model is run with modifying resource parameters r_{d}, r_{r} and r_{m}. In



(a) Parameters r_{d}, r_{r} and r_{m} changed at the same time

(b) Parameters r_{d}, r_{r} and r_{m} changed one at a time

Figure 9: Average queue for the inspection room with SkSP-2 inspection strategy with $i = 3$ and $f = \frac{1}{5}$ and $n_{\mathrm{sim}} = 100$

Figure 9, the average queue of incoming lots is shown with different resource parameter values. The inspection strategy SkSP-2 with $i = 3$ and $f = \frac{1}{5}$ is used and initialized to start at State 1. The reference plan is a single sampling plan with acceptance number $c = 0$ and sample size n determined from Table 5. The number of simulations n_{sim} is set to 100, the working hours per day w_{h} is set to 8, and the simulation starting time t_{start} is set to 1st March 2025. Furthermore, the unit time for a sample-based inspection is determined by (6). The parameter variation is done by tuning r_{d}, r_{r} and r_{m} at the same time in Figure 9a and separately in Figure 9b. As expected, when increasing the number of resources in Figure 9a, the lots are processed in a shorter time interval. When increasing from the total of 3 resources to 12 resources, the total processing time decreases much more compared to increasing from 12 resources to 21 resources.

When looking at Figure 9b, increasing only one of the parameters at a time leads to diverse results. Increasing the number of Romers r_{r} leads to the shortest total processing time whereas increasing the number of Manuals r_{m} the longest. This difference is related to nature of the data in the generated dataset, as every lot can be inspected with Romers whereas only the lots containing materials 9 or 10 can be inspected with Manuals.

4.1.2 Varying inspection strategies

An important part of guiding the sample-based inspections is the inspection strategy. Three different strategies are compared against each other. The first strategy is the SkSP-2 inspection strategy with $i = 3$ and $f = \frac{1}{5}$. The reference sampling plan is a single sampling plan with $c = 0$ and n determined from Table 5. The second inspection strategy is the case company's Inspection strategy A and the third one is the case company's Inspection strategy B. All of these inspection strategies are based on skip-lot sampling. In this comparison of inspection strategies, the number of simulations n_{sim} is set to 100. The resource parameters r_{r}, r_{d}, and r_{m} are set to 2, w_{h} is set to 8, and t_{start} is set to 1st March 2025. The unit time for a sample-based inspection is determined by (6).

As the arrival dates of the incoming lots are deterministic, the handling of the lots from the same material-supplier combination is done the same way during every simulation, leading to the same performance of the strategy. To test how the inspection strategies perform independently of the arrival order, the arrival dates in the dataset are drawn from a uniform distribution spanning the weekdays of March and April 2025 in each simulation. This ensures that one lucky or unlucky arrival order of the lots is not impacting the results. Moreover, the faults in the dataset are not impacted by the sampling of arrival dates.

The states of the strategies are initialized randomly. This means that the initial state of every material-supplier combination's inspection strategy is not the same rather some strategy can start in the skipping phase and some in the inspection phase. For all the strategies, the state is initialized randomly between every possible state of the strategy. Furthermore, if the state contains many actions, e.g. inspecting one lot first and then skipping four, the state of this inner state is randomly chosen.

In Figure 10, the average queue for the inspection room with different inspection strategies can be seen over 100 simulations. The SkSP-2 inspection strategy with

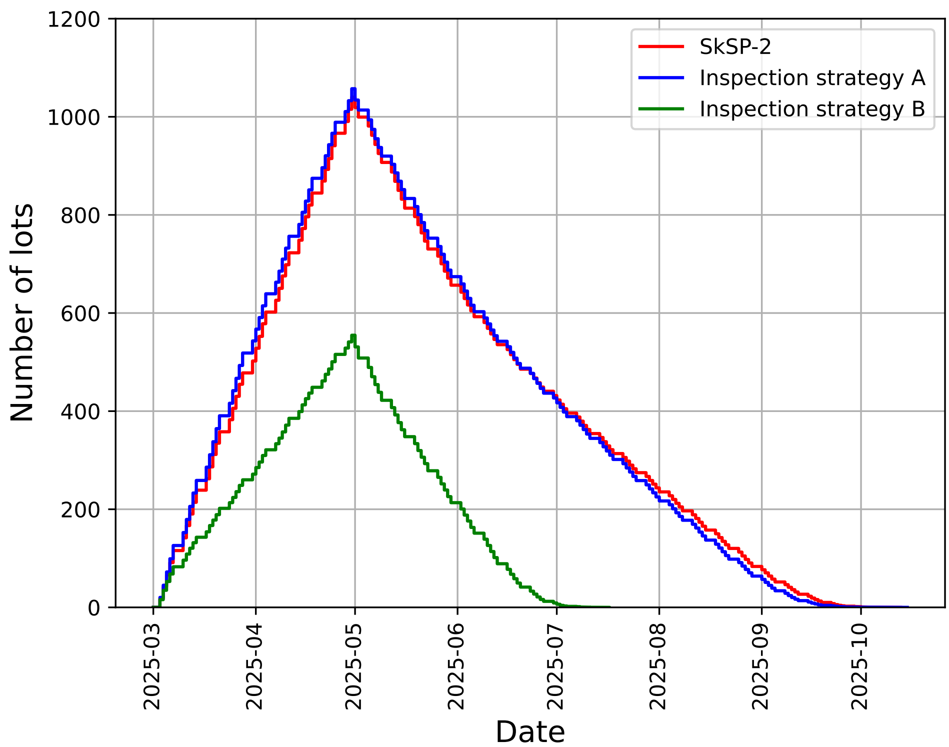


Figure 10: Average queue per date with different inspection strategies, 100 simulations per strategy

$i = 3$ and $f = \frac{1}{5}$ and Inspection strategy A seem to lead similar queues on average. Inspection strategy B leads to considerably smaller queue on average. The queue of SkSP-2 is lower compared to the one in Figure 8 due to the initialization of the strategies' states. In Table 8, statistics relating to the inspection room can be seen with different inspection strategies across 100 simulations. Each metric is reported in terms of its average value and its 90% empirical interval.

Strategy	Inspections		Inspection efficiency		Detect rate	
	AVG	[5%, 95%]	AVG	[5%, 95%]	AVG	[5%, 95%]
SkSP-2	983	[928, 1041]	0.324	[0.307, 0.338]	0.620	[0.563, 0.676]
Strategy A	961	[901, 1020]	0.326	[0.310, 0.345]	0.608	[0.551, 0.672]
Strategy B	577	[528, 612]	0.322	[0.292, 0.345]	0.362	[0.299, 0.408]

Table 8: Statistics of the inspection room across 100 simulations with three inspection strategies

Inspection strategy A and SkSP-2 lead to the inspection of almost half of the lots, whereas using Inspection strategy B leads to the inspection of approximately 29% of the lots. All the inspection strategies seem to perform similarly with respect to the inspection efficiency.

When looking at the detect rates in Table 8, SkSP-2 and Inspection strategy A lead to detecting over 60% of the defective lots whereas Inspection strategy B has much lower detect rate. This is explained by the number of inspections. The more inspections are performed the more defects are found and the higher the detect rate is.

These results illustrate the model's usefulness for the decision-makers when choosing an inspection strategy. If they prefer inspecting fewer lots, Inspection strategy B could be a viable option for this purpose. On the other hand, choosing Inspection strategy B leads to a lower detect rate. Thus, the decision-makers need to decide whether the benefits of having fewer inspections outweigh the downsides of the lower detect rate.

4.2 Validation with the case company's data

In Section 4.1, the developed discrete-event simulation model is investigated with different resourcing and inspection strategy options and generated data. To investigate the case company's inspection room operations, the generated data is replaced with the case company's operational data, and the model is validated against the historical scenario.

The operations in the inspection room are restricted to only contain two inspection categories presented in Table 4: initial inspections and sample-based inspections. These categories are responsible for the largest share of the inspections. Even though the main interest is in the sample-based inspections, the initial inspections need to be considered to investigate the total inspection capacity. In other words, the initial inspections are used to represent the other inspection operations that require the inspection room capacity.

First, the input data is described in Section 4.2.1. Then, the time parameters for the sample-based inspections (T_s) and the initial inspections (T_i) are configured in Section 4.2.2 by comparing the queues and utilizations provided by the model against the historical data. Lastly, the whole model is validated against the historical data with the extended input data in Section 4.2.3.

4.2.1 Description of input data

The input data is a dataset containing information about the usage decisions of a four-month period. There can be different usage decisions depending on the inspection result. In the data, these decisions are labeled in different categories presented in Table 9.

Usage decision label	Description
A	Accepted without notification.
AXX	Accepted with some notification.
RXX	Partially rejected.
R	Rejected.
SKIP	Lot is not inspected, automatically accepted lot.

Table 9: Usage decision labels from the system

In the analysis of the data, all the usage decisions starting with a letter A are categorized as accepted and starting with a letter R are categorized as rejected. Usage decisions with label "SKIP" are categorized as skipped lots.

During the time period, the total of 18156 usage decisions were given. From these usage decisions, 1284 usage decisions were either accepted or rejected, indicating this number of lots were inspected in the inspection room. The rest of the lots were skipped. The distribution of usage decisions based on inspection can be found in Table 10.

	Usage decision	
Inspection category	Accepted	Rejected
Initial inspection	237	26
Sample-based inspection	958	63

Table 10: Usage decisions made at the inspection room during the selected time period

As shown in Table 10, most of the usage decisions ($\approx 93\%$) are accepted. Furthermore, approximately 80% of the lots belong to the sample-based inspection category.

The usage decision date distribution of inspected lots during the time period can be seen in Figure 11. The average number of usage decisions per date is ≈ 10.52.

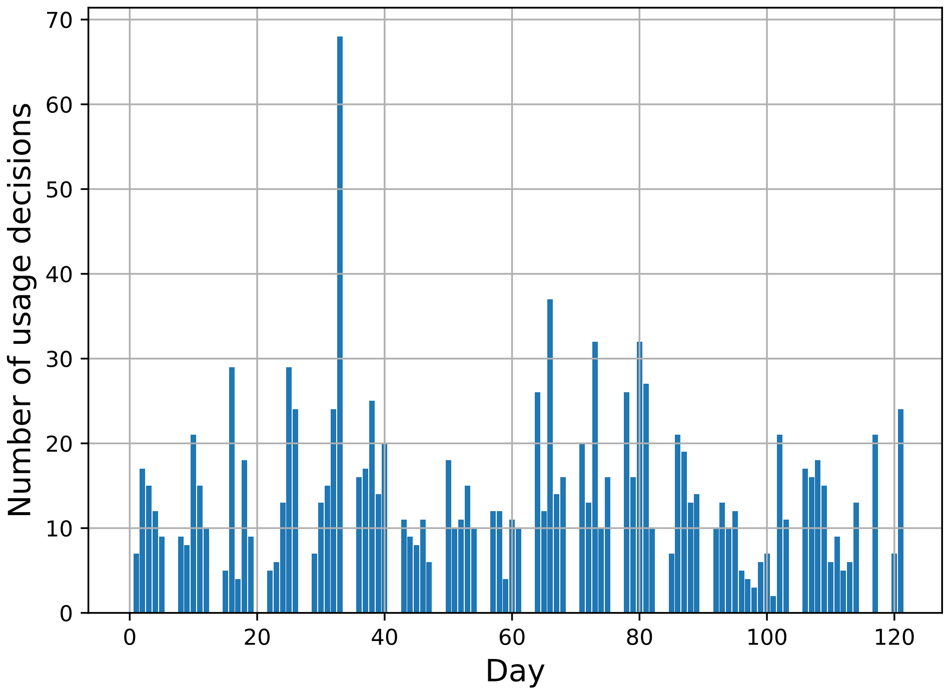


Figure 11: Usage decision count per date in the selected time period

This average also contains the dates without usage decisions (e.g. weekends). When looking into the figure in more detail, there exists one spike of 68 usage decisions in the data. On this date, there have been made 57 usage decisions for the lots from a certain material-supplier combination. After discussing the matter with an expert on the substance, this is not possible, as inspecting samples from all these lots would take more than a day. This implies that there may be some off-standard procedures of documenting the usage decisions. It is also possible that in reality, only the first lots of the same material-supplier combination are inspected, and the rest are given the same usage decision as the first usage decisions. This impacts the protection the skip-lot sampling inspection strategy creates against the defective lots. Overall, this implies that extra caution is needed when working with this usage decision data.

There are three important features for the input data that are not directly available from the data and need to be estimated: material-specific unit inspection times, fault rates for material-supplier combinations, and feasible inspection resources for the materials.

Time parameters

An important part for the inspection operation is the time it takes. In the expert interviews, it was found out that different materials require different inspection times. For example, some inspections can take more than a day in reality, whereas some can take only an hour or less.

In this thesis, a heuristic assumption is made to model the unit inspection times. As known from the interviews, the initial inspections require more inspection time per unit compared to the sample-based ones. Thus, the inspection times are modeled with two parameters, the unit time taken to inspect a material belonging to the sample-based inspection category T_s and the unit time taken to inspect a material belonging to the initial inspection category T_i. These parameters are determined in the configuration phase of the model in Section 4.2.2.

Fault rates

When using the generated dataset in Section 4.1, it is known whether a lot is defective. In the case company's data, many of the lots are skipped, and for these lots no direct data of defects is available. When using different inspection strategies, there must be data about defects in the skipped lots. This problem is approached by using fault rates to generate defects to the dataset, and each material-supplier combination is assigned a fault rate. These rates are then used to determine whether an incoming lot is defective.

Fault rates are determined by combining information in Enterprise Data Warehouse (EDW). This data is not limited to the selected time period. For each material-supplier combination, the number of arrived units to the case company's facility and the number of defective units are searched. If either of these numbers is not found, the combination is excluded from the data. One row of this data represents the number of arrived units and the number of defective units of a material-supplier combination.

As every material-supplier combination in the selected time period may not have a specific fault rate, a systematic approach for the fault rate determination is constructed. This procedure also prevents outliers in the fault rates. The general idea is to calculate the supplier and material-specific fault rates in addition to the material-supplier-specific fault rates. Thus, if the fault rate for the material-supplier combination is not found, the fault rate for the supplier or material in question can be used for the lot. This requires grouping the data described above by suppliers and materials. The fault rate for each grouping is calculated by dividing the number of defective units by the number of arrived units. As there may occur a situation, where no material-supplier combination, supplier or material-specific fault rate is found, these combinations are assigned a default fault rate p, which is calculated by dividing the number of all defective units in the data by the number of all arrived units in the data. In the simulation process, a binomial distribution with the fault rate is used to label the lot as defective or not.

Let p_{ms} represent the probability of a material-supplier pair (m, s) having a fault in the incoming unit, p_m represent the probability of the material m having fault in the incoming unit and p_s the probability of the supplier s having a fault in the incoming unit. Let p represent the default fault rate. The procedure for determining the fault rates for the incoming lots is the following:

1. If p_{ms} for the material-supplier combination of the lot is found from the data and $0 < p_{ms} < 0.2$, p_{ms} is used as the fault rate for the lot.

2. If 1. is not fulfilled, but p_s is found and $0 < p_s < 0.2$, p_s is used as the fault rate for the lot.

3. If 1. and 2. are not fulfilled, but p_m is found and $0 < p_m < 0.2$, p_m is used as the fault rate for the lot.

4. If none of the steps above can be used to determine the fault rate, the default fault rate p is used for the lot.

This procedure assumes that the default fault rate $p \in (0, 0.20)$. By following the procedure above, it is ensured that no lot can have exactly zero probability of failure and the fault rate is lower than 0.20. As the skip-lot sampling procedures should be used only for the products with good quality history, the fault rate limit of 0.20 may be a bit too high. However, using this limit allows lots to have poor quality, which may be true in the reality.

Inspection resource allocation to the incoming lots

Another important aspect of the model is the allocation of inspection resources to the incoming lots. In general, the resource on which the sample of the lot is inspected is dependent on the material. As the material-specific information is not available, the allocation decision is made based on the inspection type. If a lot belongs to the initial inspection category, it can be inspected by Romers or Devices. If a lot belongs to the sample-based inspection category, it can be inspected by any of the Romers, Devices or Manuals.

4.2.2 Configuring the model by selecting time parameters

The time parameters need to be selected as they are not directly known. The determination of the time parameters is done by running the 1284 lots inspected during the selected time period through the model with different T_{s} and T_{i}, and selecting the ones that lead to processing of the lots in that time interval. Also, the resulted queue should be somewhat similar compared to the queue calculated from the data. Furthermore, the utilization of resources needs to be high as it is known that the inspection room has been operating with its full capacity during this time interval.

When selecting the time parameters, a specific inspection strategy is not needed whereas all the 1284 lots are inspected. In other words, the decision whether or not to inspect a lot is taken from the data. As the data contains information whether the inspected lot is defective or not, no fault rates are used in the time parameter configuration. This leads to a deterministic simulation and only $n_{\mathrm{sim}} = 1$ is needed. The number of Romers r_{r} is set to 2, the number of Devices r_{d} is set to 3, the number of Manuals is set to 3, and the working hours per day w_{h} is set to 8. The starting day is the beginning of the selected time period. The time parameters T_{i} and T_{s} are deterministic, so all the lots belonging to the same inspection category have the same unit inspection time. In Figure 12, the queues of incoming lots waiting for the usage decision is shown

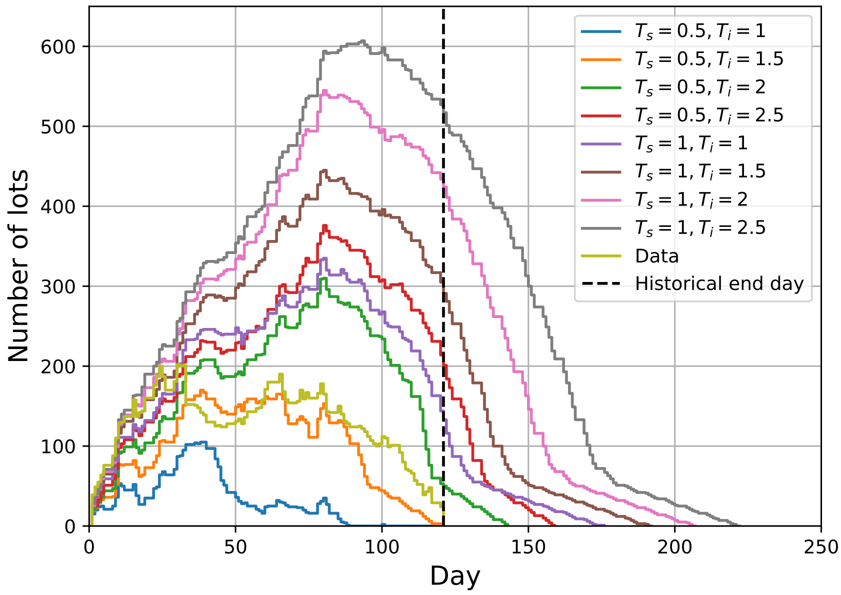
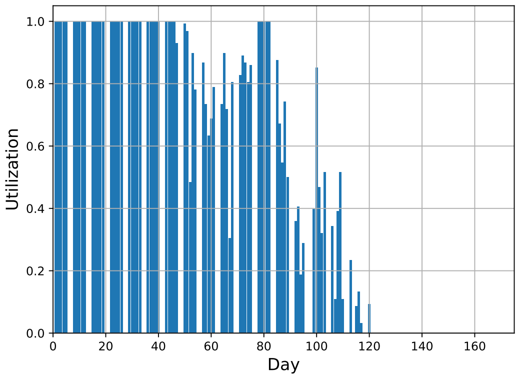


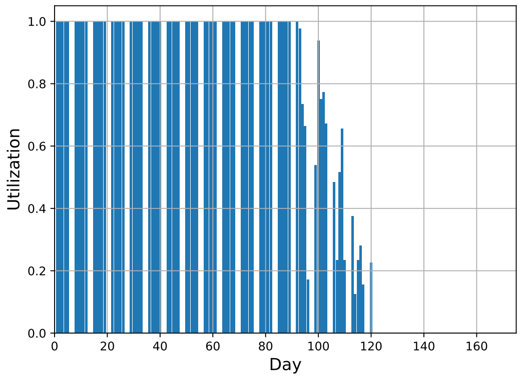
Figure 12: Queue of incoming lots waiting for the usage decision with different T_{s} and T_{i}

with varying T_{i} and T_{s}. The trajectory "Data" is the historical queue calculated from the data. The vertical line "Historical end day" is the day the selected time period ends, 121 days from the starting date. If the trajectory of a queue exceeds this day, it indicates that some of the lots are inspected after the selected time period. As can be seen, most of the parameter combinations end up handling lots after the selected time period, which indicates that the values of these parameters may be too high. The parameter combination $T_{\mathrm{s}} = 0.5$ and $T_{\mathrm{i}} = 1.5$ has the most similar queue compared to the data. Using the parameter combinations $T_{\mathrm{s}} \in \{0.5\}$ and $T_{\mathrm{i}} \in \{1, 1.5, 2, 2.5\}$ leads to the inspections ending closest to the historical end day. The daily resource utilization with these parameter combinations is presented in Figure 13. As seen in Figure 13, with parameter combinations $T_{\mathrm{s}} \in \{0.5\}$ and $T_{\mathrm{i}} \in \{1, 1.5\}$ all the lots can be inspected in the selected time period, whereas with other parameter combinations, some resources are utilized after it. With these parameters, there are also some moments, when the utilization drops under 1, which may be related to not having enough incoming lots.

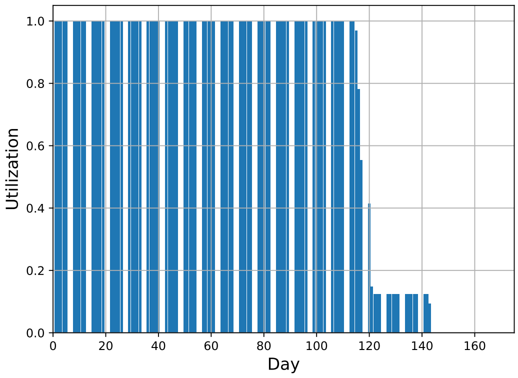
In Figure 13c the utilization drops to a level of $\frac{1}{8}$ around the day 120, and the same phenomenon is also seen in Figure 13d around the day 135. This relates to the fact that all the remaining lots are from the same material-supplier combination. As the model is adjusted to a dynamic environment with the usage decisions impacting the



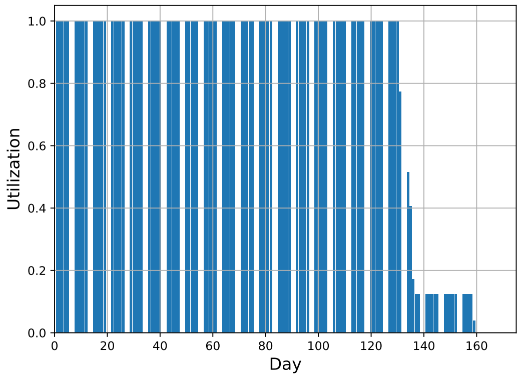
(a) Resource utilization with $T_s = 0.5$ and $T_i = 1$



(b) Resource utilization with $T_s = 0.5$ and $T_i = 1.5$



(c) Resource utilization with $T_s = 0.5$ and $T_i = 2$



(d) Resource utilization with $T_s = 0.5$ and $T_i = 2.5$

Figure 13: Model resource utilization with varying T_s and T_i

state of the certain material-supplier combination, it is not possible to inspect multiple lots from the same material-supplier combination in parallel. Thus, the behavior is as expected.

Based on these figures, the parameters $T_s = 0.5$ and $T_i = 1.5$ provide the best capacity match. The queue of the incoming lots to the inspection room is quite close to the queue calculated from the data. Also, the resources are utilized more compared to the utilization of the combination $T_s = 0.5$ and $T_i = 1$, and no lots are pushed to be inspected after the selected time period.

4.2.3 Validating the model

In Section 4.2.2, the configuration of the model is done based on the historical data without the use of the model's inspection strategy or obtained fault rates. To see how the model performs with the inspection strategy used in that time period, the model is run with extended input data. This data contains:

- All the lots inspected in the selected time period. (Including both sample-based and initial inspections.)

- All the lots that had usage decision "SKIP" in the selected time period but have the same material-supplier combination than the ones inspected. (Including sample-based inspections but not initial inspections.)

By this approach, the input data contains 2315 lots. This enables the inspection strategy to update its state depending on the usage decision made based on the inspection. The overall objective of this validation is to check if the numbers of different usage decisions made by the model match the numbers of the actual usage decisions. The number of initial inspections is the same to mimic the actual inspection room capacity.

In this extended data, there are in total 2052 lots belonging to the sample-based inspection category. When looking into the strategies of these sample-based lots, there are 1895 lots directed by Inspection strategy A, presented in Section 2.4.2. As Inspection strategy A is the most common one with $\approx 92\%$ coverage, all of the material-supplier combinations in the sample-based inspection category are assumed to use this strategy. This decision follows a simplicity principle, as the objective is to have a model as precise and simple as possible.

When looking into the material-supplier combinations of the lots belonging to the sample-based inspection category, there are 39 combinations that have 10 or more lots in the data. In total, these material-supplier combinations account for more than half of the inspection lots. On the other hand, there are 296 material-supplier combinations that have only three or fewer lots which account for around 23% of the inspection lots. As the number of lots for some material-supplier combinations is low, this may generate some inaccuracy in the results.

When using an inspection strategy, the state of the strategy needs to be initialized. As the inspection strategy may have been used for a longer time for some material-supplier combinations, it is not probable that every combination has its strategy at State 1. As the information of the state of the strategy is not known on the starting date, the initial state is randomly selected between State 1 and State 2. As also done in Section 4.1.2, if the state contains many actions, the state of this inner state is randomly chosen. This initialization decision is based on the fact that in the extended input data around 50% of the lots belonging to the sample-based inspection category are inspected.

The fault rates for the material-supplier combinations are determined as presented in Section 4.2.1. In Figure 14, the fault rates of all the incoming lots belonging to the sample-based inspection category are shown as histogram. As can be noticed, the fault rates are concentrated to low frequencies under the rate of 0.1. The most fault rates are between 0.00 and 0.01, as there are over 700 fault rates in that bin. Only a small share of the fault rates is higher than 0.1. This is in line with the assumption that the skip-lot sampling is used for the material-supplier combinations with a good quality history.

As previously determined, parameter T_s is set to 0.5 and T_i is set to 1.5. Since the inspection time may vary a bit, some small stochasticity is added to the unit inspection time without changing the mean of the distribution too much. Thus, the inspection time for a unit in a lot belonging to the sample-based inspection category is determined

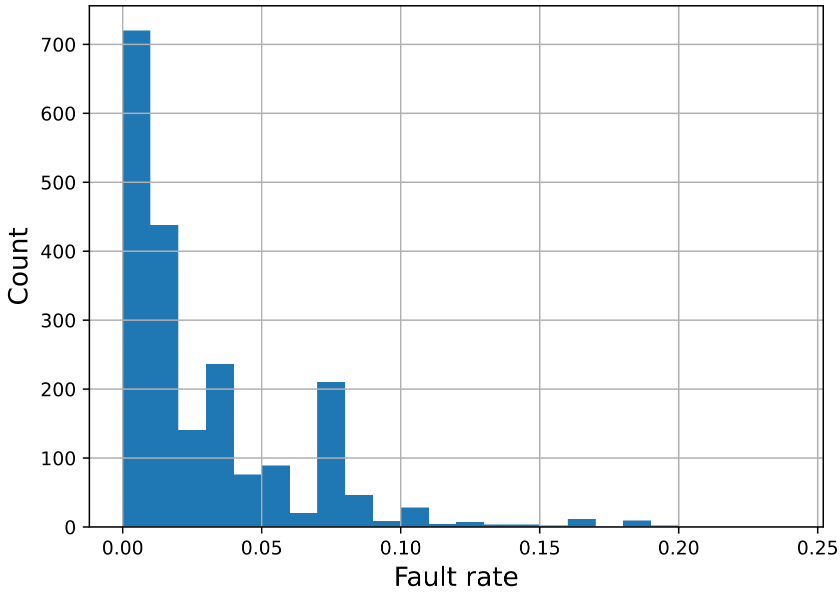


Figure 14: Distribution of the fault rates of the incoming lots belonging to the sample-based inspection category with the bin width 0.01

by

$$T_s = \begin{cases} 0.5, & \text{with } p = 0.8 \\ 1, & \text{with } p = 0.2 \end{cases} \tag{7}$$

and the time for a unit in a lot belonging to the initial inspection category is determined by

$$T_i = \begin{cases} 1, & \text{with } p = 0.2 \\ 1.5, & \text{with } p = 0.6 \\ 2, & \text{with } p = 0.2. \end{cases} \tag{8}$$

The total inspection time for a lot can be derived with the unit time parameters and sample size with (5). The simulation starting date t_{start} is set to the starting date of the selected time period. The number of Romers r_{r} is set to 2, the number of Devices r_{d} is set to 3, the number of Manuals is set to 3, and the working hours per day w_{h} is set to 8.

After all the data is prepared and strategies determined, the model is run with $n_{\mathrm{sim}} = 100$ simulations. The results of the simulation runs can be seen in Figures 15 and 16. In Figure 15, the average utilization of resources during the selected time period is shown. Resources are 100% utilized to almost end of the selected time period and then the utilization drops down. Some of the lots are still pushed to outside of the selected time period, but not many.

In Figure 16, the model output is compared to the actual output of the inspection room. As can be seen in Figure 16a, the model output does not have significant sudden increases in the number of usage decisions per date. When looking at the same data in a histogram format in Figure 16b, it is clear that the variance of the usage decisions

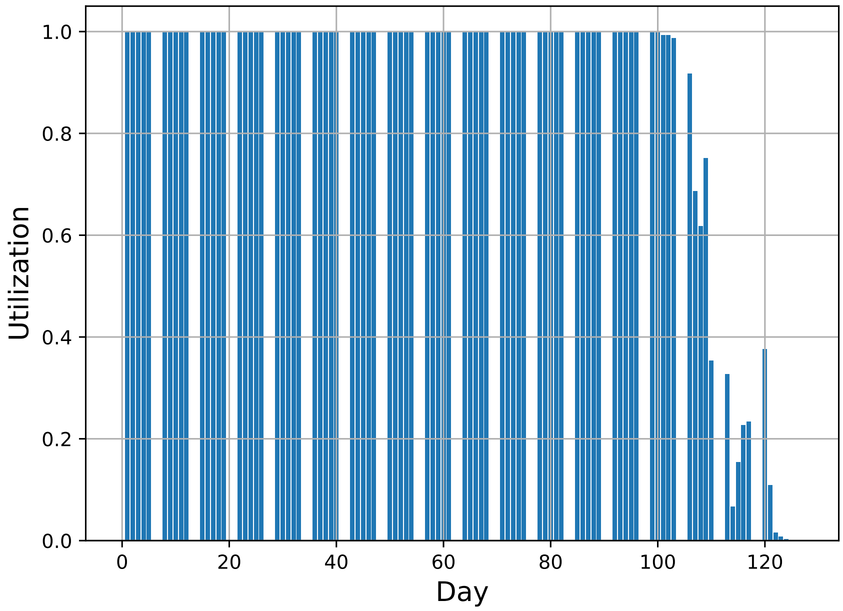
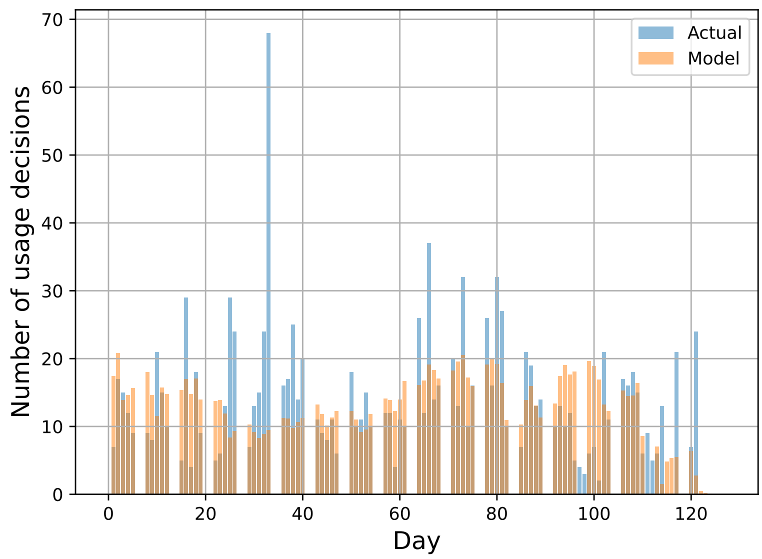


Figure 15: Average utilization of resources in the selected time period with Inspection strategy A averaged over 100 simulations

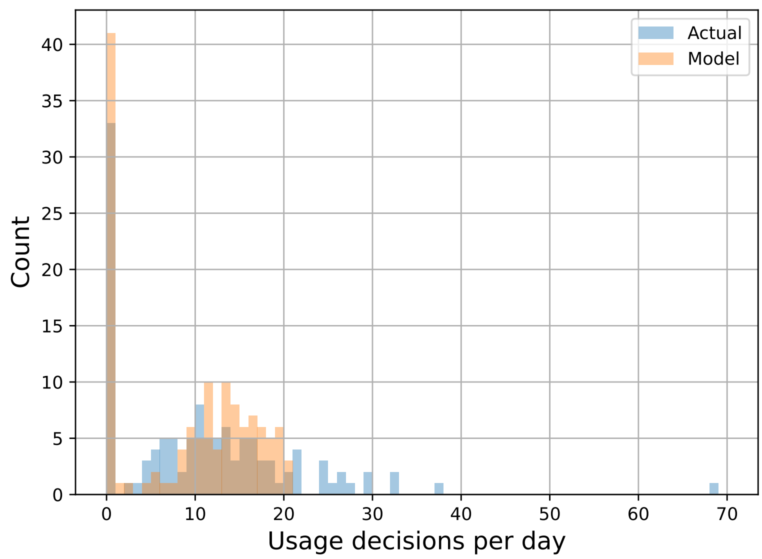
per date made by the model is smaller compared to the variance of the actual usage decisions made per date. A full numerical comparison of the model output and actual data is presented in Table 11.

	Usage decisions			
Inspection category	Actual	Model results	% Diff	[5%, 95%]
Sample-based inspections				
Accepted	958	883	-7.8%	[858, 909]
Rejected	63	29	-54%	[20, 39]
Skipped	1031	1140	11%	[1106, 1168]
Total	2052	2052	0%	[2052, 2052]
Initial inspections				
Accepted	237	237	0%	[237, 237]
Rejected	26	26	0%	[26, 26]
Total	263	263	0%	[263, 263]
All inspections				
Accepted	1195	1120	-6.3%	[1095, 1146]
Rejected	89	55	-38%	[46, 65]
Skipped	1031	1140	11%	[1106, 1168]
Total	2315	2315	0%	[2315, 2315]

Table 11: Comparison of the actual and modeled usage decisions



(a) Usage decisions per day with model and actual output



(b) Usage decisions per day count with model and actual output

Figure 16: Model output compared to the historical data with Inspection strategy A averaged over 100 simulations

In Table 11, the model results are rounded to the nearest integer, and the % Diff-column is the difference between the rounded model results and the actual output divided by the actual output. The [5%, 95%]-column contains the 90% empirical intervals of the model output. As seen in Table 11, the difference of the model and actual output of the initial inspections is zero. This happens since the initial inspections are inspected according to the actual data, meaning that the usage decisions are also made based on the data. The largest difference percentage between the model and actual output is seen in the rejections of the sample-based inspections. When looking at the whole time interval, there exists 54% less rejected lots belonging to the sample-based inspection category, indicating that the model did not find as many defective lots from this category as actually were found. This is a relatively large percentage, but on the absolute level the difference to the actual output is smaller than with accepted or skipped lots. The model skips 11% more lots compared to the actual data, leading to a lower likelihood of discovering defects in the data. Also, the number of accepted, rejected, and skipped lots in the sample-based and all inspections of the actual data are not fitting in the 90% empirical intervals of the model results. Thus, some more modeling and development should be done to get the differences smaller. The reasons for the differences are discussed more in Section 5.2.

However, the model has still explanatory value. Even though its ability to match the actual output is not high, it can be used to compare the different inspection strategies and their impact to the inspection capacity. Also, it can give insights into how the change in the inspection resources impacts the key metrics. Still, the difference may cause some inaccuracy when it comes to deriving conclusions based on the results.

4.3 Results with the case company's data

Next, the model is used to investigate how the decisions on resourcing and switching the inspection strategies impact the capacity of the inspection room and the defects found with the inspection operations.

4.3.1 Assessing the impact of resourcing

Let the number of Manual resources be $r_\mathrm{m} = 3$, the number of Device resources be $r_\mathrm{d} = 3$, the number of Romer resources be $r_\mathrm{r} = 2$, and the number of working hours be $w_\mathrm{h} = 8$. The simulation starting date t_start is set to the starting date of the selected time period. The unit inspection for the sample-based inspections is determined by (7) and for the initial inspections by (8). Let the inspection strategy be Inspection strategy A with the same state initialization than in Section 4.2.3. In Figure 17, the average

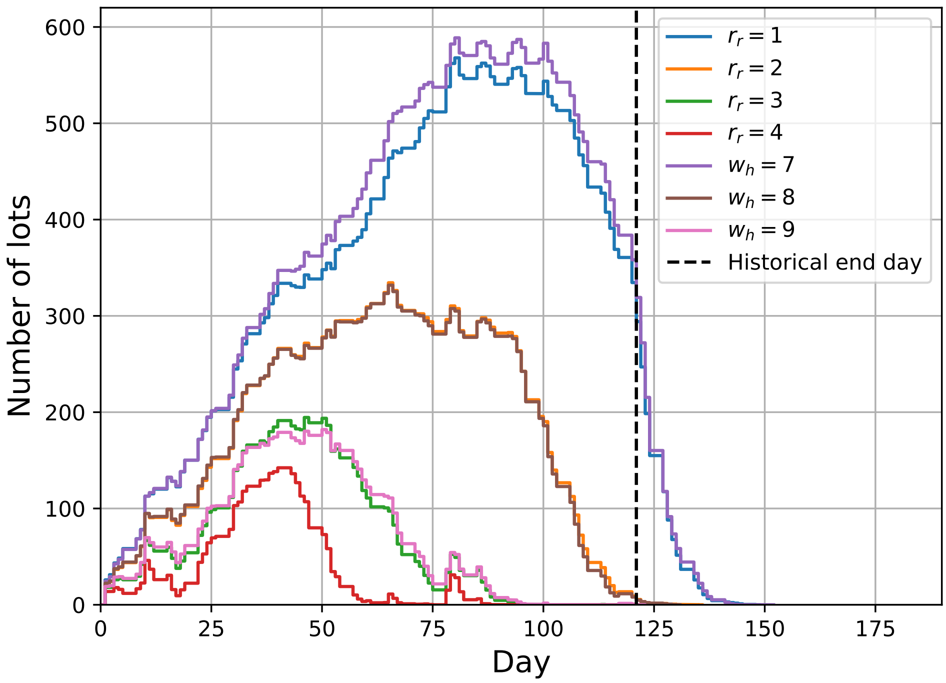


Figure 17: Average queue for the inspection room across 100 simulations with different resource parameters

length of the queue of the lots waiting for the usage decision is shown with different parameter values with 100 simulations of each setup. Only the parameter in the legend of Figure 17 is changed, and the others remain the same. As expected, increasing r_r or w_h leads to smaller queues on average. The results are collected in Table 12, where the day of the last usage decision and the utilization are shown for each setup. The [5%, 95%]-columns contain the 90% empirical intervals of the performance metric in question.

Resource changed	Last UD date		Utilization	
	Med	[5%, 95%]	AVG	[5%, 95%]
$r_r = 1$	136	[130, 143]	0.933	[0.898, 0.966]
$r_r = 2$	121	[121, 124]	0.914	[0.891, 0.940]
$r_r = 3$	121	[121, 122]	0.813	[0.794, 0.835]
$r_r = 4$	121	[121, 122]	0.734	[0.712, 0.758]
$w_h = 7$	136.5	[131, 143]	0.926	[0.893, 0.954]
$w_h = 8$	121	[121, 124]	0.912	[0.893, 0.936]
$w_h = 9$	121	[121, 121]	0.817	[0.795, 0.834]

Table 12: Statistics of different parameter combinations across 100 simulations

The historical end day is the day 121. Therefore, if the median date of the last usage decision exceeds this date, it implies that according to the model, the given parameter setup likely results in overtime in the inspection of the lots. With parameter changes to $r_r = 1$ or $w_h = 7$, it is likely that some lots are pushed outside the time period as the median of the last usage decision dates is over 121. With parameters $r_r \in \{2, 3, 4\}$ or $w_h = 8$, the median last usage decision date is 121, but it is still possible to have some lots pushed outside the time period as the upper empirical interval is over 121.

The utilization of resources is over 70% with all the parameter setups, varying in the range of 0.73 to 0.93. Increasing the resources seems to decrease utilization. However, when there are fewer resources, $r_r \in \{1, 2\}$ or $w_h \in \{7, 8\}$, the increasing impact on the utilization is not as certain, because the average utilizations and their empirical intervals are quite close to each others.

Based on these results, increasing the number of Romer devices decreases the queues on average. Thus, if the decision-makers are interested in lowering the queues, more Romer devices could be acquired. On the other hand, this may lead to the lower utilization of resources if the scenario of the incoming lots stays similar. Thus, the decision-makers should consider this decision carefully and also think about the level of inspection activity in the future.

4.3.2 Changing the inspection strategy

Next, the impact of changing the inspection strategy is investigated. The number of Manual resources is set to $r_m = 3$, the number of Device resources is set to $r_d = 3$, the number of Romer resources is set to $r_r = 2$, and the number of working hours is set to $w_h = 8$. The simulation starting date t_{start} is set to the starting date of the selected time period. The unit inspection for the sample-based inspections is determined by (7) and for the initial inspections by (8). In Figure 18, the average queue with Inspection strategy A, Inspection strategy B, and SkSP-2 with $i = 3$ and $f = \frac{1}{5}$ are shown as an average over 100 simulations. When running the simulations, each inspection strategy is initialized randomly. Inspection strategy A is initialized similarly as in Section 4.2.3. Inspection strategy B and SkSP-2 are initialized between all the states. If the state contains many actions, the state of this inner state is also randomly initialized.

As can be seen, using Inspection strategy A leads to the highest queue on average.

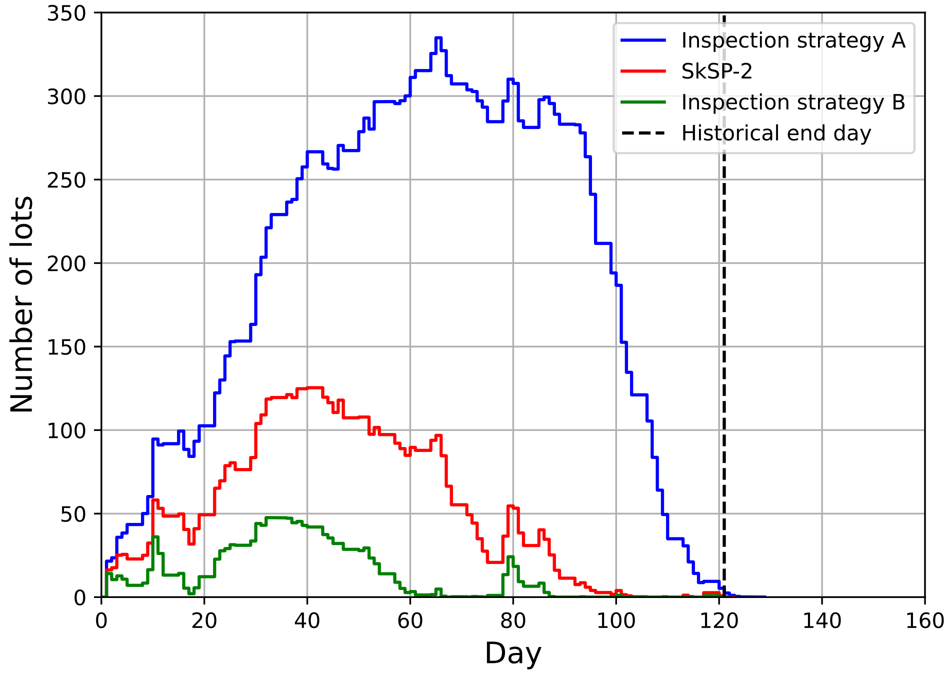


Figure 18: Average queue for the inspection room across 100 simulations with different inspection strategies

Inspection strategy B and SkSP-2 lead to considerably lower queues on average. All the inspection strategies seem to finish the inspections quite close to the historical end day.

Strategy	Inspections		Inspection efficiency		Detect rate	
	AVG	[5%, 95%]	AVG	[5%, 95%]	AVG	[5%, 95%]
SkSP-2	1010	[977, 1041]	0.051	[0.042, 0.060]	0.420	[0.302, 0.535]
Strategy A	1177	[1151, 1213]	0.047	[0.040, 0.055]	0.498	[0.389, 0.605]
Strategy B	800	[776, 823]	0.055	[0.048, 0.063]	0.314	[0.212, 0.417]

Table 13: Statistics of different inspection strategies across 100 simulations

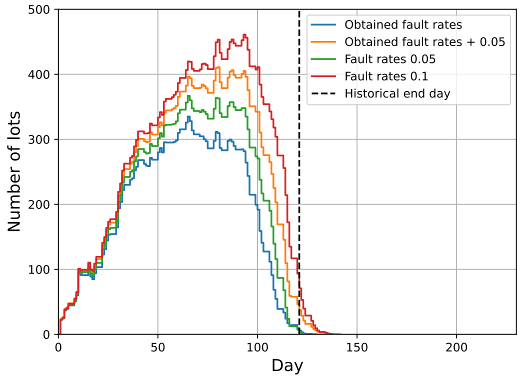
These results are also shown numerically in Table 13. The average number of inspections are rounded to the nearest integer, and the [5%, 95%]-columns contain the 90% empirical intervals of the metric in question. The inspection efficiencies are calculated across all the inspection categories, so the lots belonging to the initial inspection category are also considered. The detect rate is calculated from the lots belonging to the sample-based inspections, as the defects in the initial inspections are deterministic and do not change between the simulations.

As can be seen, using Inspection strategy A leads to the most inspections on average. When looking at the inspection efficiencies, the strategies perform quite similarly with around 5% inspections leading to a negative usage decision. This implies that the quality of the incoming lots is quite good, which is in line with the moderate fault rates used for the lots. Inspection strategy B has the lowest detect rate on average whereas Inspection strategy A the highest.

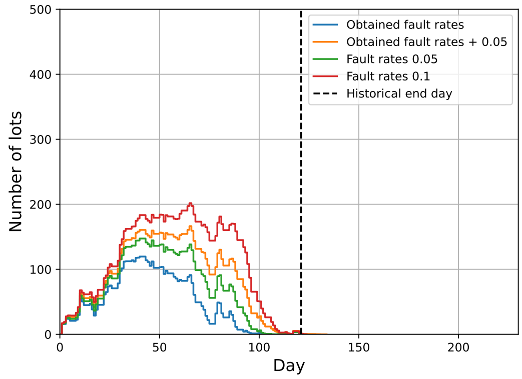
If the decision-makers in the case company are interested in changing the inspection strategy from Inspection strategy A, they need to decide how much they are willing to inspect. The compared inspection strategies here lead to fewer inspections and lower detect rates. If the decision-makers want to inspect fewer lots, they could change the inspection strategy to SkSP-2 or to Inspection strategy B. Based on the detect rates and their empirical intervals, SkSP-2 inspection strategy provides higher detect rate compared to Inspection strategy B.

4.4 Sensitivity analysis

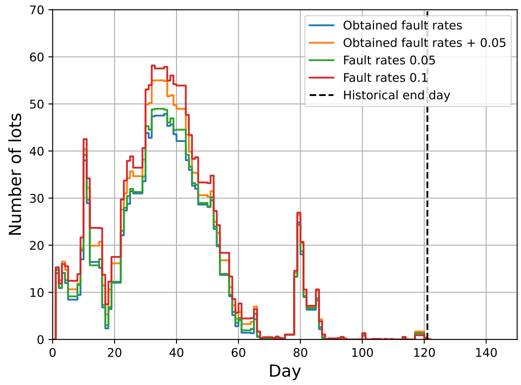
As the fault rates are used to create defective lots to the case company's dataset, they are directly connected to the number of inspections and thus the capacity of the inspection room. Therefore, a sensitivity analysis regarding the fault rates is conducted with different inspection strategies. The inspection strategies analyzed are Inspection strategy A, Inspection strategy B, and SkSP-2 with $i = 3$ and $f = \frac{1}{5}$. The parameters r_m, r_d, r_r, w_h, t_start, T_s, and T_i are kept the same as in Section 4.3.2.



(a) Inspection strategy A



(b) Inspection strategy SkSP-2



(c) Inspection strategy B

Figure 19: Average queue of different inspection strategies across 100 simulations

In Figure 19, the average queue of lots waiting for a usage decision is presented for each inspection strategy with different fault rates. First, the fault rates obtained with the method described in Section 4.2.1 are used, followed by increasing all the fault rates by 0.05, then setting all the fault rates to 0.05, and lastly setting all the fault rates to 0.1. As can be seen in Figures 19a and 19b, increasing the obtained fault rates by 0.05 or using 0.05 or 0.1 fault rates with Inspection strategy A or SkSP-2 increases the queue on average compared to the use of the obtained fault rates. When it comes to using Inspection strategy B, there exist some similar behavior between the average queues with different fault rates. However, the differences are converging when the end of the time period is approaching, as seen in Figure 19c. Furthermore, the differences seem to be very small. This is likely happening since Inspection strategy B contains many skips. Therefore, the impact of small changes in the fault rates with Inspection strategy B is not as significant compared to Inspection strategy A or SkSP-2.

Inspection strategy	Last UD date		Number of inspections	
	Med	[5%, 95%]	AVG	[5%, 95%]
Inspection strategy A				
Obtained fault rates	121	[121, 124]	1177	[1143, 1213]
Obtained fault rates + 0.05	123.5	[121, 134]	1236	[1192, 1269]
Fault rate 0.05	121	[121, 123]	1208	[1169, 1241]
Fault rate 0.1	128	[121, 137]	1278	[1231, 1318]
Inspection strategy B				
Obtained fault rates	121	[121, 121]	800	[776, 822]
Obtained fault rates + 0.05	121	[121, 121]	832	[803, 860]
Fault rate 0.05	121	[121, 121]	815	[788, 835]
Fault rate 0.1	121	[121, 121]	851	[824, 880]
SkSP-2				
Obtained fault rates	121	[121, 122]	1006	[975, 1039]
Obtained fault rates + 0.05	121	[121, 123]	1070	[1039, 1115]
Fault rate 0.05	121	[121, 121]	1040	[1000, 1084]
Fault rate 0.1	121	[121, 123]	1100	[1062, 1137]

Table 14: Sensitivity analysis results of the inspection strategies across 100 simulations

The results are also gathered to Table 14 in which the number of inspections and the last usage decision date metrics are presented with 90% empirical intervals for each inspection strategy with different fault rates. As can be seen, when using Inspection strategy B or SkSP-2, the median last usage decision date is not changing with small changes in the fault rates. When increasing the fault rates from the obtained fault rates to the obtained fault rates + 0.05 or from 0.05 to 0.1, the average number of inspections is increasing with each inspection strategy, meaning the inspection strategies lead to more inspections when the quality of the incoming lots is poorer. When using Inspection strategy A or SkSP-2, the average number of inspections is higher than with Inspection strategy B.

With these observations, it can be interpreted that small changes in the fault rates of the lots have some impact on the DES model results. It is also clear that Inspection strategy B leads to the least inspections and thus to the least average queue.

5 Discussion

The discussion is divided into three parts: model findings and possible applications, limitations of the results with the case company's data, and model limitations and suggestions of possible future improvements.

5.1 Model findings and possible applications

In this thesis, a DES model is developed to investigate how resourcing and different inspection strategies impact the operation of the inspection room, and how well different inspection strategies find defective lots. Based on the model results with the case company's data, increasing the working hours per day or the number of Romer inspection devices decreases the queue for the inspection room on average. On the other hand, increasing the resources while keeping the number of incoming lots the same decreases the resource utilization on average. When it comes to the different inspection strategies, using the SkSP-2 inspection strategy or Inspection strategy A leads to a higher number of inspections and thus higher detect rates compared to Inspection strategy B. All of the compared inspection strategies find the lot defective in around 5% of the inspections.

The decision-makers can use the model to get supporting information to guide their decisions. When the decision-makers, e.g. quality managers, are interested in changing something in the incoming materials inspection process, they can first use the model to see how the change impacts the operation of the inspection room. As discussed briefly in Sections 4.1 and 4.3, the model can provide important performance information about the different inspection strategies for the decision-makers. For example, using different inspection strategies led to the different number of inspections and detect rate. If the decision-makers are interested in choosing an inspection strategy, with the performance metrics provided by the model, they can decide which inspection strategy suits their preferences the best. It is clear that the fewer inspections are done the fewer defects are found. Therefore, the decision-makers also need to be aware of the negative impacts of inspecting fewer lots and compare those impacts against the benefits.

The model is a promising test ground for introducing new inspection strategies. When the decision-makers are interested in how a new inspection strategy impacts the inspection room operations, they can implement the strategy into the model, run the simulations with historical data, and compare the output with the output of other inspection strategies. The decision-makers are able to see if the new inspection strategy leads to higher queues on average, if the strategy pushes some of the inspections outside the historical scenario's time interval or whether the strategy leads to a higher or lower number of inspections. Also, they can investigate which share of the defects are detected on average.

In general, the results imply that modeling the inspection operations with a discrete-event simulation model is a viable option for gathering new insights. Furthermore, the discrete-event simulation modeling approach is quite flexible, and new operations, resources or dynamics may be implemented into the model with a relatively low effort.

5.2 Limitations of the results with the case company's data

The accuracy of the DES model results is difficult to estimate, as the inspection room operations at the case company's facility are complex. In the model, the inspection room is described with two kinds of activities: initial inspections and sample-based inspections. This assumption makes the model and its results easier to interpret but neglects other possible resource consuming activities taking place in the inspection room. For example, the notification-based inspections are not considered in the model. These other operations impact the real capacity of the inspection room, and thus the model is not capturing everything.

At the validation phase, the results are compared to the historical data, and differences between the model output and the historical data are noted. The largest difference between the model and actual output is noted in the number of rejected lots belonging to the sample-based inspection category, which is -54%. Also, the model ends up skipping almost 11% more lots compared to the actual output. These differences may occur due to many reasons.

First, the input data of the incoming lots during the selected time period has a big impact on the results. In the analysis of the input data, an outlier is detected which raises a concern about the data quality. If the input data does not represent the actual inspections in the inspection room, the results cannot be trusted. For the validation phase, in addition to the lots belonging to the initial inspection category, the input data consisted of the inspected lots belonging to the sample-based inspection category, and the skipped lots belonging to the sample-based inspection category that had the same material-supplier combination as the inspected ones. This selection neglects possible material-supplier combinations belonging to the sample-based inspection category that have only skipped lots during that time interval. This may also impact on the validation results.

Second, the initialization of the inspection strategies' states impacts the results. If the strategies are initialized to start from the earlier states that involve more inspections and fewer skips, the number of inspections is higher in the limited time interval. The state of each material-supplier combination's strategy is not available during the selected time interval. Therefore, the states are initialized randomly between State 1 and 2 and possible inner states, and this leads to more inspections. This decision is supported by the number of skipped lots during the selected time period, but the states of the strategies may have been different in reality. If the selected time period is increased, the impact of this initialization may decrease. Thus, in the future, the selected historical time period could be increased to smoothen the impact of the initializations.

Third, according to the sensitivity analysis in Section 4.4, the fault rates have some impact on the number of inspections. In the simulation runs with the case company's data, the ground truth of whether the certain lot is defective is generated from a binomial distribution with a fault rate observed from the data. Due to possible non-standardized data collection and recording methods and complex nature of the table joins from the database, the fault rates may be inaccurate and therefore impact the validation differences. Furthermore, the fault rates are restricted between 0 and 0.20, as they should not be too high for material-supplier combinations that are qualified for skip-lot sampling. This restriction may generate some inaccuracy for the results, but it ensures that no absurd probabilities can be used in the model. Moreover, as the fault rate is calculated as the average fault rate, the rate does not consider the trend of the faults. It may be that a supplier with very poor quality in the past has improved quality over time and has recently not been delivering any poor-quality lots.

One data-related assumption is related to the allocation of lots to the different inspection resources. The model assumes that this information is known for each incoming lot. When using the case company's data, this information is not known. It is decided to use a heuristic approach and allocate the lots belonging to the initial inspection category to Romers and Devices and the lots belonging to the sample-based inspection category to Devices, Manuals and Romers. This allocation is better than a random allocation of every lot between all the inspection resources, as the initial inspections tend to need more accurate measurements which can be performed with Romers and Devices. This assumption also keeps the model simpler than with more complex allocation logic. However, there are some other factors than the inspection type impacting the allocation decision. In reality, the unit size of the product and the specifications of the measurements also have an impact on this decision. For the future, the model could be improved by utilizing data about the possible inspection resources for each product.

5.3 Model limitations and future improvements

The assumption of defects is impacting the model results. First, with the fault rate approach the defective lots are assumed to be independent of each other. In reality, this is not the situation as a supplier may have a failure in their process leading possibly to sequential lots having defective units. Second, every lot is assumed to be either fully conforming or non-conforming. In the big picture, the material-supplier specific fault rates are determining the proportion of defective lots for material-supplier combinations, not the proportion of defective units in the lots. In reality, lots may contain both conforming and non-conforming units at the same time. This assumption allows to simplify the process and in the longer time period, the impact of this choice is assumed to be small. This assumption also restricts the usefulness of the reference sampling plan. As every unit in the lot is either defective or not defective, there is not a possibility that only some of the inspected units are defective. When a lot with only defective units is inspected, the time for inspecting all the units in the sample is counted for the total inspection time whereas in theory, the first defective unit would be enough to give the negative usage decision if no defective units are allowed in a sample. In the future, the model could be made more precise by allowing the lots to contain both defects and non-defects.

There are also other more general limitations for the model. The unit inspection times were modeled with just two parameters: one for the sample-based inspections and one for the initial inspections. This assumption is a heuristic simplification and may neglect some important differences between unit inspection times of different materials. In the future, the model could be developed to consider this material-specific information, which could make the results more precise.

Updating the state of the inspection strategy generated some difficulties in the model implementation. As the inspection strategy is a separate entity for each material-supplier combination, two lots from the same combination cannot be inspected at the same time, as it would result in parallel updates of the strategy. This may lead to resources staying unutilized while some queue is still existing, if all the lots waiting for the inspection are from the material-supplier combinations currently under inspection. Furthermore, one possible improvement in the future would be to gather data from the future incoming inspection lots and run the model with that data. By this approach, the model could reflect the future more accurately and support the decision-making on spot.

When it comes to the model dynamics, the parameter indicating working hours per day could be reconsidered. Currently, it is modeled with one parameter, but it turned out that there is also an evening shift in the inspection room. In the future, the model parametrization could be improved to also consider this shift.

6 Conclusions

In this thesis, the incoming materials inspection operation at a case company's facility was studied. After the literature review on acceptance sampling, standards, and applications of discrete-event simulation models, a discrete-event simulation model of the studied system was developed. The model was first run with a generated dataset following with the usage of the case company's data. Then, the model was validated against the actual data, after which the inspection room capacity and different inspection strategies were investigated. Lastly, the model was run with different fault rates to test the sensitivity of the model.

Results with the generated dataset demonstrated the difference between the compared inspection strategies: Skip-lot Sampling Plan-2 (SkSP-2) by Perry (1973) and Inspection strategy A led to more inspections and higher detect rate compared to Inspection strategy B.

With the case company's dataset, it was discovered that the model skips 11% more lots than was skipped in the actual data. However, the model has still explanatory value. From the compared inspection strategies, Inspection strategy A led to the most inspections and the highest detect rate in the historical scenario. Inspection strategy B led to the least inspections and the lowest detect rate. The sensitivity analysis with respect to the fault rates suggested that small changes in the fault rates have some impact for the model output.

Overall, this thesis demonstrates the possibilities of DES-models in the field of quality control. The complexity of the system in question and the quality of the data may pose limitations for the modeling, but the presented approach can be used to produce science-based information for supporting the decision-making process.

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