MASTER

Use of OEE in the packaging industry

designing a decision support system to obtain lean buffers levels in manufacturing lines under efficiency constraints

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Use of OEE in the Packaging Industry:

Designing a Decision Support System to obtain Lean Buffers levels in manufacturing lines under efficiency constraints

by

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I. Abstract

This master thesis report addresses the performance evaluation of to-be designed continuous manufacturing lines with limited buffers and limited repair capacity. Bosch delivers packaging lines to customers under strict Overall Equipment Efficiency requirements. In the current situation Bosch is unconfident if they can fulfil the efficiency requirements and within the company, ambiguity exist around the use of these performance measures. Within this research, we evaluate the concept of performance measures for manufacturing lines, outline its difficulties and develop a Decision Support System. The difficulties in performance evaluation of manufacturing lines is discussed in the Literature Review. We suggest the Line Efficiency performance measure as primary performance measure and identified that the use of limited buffers and the influence of operators on repairable systems makes the evaluation of manufacturing lines complex.

Based on the review, we developed a Decision Support System (DSS) to overcome the main difficulties and facilitate Bosch in determining the smallest buffer size necessary and sufficient to ensure the required Line Efficiency with closed form formula's. The unreliable, repairable, machines are characterized by general distributed repair and failure times. The DSS accounts for operator waiting times with a two-stage cyclic queueing network.

Validation with discrete-event-simulation shows that the DSS copes very well with non-identical machines, but tends to overestimate the buffer size when the coefficient of variation of the downtime is high. The calculated buffer sizes are mostly sufficient, although not always lean. In the area of Lean Level Buffering literature, we contributed by showing that for non-identical machines the Global Upperbound is inferior to the Local Upperbound method under our assumptions. For practitioners, the closed form equations provide a quick calculation method for scenario-testing, thereby providing a major advantage over discrete event simulations.

II. Management summary

This research is performed at Bosch Packaging Technology in Weert. This master thesis applies for transfer lines, and for the packaging lines of Bosch in particular. It extends the research on Lean Buffering for the special case of limited repair capacity.

Problem statement

Within Bosch, originally a packaging machines manufacturer, a transition towards integral packaging line solutions resulted in ambiguousness concerning the performance measurement of the packaging lines. The packaging lines are designed upon customer specifications and the definitions of these requirements often vary and are based on the Overall Equipment Effectiveness (OEE) metric, which is commonly used in capital intensive industries. Bosch wants to be in control of the performance evaluation during the design phase of the packaging line and wants to optimize the buffer levels such that is meets or exceeds the customer requirements.

Performance Evaluation

As mentioned above, OEE is a commonly used metric within the capital-intensive industry. However, OEE is an efficiency measure for one piece of equipment, therefore it is hard to use for manufacturing lines. On top of that, it does not incorporate operators.

Line Efficiency is a good alternative performance metric for evaluation of packaging lines. Line Efficiency is less complex than OEE and commonly used in scientific literature, thereby increasing its applicability. Line efficiency measures the efficiency of the line by evaluating the actual production, relative to the throughput of the real bottleneck over time: $E = \frac{actual\ production}{t_w * TH_{RCO}}$. Buffers can be placed in the manufacturing line to increase the Line Efficiency when it is still below the customers' requirement. An objective to determine the size of the buffers, according to Papadopoulos, O'Kelly, & Tsadiras (2013), is minimizing the number of buffer slots to achieve a pre-specified throughput level. This objective is in accordance with the objective of the Lean Buffering approach, a rule based approach with rules for the optimal or near optimal buffer size using analytical approximations.

Based on the findings above and the company problem the research assignment is formulated as follows:

Develop a Decision Support System (DSS) to provide the smallest buffer levels necessary and sufficient to ensure the desired Line Efficiency of an unreliable manufacturing line with limited repair capacity.

Model

The aim of the model is to provide the smallest buffer levels necessary to ensure the customers requested Line Efficiency. As stated in above, the Lean Buffering approach is most suitable to determine the buffers levels. Unfortunately, this approach is not sufficient to cover all the conditions of the DSS.

To design a model congruent with the DSS conditions we have the adopt the Lean Buffering model within these three areas: Multiple unreliable components, Limited Repair capacity and Non-identical machines. This results in the following final model as shown in Figure 1, which minimizes the total buffer size given a required Line Efficiency and the number of operators.

The layout of a machine line is, inter alia, characterized by the machines with multiple components and the possibility to place buffers between the machines. Based on this line layout information, the multiple failure/repair distributions are aggregated. The calculation of these distributions is case specific, since every line is different, and therefore not included the DSS model. However, the aggregated failure distributions are inputs for the DSS model.

The Waiting Time to Repair (WTTR) will be estimated with a Cyclic Queueing Network (CQN) based on the inputs of the model and the number of operators. With this WTTR we calculate the total downtime. The two moments of the total downtime and the required Line Efficiency, determine the required Lean Buffer levels.

In conclusion: based on the line lay-out and number of operators, the optimal buffer size will be calculated to comply with the required Line Efficiency.

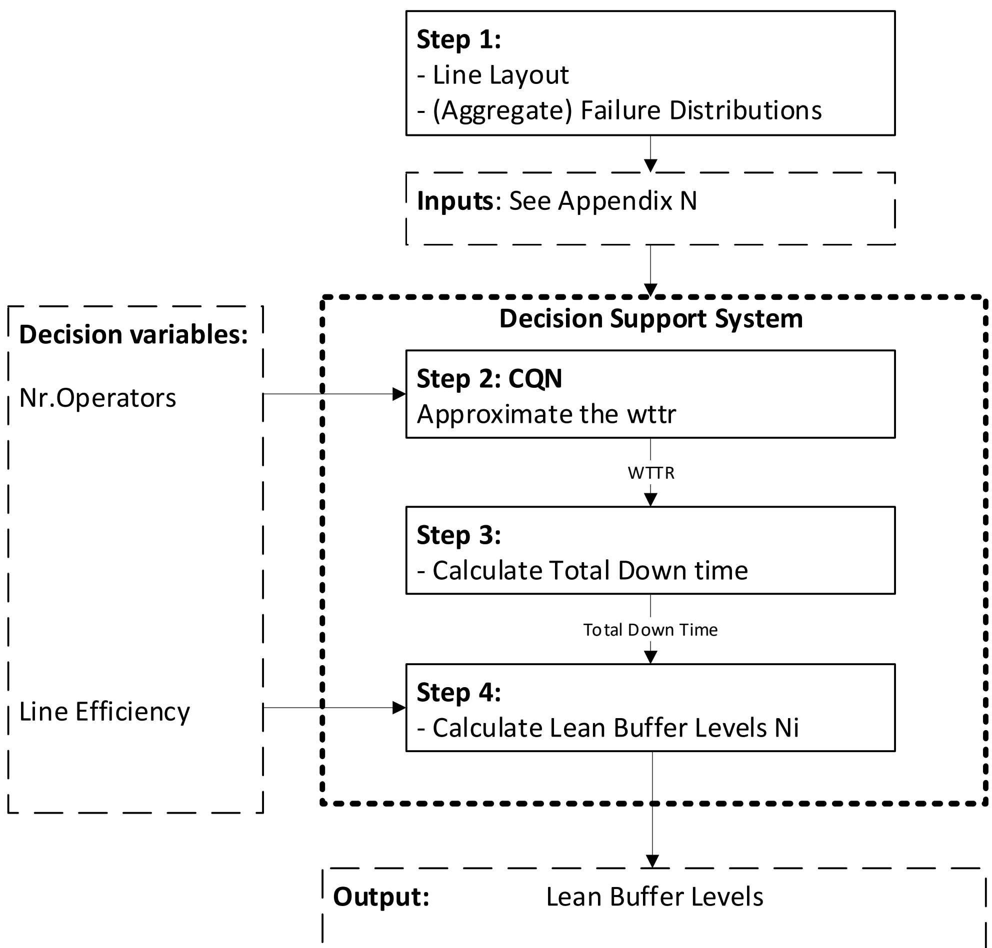


Figure 1: The Decision Support System Overview

Conclusion

The model is tested with randomly generated input. The domain of the input was such that it fits the scope of the packaging lines from Bosch. Also, we tested the model with a case provided by Bosch, with Bosch' vertical packer/multihead-weigher combination modeled as the packaging lines bottleneck. Additionally, a sensitivity analysis on multiple levels of desired Line Efficiency and differing number of operators provided insights in the limitations of the model.

This resulted in the following findings: (1) the model copes well with non-identical machine efficiencies within the range {0.950; 0,999}. (2) the model tends to overestimate when the coefficient of variation of the downtime, CV_{down}, is high. The CV_{down} increased when the number of operators was reduced, or when distributions were aggregated.

The major advantage of this model is that it provides quick calculations to evaluate scenario's and it sees the trade-off between buffer size, Line Efficiency and operators. In general, the model provides good directions about the necessary buffer size for lower levels of CV_{down}, still it is suggested to perform discrete event simulation to validate the performance of the chosen scenario.

Limitations

Based on data provided by Bosch, which was limited, we had to make assumptions about failure and repair distributions. We assumed that the repair time was normally distributed and the failure generally distributed. Due to the scope of this research it was not possible to validate the model for different distributions.

Further, the Lean Buffering approach only works for serial manufacturing lines, which is common for packaging lines. For the case of parallel systems, discrete event simulation is advised.

The model as used in our DSS, tends to overestimate the lean buffers when the CV_{down} is high. Therefore, the DSS' performance is limited for high levels of CV_{down} and more research into this area is suggested.

Recommendations

This research is concluded with recommendations concerning the original problem statement:

(1) OEE should be used for the performance evaluation of one machine, whereas Line Efficiency should be used when expanding the scope to manufacturing lines. Additionally, the OEE can be useful for evaluation the bottleneck machine in the line, as it has the largest improvement opportunity.

(2) Collect and validate reliability data from own machines and suppliers in a database. And standardize the design process and performance evaluation of the manufacturing line.

(3) Use the DSS to see trade-offs, do quick scenario-testing and obtain initial values for the Buffer Levels. However, it is advised to use discrete event simulation to assure the performance of the chosen scenario.

III. Preface

This thesis: “Use of OEE in the Packaging Industry: Designing a Decision Support System to obtain Lean Buffers levels in manufacturing lines under efficiency constraints” is the result of a graduation project which I conducted at Bosch Packaging Technology in Weert. I wrote this thesis in partial fulfillment of the requirements for the MSc. in Operations Management and Logistics at the Eindhoven University of Technology. I would like to express my appreciation to everybody who supported me during my study, extracurricular activities and especially during this graduation project.

First, I want to express my gratitude to Bosch for giving me this opportunity to write my thesis. During the project I gained valuable insights in the gap between university and the industry, therefore I hope to use my personal findings for my future career. I would like to thank André Philipp for helping me set up the project and his involvement during the project. Special thanks to Tom Kok for his motivation and help during the project and for keeping me on track.

Second, I want to express my gratitude to my supervisors at the university. My mentor and first supervisor Henny van Ooijen for his critical view on the project, thereby challenging me to get to the core of the problem: during our meetings, long discussions left me with more questions than solutions. I would also like to thank my second supervisor Joachim Arts for helping me to make my project more focused and my thesis more concise.

Lastly, I would like to thank all my closest friends and family around me during my studies and this project. Thanks to all my friends and roommates who made me feel at home in Eindhoven the past few years. Thanks to my parents, for their genuine concerns, generous support and confidence in me. Thanks to Celine for improving my academic writing abilities. And Karin, thank you for your help as a sparring partner on my thesis, but even more for your enthusiasm and drive, giving me the strength when I needed it.

IV. Table of Contents

1 Introduction

In this thesis we present the results of a research in collaboration with Bosch and the Technical University Eindhoven. The aim of this research is dual: (1) to contribute to scientific knowledge on Lean Buffering and Overall Equipment Efficiency (OEE) for manufacturing lines and (2) to increase the capabilities of Bosch in evaluating the performance and efficiency of their manufacturing lines, within the scope of this research.

Formerly, Bosch used to deliver single packaging machines to its customers under OEE requirements. Currently, Bosch provides integral line solutions and problems arise with using OEE as a performance measure for these manufacturing lines. The characteristics of Bosch's Packaging lines defines the scope of the research: continuous (high volume and high speed) unreliable machines with constant throughput rates and finite buffers, general failure distributions and repairs with pooled operators.

Although, OEE is commonly used in Capital Goods industries as a descriptive performance measure, definitions frequently vary due to the complexity of the measure (Jonsson & Lesshammar, 1999). For single machines, the solution to this problem comes with the (DIN) Industry Standard. However, directly applying these OEE-measures on manufacturing lines with buffers results in incorrect statements. Moreover, current literature does not provide clear directions for the use of OEE in a prescriptive (normative) approach during the manufacturing line design phase.

To close the literature GAP regarding the use of performance measures on machine lines, in combination with limited buffers and limited repair capacity and to provide Bosch with such a model, the research assignment is formulated as follows: "Develop a Decision Support System (DSS) to provide the smallest buffer levels necessary and sufficient to ensure the desired Line Efficiency of an unreliable manufacturing line with limited repair capacity." The aim of the model in the DSS is to provide a required buffer size, which is necessary and sufficient to ensure the desired Line Efficiency of manufacturing line as defined by our scope.

In this research we provide a solution for the use of OEE related measures for manufacturing lines. Therefore, we define a metric for evaluating a manufacturing lines performance suitable for the line design phase. Besides that, we contribute to the Lean Buffering literature by combining Non-Exponential and Non-Identical unreliable machines in one model. And at last, include the operator interference times in DSS.

Bosch incentive to start this research was to reduce ambiguousness around the OEE measure and ensure the performance of a manufacturing line to its customers. This research provides the necessary information about OEE for manufacturing lines and motivates the use of the DSS as a faster alternative to discrete-event simulation.

The outline of this report is as follows: In Chapter 2 we introduce the company problem, based on the description of Bosch. Chapter 3 starts with a literature review on OEE for Manufacturing lines and a brief literature review on Lean Buffering. Then, the Research Assignment is formulated and scoped based on the findings in the literature review and the company problem.

Chapter 4 provides a detailed analysis on the characteristics of Bosch' manufacturing lines system dynamics. Chapter 5 starts with a short introduction of modeling approach. Afterwards, the model is described in more detail to increase reproducibility of this research. The organization of all the model's components is shown in the total model (Chapter 5.3). Chapter 6 is a Case Study, which aims at validating the model, and evaluating the applicability on a case. In Chapter 7, final conclusions regarding the research assignment are drawn, including a discussing on the limitations and accompanied by recommendations for the use of the DSS and for Bosch' problem in general, we conclude Chapter 7 with the academic relevance of this research and suggestions for future research in this area.

2 Company Background

This chapter briefly describes the case study and thereby provides the context of the research (2.1). Thereafter, the company problem is described and defined (2.2).

2.1 General company background

Robert Bosch Packaging Technology ("Bosch" from now on) is a capital-intensive machine manufacturing company, selling to B2B customers globally. Bosch makes vertical and horizontal packaging machines. However, this research takes places at the location in Weert (NL), which is specialized in making vertical packaging machines and its primary market is the food industry.

Bosch has a rich history, and is making high quality packaging machines for many years. To stay competitive, they must innovate and engage in new business opportunities. Two of these opportunities are fundamental causes of the current problem, which will be introduced briefly. Firstly, Bosch is shifting from being only a technology provider into being a service provider. Current service provider trends, where companies are actively supporting their clients by providing services instead of only performing manufacturing activities based on specifications, give companies great potential to increase margins and build better customer relationships. Secondly, and more importantly, Bosch wants to provide integrated solutions i.e. designing manufacturing lines including their machines and machines sourced from external companies (preferably within the Bosch Group). The latter shift is a major change as their focus used to be on single packaging machines only.

2.2 Company problem

When customers buy a packaging line, they generally ask for a certain capacity. The customers generally express this capacity as the production rate in combination with a certain OEE level. Unfortunately, Bosch does not know the OEE of the packaging lines because each packaging line is a custom solution for the customers. Therefore, Bosch realized that it would be very beneficial if they were able to accurately predict the OEE of a certain manufacturing line, with certain parameter settings, while in the design-phase. A visual representation of Bosch current situation and future situation are shown in Figure 1.

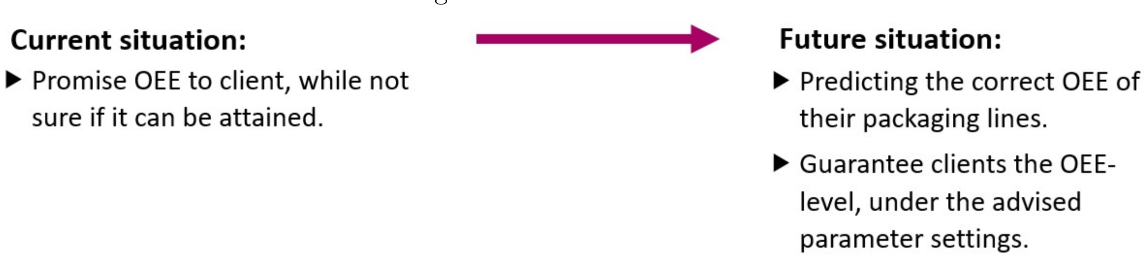


Figure 1: Current and Future situation for Bosch Systems Engineering Department

Based on the current situation and the desired future situation, the problem of Bosch comes in threefold: (1) It wants to know how to evaluate the performance of their packaging lines in the design phase with OEE related measures. (2) It wants to know with a certain level of accuracy if the designed packaging line is feasible and in accordance with the OEE requirements. (3) It wants to communicate the parameter settings to assure the customer to attain the required packaging line performance.

2.3 Practical issues

One of the reasons why Bosch wants a model to estimate the OEE is because they have limited information about the behavior and failure data of packaging lines. The result is that they do not know what the OEE of their packaging line is, which factors impacts the Line Efficiency the most or which data needs to be validated. Additionally, financial data about profits and (holding)costs per produced unit are absent, because this data is at the customers site. Two practical issues are deducted: (1) There is limited data available of the machines, therefore the accuracy of the model will be somehow restricted. (2) No financial data is available.

2.4 Characteristics of the Packaging Lines

The characteristics of the capital-intensive packaging lines at Bosch are described to better understand the scope of the problem.

- Push systems: the packaging lines are push systems without a control policy. This means that it starts to run when the first product has arrived, and it stops or goes to back-up mode when there is no product anymore.
- Constant throughput rates: the throughput rates of the machines are assumed to be constant.
- Continuous Production: The machine lines are producing high volume at very high speed. The manufacturing lines are highly standardized and automated.
- Limited Repair Capacity: The performance of the system is influenced by operators: they are needed for repairs and set-ups.
- Finite Buffers: The buffers between machines have a limited capacity.
- Unreliable machines, with possibly multiple unreliable component in one machine.
- Generally distributed repair and failure times.
- Non-identical machine efficiencies

3 Assignment

In this chapter we start with a Literature survey on OEE for manufacturing lines (3.1). We discuss use of the Line Efficiency measure (3.1.4) and a short Literature Survey on Lean Buffering is included (3.2). Based on the findings in the literature review and the company problem we define our research assignment (3.3).

3.1 Literature Survey on OEE

The literature review of de Groote (2017) focused on OEE applications for packaging lines. In this chapter the main findings are presented. Firstly, we provide background information by introducing the general OEE measure and its advantages. Secondly, limitations and research applications relevant to the company problem are evaluated. Thirdly, we present and evaluate 4 alternatives to cope with the limitations. Lastly, we introduce Line Efficiency as a suitable metric for packaging line evaluation.

3.1.1 Background

Overall Equipment Effectiveness (OEE) is a metric to measure the performance of a piece of equipment. OEE has been increasingly used in the last 3 decades, especially in capital intensive industries.

Being a performance indicator, OEE empowers decision making in parameter setting and is an initiator for improvements projects (De Ron & Rooda, 2006; Mathur, Dangayach, Mittal, & Sharma, 2011). The OEE-metric has often been used due to its high level of aggregation. It is the product of three factors: availability efficiency, performance efficiency and quality efficiency:

$$\mathrm{OEE} = \mathrm{A_{eff}} \times \mathrm{P_{eff}} \times \mathrm{Q_{eff}} \tag{1}$$

By separating the factors, inefficiencies can be assigned to more specific causes, thereby increasing the potential of the metric for improvement projects. These causes are typically called “losses” and match the state of the equipment. The six big losses as originally defined are: Equipment Failure, Setup & adjustment, Idling & minor stoppage, Reduced speed, Defect in process and Reduced yield.

In conclusion: the major advantages of using OEE are (de Groote, 2017):

- Aggregated view, for quick managerial insights and enough information for decisions making. Moreover, it is often used for internal, industry and external benchmarking.
- Ability to detect where losses take place (six big losses), thereby promoting improvement projects

3.1.2 Limitations and research implications

In the literature review six major limitations and research implications of the OEE metric were distinguished (de Groote, 2017).

- Unsuitable for line evaluation
- Use in prescriptive models
- Men (operators)
- Absence of financial measures
- Data Accuracy
- Complexity

3.1.2.1 Unsuitable for line evaluation

Losses as a result of the whole production system cannot be accounted to a machine solely (De Ron & Rooda, 2005). Currently, this is falsely accounted for by the machine. The latter limitation is due to the fact that OEE is an efficiency measure for one piece of equipment. Many other efficiency losses occur independent of the machine characteristics e.g. starving or blocking. This limitation is known in the literature and therefore there has been some research in de direction of OEE for manufacturing lines. We conclude that OEE is not suitable for the performance evaluation of manufacturing lines.

3.1.2.2 Use in Prescriptive models

OEE is as a descriptively used metric. Later, when digitalization made it easier, it was also used for ‘real time’ performance evaluation. A potential use of the OEE-metric is using it in models: using simulation and optimization models to achieve the goal level of OEE. In the literature, some suggestions for the potential use of such a tool are found e.g. to perform scenario analysis for a new factory design (Muthiah & Huang, 2007) or adjusting non-bottleneck equipment to lower settings for a more sustainable use of energy (Horenbeek, Pintelon, Bey-temsamani, & Bartic, 2014). However, up till now, there is no sufficient research on which OEE- metric suits best for the prescriptive models.

3.1.2.3 Men (operators)

It is suggested to make a framework to address the operator influenced loss times (Hedman, Sundkvist, & Almström, 2014; Jeong & Phillips, 2001; Mathur et al., 2011). With a decent sensitivity analysis of the influencing factors, the future potential could include trade-offs between training/hiring operators or lost performance.

3.1.2.4 Absence of financial measures

The absence of financial measures results in lack of decision making power(Muchiri & Pintelon, 2008). Everything in the OEE measure is time or quantity based, but a trade-off in costs is not made in this performance measure. When OEE values are accompanied by a monetary expression, it is expected to have more significance to management.

3.1.2.5 Data Accuracy

Jeong & Phillips (2001) stated that the accuracy of the data will greatly influence the OEE. Better data collection abilities leading to a higher data accuracy create higher potential use of OEE: more potential to distinguish different loss states and more accurate estimations (De Ron & Rooda, 2006). It is suggested to perform research in new data collections methods and evaluating its costs and benefits (Muchiri & Pintelon, 2008).

3.1.2.6 Complexity

Although the Overall Equipment Efficiency is so commonly used, definitions frequently vary due to its complexity (Jonsson & Lesshammar, 1999). These varying definitions motivated research to be done in this area. One major advantage of the OEE is that it is a very aggregated measure. Unfortunately, this aggregation leads to a high degree of complexity in the way the OEE measure is organized and set-up: definitions vary. Companies and industries measure the OEE based on the data available or the wanted outcome, this results in differing definitions across industries or even companies. To cope with this arising problem, many industries set an "industry standard". It helps avoiding ambiguity, improves the power of benchmarking and is necessary for industries when compliance to an OEE objective is needed.

3.1.3 Alternative OEE frameworks

To cope with the limitations of OEE, four alternative metrics have been found, each having its own characteristics, advantages and disadvantages (de Groote, 2017). The four metrics are: Overall Throughput Efficiency (OTE), Overall Line Effectiveness (OLE), Overall Equipment Effectiveness of a Manufacturing Line (OEEML) and Overall Equipment Cost Loss (OECL). Although more OEE based metrics are found in the literature, these four are chosen to keep the framework concise and a reasonable embodiment of all current metrics.

Overall Throughput Efficiency (OTE), as introduced by Huang et al. (2003), has a more complex mathematical structure: it divides the production system in 4 subsystems which can be calculated separately and combined in the end in order to determine the final OTE. The four subsystems are: serial, parallel, assembly and expansion. This method enables the user to identify bottlenecks (overall and within subsystems). Unfortunately, the metric does not provide a method explaining how to cope with buffers. Appendix C

Overall Line Effectiveness (OLE) was proposed by Nachiappan & Anantharaman (2006). OLE is mainly focused on continuous production systems and it has a rather simple mathematical structure. This comes with the compromise that it underestimates the efficiency when working with buffers or decouplers (Braglia, Frosolini, & Zammori, 2009). Appendix D

Wudhikarn (2016) developed the Overall Equipment Cost Loss metric to increase the decision-making power by combining OEE with financial methods for performance evaluation of equipment. For the factors availability and performance: the losses are calculated by the sum of (1) attributing the relevant production costs to the time loss and (2) the opportunity costs. Opportunity costs are the potential (unit) profits which are now missed due to the lower equipment effectiveness. For quality losses the cost calculation holds that it accounts the monetary losses of both production of faulty products and the costs of needed rework. The formulas can be found in the paper of Wudhikarn (2016).

Although OECL gives some new and more insights, it is unable to correctly identify bottlenecks. OECL indicates the piece of equipment with the highest monetary loss as bottleneck, whereas this does not necessarily equal the throughput bottleneck machine. It is concluded that bottleneck identification in a manufacturing line setting is not supported by OECL. Therefore, attention must be paid to evaluating bottlenecks machines and the potential of their improvements. Additionally, OECL is limited due to its dependency on one product accounting method. Therefore, product variations and pricing strategies strongly influence the outcome of OECL. Another limitation of the OEE is that it should be adapted to better cope with line manufacturing and an extension with investment costs relative to an increase in capacity would be more beneficial to managers.

Braglia et al. (2009) presented the Overall Equipment Effectiveness of a Manufacturing Line (OEEML) metric to incorporate equipment independent losses (EIL) in a metric, without underestimating the effects of buffers. This is done by comparing the effectiveness of the last machine and the bottleneck throughput rate. The authors showed that the calculation is correctly assessing the effectiveness. The OEEML is calculated by dividing the actual production with product of the total working time t_w and the theoretical throughput rate of the bottleneck station TH_{TBN}.

$$OEEML = \frac{actual\ production}{ideal\ production} = \frac{actual\ production}{t_w\ * TH_{TBN}} \tag{2}$$

Each of the four metrics covers some of the limitations of OEE. Unfortunately, none of them covers all limitations. The major characteristics of each metric are shown in Table 1.

Metric	Continuous Line	Bottleneck Identification	Buffer/ decoupler	Cost-based	Other Remarks
OEE					Only for single machines
OLE	✓				Underestimates efficiency in decoupled lines
OTE	✓	✓			
OEEML	✓	✓	✓		
OECL				✓	Product variations & pricing strategy influence the outcome

Table 1: Metric characteristics (de Groote, 2017), revised.

We conclude that OEEML appeared to be the most suitable method for line evaluations. Although, the limitations of data accuracy and complexity still hold for OEEML, we argue that this model outperforms OLE and OTE due to its feasibility with buffers and decouplers. Since, no financial data is available in this research this limitation is not our primary interest and therefore applying OECL as measure is not preferred.

3.1.4 Line Efficiency

Although OEEML is suggested as the most suitable method, it is still subject to complexity due to differing definitions of OEE. Therefore, we suggest excluding the performance measure OEE. We recall the equation for the Overall Equipment Effectiveness of a Manufacturing Line (OEEML) (Braglia et al., 2009)

$$OEEML = \frac{actual\ production}{t_w\ * TH_{TBN}} \tag{3}$$

Since, the machines in the manufacturing lines within our review have equal processing times, the theoretical throughput rate of the bottleneck station, TH_{TBN}, is the same for all machines and equals the speed of the packaging machine. However, the theoretical throughput rate will never be met on long term average. Machines break down causing downtimes in the manufacturing line, leading to lower throughput rates. The adjusted throughput rate of the constraining machine is defined as TH_{RCO} and equals the theoretical throughput rate TH_{TBN} multiplicated with the real bottleneck machines OEE, the OEE_{RCO}.

$$TH_{RCO} = \ TH_{TBN} * OEE_{RCO} \tag{4}$$

Bosch want to deliver highly efficient machine lines, with the lowest throughput loss possible. To calculate the efficiency of the lines we introduce the Line Efficiency E, which measures the efficiency of the line by evaluating the actual production, relative to the throughput of the real bottleneck (TH_{RCO}) over a given time (t_w).

$$E = \frac{actual\ production}{t_w * TH_{RCO}} \tag{5}$$

Using the definition of and the relationship in equation 3 we can rewrite OEEML as Line Efficiency multiplied by the OEE of the machine.

$$OEEML = \ E * \ OEE_{RCO} \tag{6}$$

Figure 2 shows a graphical representation of the relation between the OEEML measure and the Line Efficiency measure. The upper part of graph represents the throughput degradation due to machine inefficiencies, which is accounted for by the OEE_{RCO}. Beneath the limit from the TH_{RCO}, the throughput degradation due to line inefficiencies is accounted for by Line Efficiency E.

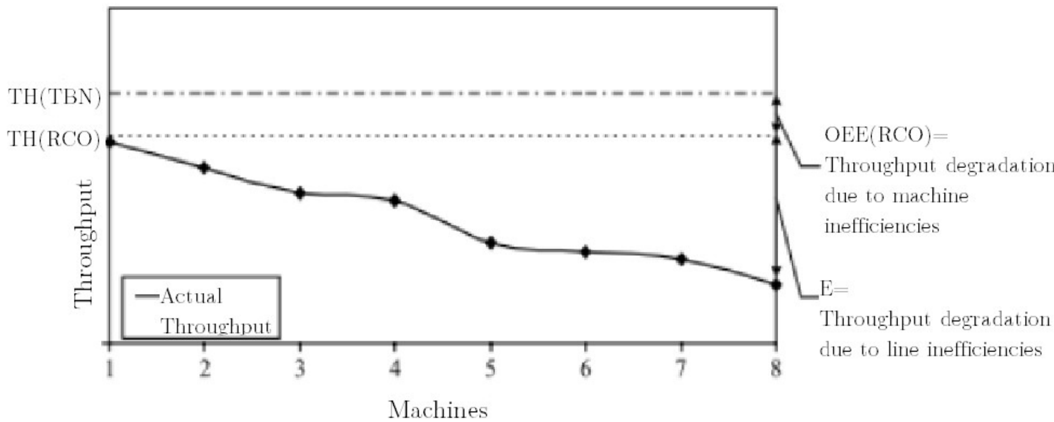


Figure 2: Throughput degradation due to machine and line efficiencies

Using Line Efficiency is more convenient since we do not have to conform to the complexity of differing OEE definitions. Additionally, Line Efficiency is much used in scientific literature, whereas OEEML is less adopted in literature. Based on these reasons we will adopt Line Efficiency as the performance metric within the sequel of this research.

3.2 Literature survey on Lean buffering

Now it's known how to calculate the Line Efficiency. However, it can still occur that the Line Efficiency is beneath customer requirements. Therefore, it would be useful for Bosch to increase the Line Efficiency to meet the customer requirements. One way of increasing the Line Efficiency is placing and increasing the size of a buffer. (Chiang, Hu, & Meerkov, 2008).

Determining the model to obtain the buffer size can be split in four objective functions according to Papadopoulos, O'Kelly, & Tsadiras (2013): (1) Maximizing Throughput, (2) Maximizing Profit, (3) Minimizing the average WIP to achieve the desired average production rate and (4) Minimizing the number of buffer slots to achieve a pre-specified throughput level.

Firstly, maximizing throughput (1) is not eligible. It seeks the optimal allocation of a given total buffer capacity N^*, so that throughput is maximized (Enginarlar, Li, & Meerkov, 2005a). In the packaging lines in our scope there is no a-priori buffer capacity defined for packaging lines in the design phase, therefore maximizing the throughput with the allocation of the buffers is not expedient. Secondly, maximizing profit (2) is impossible due to lacking financial information. Thirdly, minimizing the average WIP to achieve the desired average production rate (3) is not a preferred objective: minimizing the average WIP is not of major interest in the line design phase, also because the WIP is not under review and no costs can be accounted to the WIP, because cost information is lacking. Lastly, the most suitable objective (4) is minimizing the number of buffer slots to achieve a pre-specified throughput levels, which is congruent with the research interest in the decision variable buffer size. This is motivated by the costs for floor space and the material handling mechanism. This objective is in accordance with the objective of the Lean Buffering approach (Enginarlar, Li, Meerkov, & Zhang, 2002).

Lean Buffering is a rule based approach, with rules for the optimal or near optimal buffer size using analytical approximations. The main research in the Lean Buffering domain has been conducted in (Chiang, Hu, & Meerkov, 2008; Enginarlar, Li, & Meerkov, 2005a, 2005b; Enginarlar, Li, Meerkov, & Zhang, 2002).

The lack of failure data, within the scope of this research, results in assuming general distributions, therefore rigorous analytical analysis of the line performance is impossible (Li & Meerkov, 2009). However, Li & Meerkov (2009) state that the solutions for Lean Buffering do not depend on the reliability distributions and are mostly defined by their first two moments. For both the uptime and the downtime the first moment is the expected time and the second moment the variance. This is substantiated with the research of Enginarlar, Li, & Meerkov (2005b) who conjectured that their rule based approach holds for any unimodal distribution of up and downtime. Moreover, Enginarlar et al. (2002) showed that, using the first two moments for non-exponential downtime distributions, Lean Buffer levels can be significantly reduced by adjusting it with the coefficient of variation, CV, of the downtime. Thereby justifying the effort of not only using the average value of the downtime but also its variance. We can conclude that Lean Buffering is a suitable approach when assuming general distributions. It must be noted that the first two moments are of major interest.

Due to the scope of this research, we have to cope with non-identical machine efficiencies. Within the Lean Buffering literature Chiang et al. (2008) proposed 6 approaches for calculating the buffer size when there are significant machine efficiency differences: (1) Local pairwise, (2) Global pairwise, (3), Local Upperbound (4) Global Upperbound, (5) Full search and (6) Bottleneck-based approach. It was found that the local pairwise (1) often results in a lower Line Efficiency than desired. Both the global pairwise (2) and Local Upperbound (3) resulted in a good performance, but have 4-5 times bigger buffer capacities than the local pairwise approach. The global pairwise method (3) resulted in equal buffer capacities along the line, which does not seem optimal. The Global Upperbound approach (4) substantially overestimated the level of buffering. The Full search and Bottleneck based approaches are recursive methods. The full search approach is computationally intensive but leads to the lowest buffer level. The Bottleneck approach (6) gave 2-6 times smaller buffers then approach (2-4) and was faster than the full search approach. Unfortunately approach 5 and 6 are only possible when working with exponential failures, since it us using the aggregation procedure for throughput evaluation for serial lines with exponential machine reliability. Therefore, with lower inventory levels this could give incorrect values.

Concluding, the two best options for this research are the Local Upperbound Approach (3) and the Global Upperbound (4) approach. Both methods will be used in the remainder of this research.

3.3 Research Assignment

Based on the company problem as stated in chapter 2.3 and the findings of the literature review regarding the use of Line Efficiency and the Lean Buffering approach, the research assignment is formulated as follows:

> *Develop a Decision Support System (DSS) to provide the smallest buffer levels necessary and sufficient to ensure the desired Line Efficiency of an unreliable manufacturing line with limited repair capacity.*

The DSS will be applied in the design phase and it is known that just predicting the performance is sometimes not sufficient to obtain the desired Line Efficiency. Thus, some parameter settings will have to be optimized to the customer to assure a certain Line Efficiency.

3.3.1 Objectives

To develop the DSS as stated in the research assignment, we defined three objectives:

> **Obj.1 Define a measure for evaluating the performance of a manufacturing line.**

The first objective is to define a measure to evaluate the performance of the manufacturing lines at Bosch. In section **Error! Reference source not found.** we proposed the Line Efficiency to evaluate the performance of manufacturing lines. Therefore, we will use this measure in the remaining of the research. Thus, it will be used in objective 2 and 3.

> **Obj.2 Design a Decision Support System to facilitate new manufacturing lines design with providing Lean Buffer levels**

To facilitate practitioners in design choices, decision concerning parameters and the effect on Line Efficiency should be included in the DSS. The decisions of primary interest are the buffer size and the number of operators.

> **Obj.3 Assess the applicability and validity of such a Decision Support System by a case study at Bosch.**

The desired outcomes of the DSS will be validated with the results from discrete event simulations. A sensitivity analysis on the parameters should provide knowledge about their impact on the systems performance. Interesting findings can give direction to new initiatives to improve the system. Finally, we can obtain the limitations of the DSS.

3.3.2 Scope

Given the characteristics of the Packaging Lines at Bosch, Weert, the boundaries of the research scope are drawn. The scope of this research is limited to serial unreliable manufacturing lines with continuous production. In addition, we broaden the scope of this project with the impact of limited repair capacity and limited buffers. It is expected the latter two concepts influence the Line Efficiency.

3.3.3 Project Approach

The project approach follows the regulative cycle involving 5 process steps (Van Aken, 2007). The regulative cycle method supports decision making in business problems. Five process steps are involved: problem definition, analysis and diagnosis, plan of action, intervention and evaluation. We primarily focus on the first three steps. At last, discussion and recommendations are provided to support the plan of action. The approach for this research is shown in Figure 3.

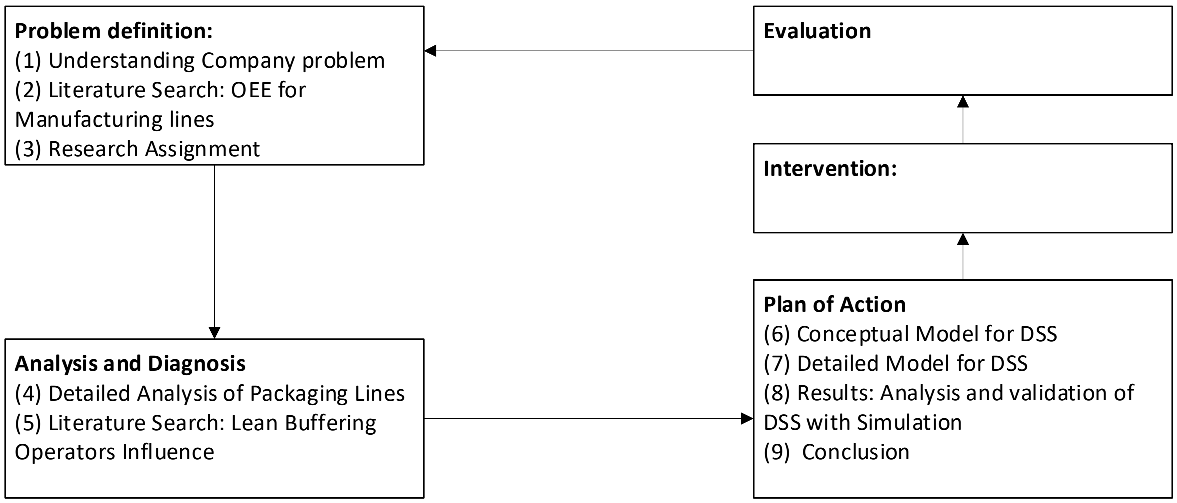


Figure 3: Research Approach: Regulative Cycle

4 System Dynamics

We will introduce a typical Packaging line, including its main components and the characteristics and assumptions for the scope of our problem are stated (4.1). Then, we elaborate on the assumptions on unreliable machines and limited operators (4.1.1) and finite buffers (4.1.2).

4.1 Description of a typical Packaging Line:

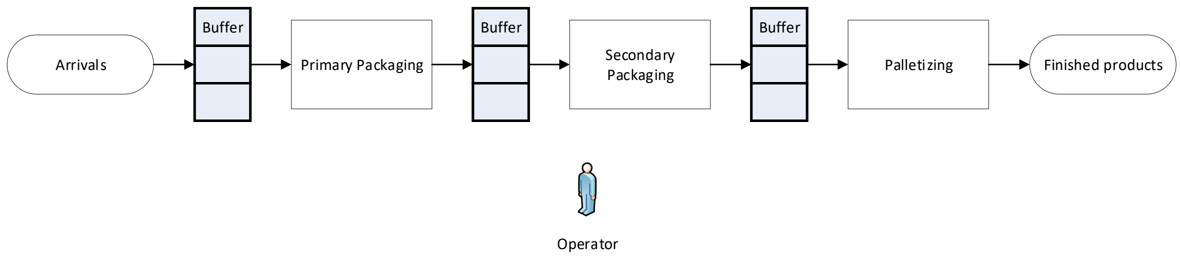


Figure 4: Packaging Manufacturing Line

To model a manufacturing line with buffers and operators, an example of a packaging line is chosen. The process of the manufacturing line is systematically shown in Figure 4. Products enter on the left side and flow to the right. The packaging processes are performed by machines. In the following paragraphs the lines elements: arrivals, processes, operators and buffers are described.

Arrivals: Depending on the previous process behaviour, arrivals can enter the system either at a constant rate or stochastically. Another possible arrival process is the batch-wise arrival of products. However, analysis on the arrival times are out of scope of this project. For this research we assume that the arrivals are constant, continuous and always fullfilling the demand of the first machine.

Process: The processes (packaging machines) are assumed to have constant throughput rates. In addition, all machines settings are such that the througput rates of all machines are equal, it follows that the production line is a paced line. The actual throughput of the machines will be lower due to unreliability, which creates the need for buffers. Ideally, without downtimes (perfectly reliable machines) buffers would not be needed and the maximum efficiency would be reached.

Buffers: The buffers have a limited size, the location of the buffers and the buffer size is determined for each newly designed layout. The size of the buffers is a variable.

Operator: At least 1 operator is needed for set-ups, planned and unplanned maintenance. More operators will increase the throughput of the system. By varying the number of operators a trade-off between the number of operators and the final machine line throughput can be observed. The number of operators will be a decision variable in the model.

A typical packaging line is a production system of the type called Flow line. Flow lines are also known as Production Lines or Transfer lines. The stages are in series and all products follow the same sequence, in contrast to job shops (Altiok, 1997). The following assumptions generally apply to flow lines (Gershwin, Dallery, & Papadopoulos, 2002):

- Unreliable machines
- Finite buffers.
- Unlimited repair personnel
- Uncorrelated failures
- Perfect yield
- The first machine is never starved and the last is never blocked
- Blocking before service
- Operation dependent failures

However, for our research assignment the assumption of unlimited repair personnel is harmed: the pool of operators (=repair personnel) is limited but at least one. All other assumptions apply to the packaging lines and thus to the scope of our problem.

The model we use to solve the research assignment is largely based on the characteristics of the unreliable machines and finite buffers, therefore we elaborate more on unreliable machines and finite buffers.

4.1.1 Unreliable machines

Unreliable machines have two states: up (working) and down (not working). When in a down state, the machine must be repaired before entering a working state. These repairable machines have a Mean Time Between Failure $MTBF$ and a Mean Time To Repair $MTTR$. For these terms, some ambiguousness concerning their definition is found in practice. We will handle the following definitions. $MTBF$ will defines the time between two down states. $MTTR$ defines the time to repair the machine. The waiting time to repair WTTR accounts for the time the machine is down, while the repair activity did not start yet, because an available operator is lacking or on the move.

During the down state, the machine will first wait for the repair activity to happen, we use the Waiting Time to Repair $WTTR$, which is a mean value as well. After waiting, the repair activity will take place with an estimated duration defined as Mean Time To Repair $MTTR$. For clarification of the terminology, Figure 5 shows the relation between up and down states, the time definitions as mentioned above and related events.

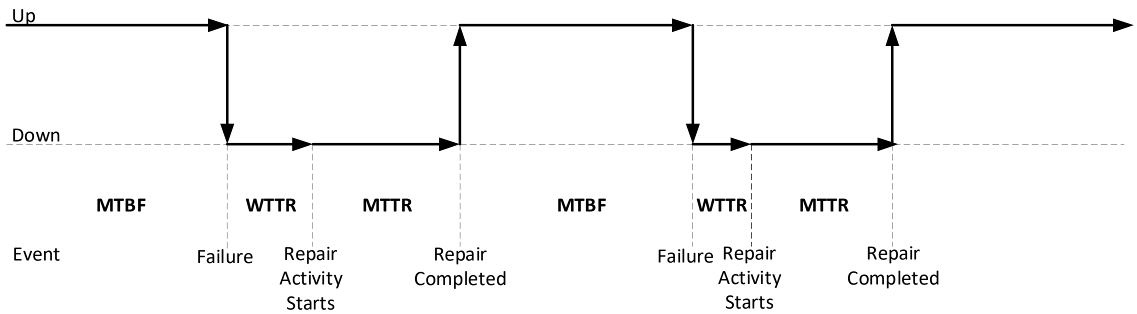


Figure 5: Graphic of Unreliable machine states

For this model, we only take small downtimes into account: these are the downtimes which occur regularly and that the packaging line should buffer against. It does not make sense to try to buffer against a downtime of hours in these type of systems as the production volume is too big. There are two types of downtimes in the packaging lines we consider. (1) Planned downtimes: these types of downtime activities are planned to occur. Packaging processes are generally dependent on the supply of a certain material. When the supply is empty, changing (filling) the supply takes time. In the case of packaging lines these are typically the actual packaging materials: the printreel/filmreels or carton boxes. (2) Unplanned Downtimes: these activities occur unplanned. This is typically a product which gets stuck in the machine, therefore blocking the production process. In the remaining of this research we will not follow this typology of downtimes. Failures due to planned and unplanned downtimes will be defined as "failure" to enhance readability. Furthermore, the general assumption of operation dependent failures (ODF) holds: failures can occur when the machine line is producing; when the machine is inactive/standby or down, there is no chance of failing.

4.1.1.1 Multiple unreliable components

In some cases, the company separated the machines failure/repair characteristics into its components characteristic. When a machine consists of multiple unreliable components, it is assumed that the machine will be down when one of the components fails and because we assume operation dependent failures, only one component can fail at a certain time (i.e. multiple failed components in one machine at the same time is impossible).

4.1.2 Finite buffers

The downtimes of the machine line will cause efficiency loss, which is not a desired outcome for a packaging line. To mitigate the a-synchronization in the line, caused by the downtimes, buffers can be used. The size and location of the buffers will be a design choice for the packaging line designer. By preventing direct propagation of failures to the sequential machines some improvement in throughput and Line Efficiency can be gained (Gershwin et al., 2002).

The influence of buffers is expected to have the following qualitative properties according to Gershwin & Schor (2000): Continuity: an increase in buffer size will lead to an increase in throughput rate. Monotocity: the throughput rate increases monotonically in a buffer increase. Concavity: The throughput rate appears to be concave of the vector of buffer size.

An unlimited buffer size will result in a throughput equal to the throughput rate of the real constraining operation TH_{RCO} and a Line Efficiency of 100%.

Although an unlimited buffer size result in an optimal Line Efficiency, the cost of buffers limits the use of buffers. There are three types of costs attached to buffers (Gershwin et al., 2002)

- In process inventory/lead time
- Floor space
- Material handling mechanism

For packaging lines, the primary cost is attached to the floor space and the material handling mechanism. However, in this project there are no cost estimates for either of those two costs factors. For the customers, in process inventory costs could play a role, however again no absolute values for process inventory costs are present for the packaging lines under review.

5 Model

This chapter explains how to solve the research assignment. First, the Modelling Approach is introduced (5.1) where we explain how we model a solution for the Research Assignment, based on the knowledge gained from the Literature Review and the System Dynamics. Secondly, the model is stated in more detail, covering the necessary equations (5.2). Thirdly and finally, we show the total model, which is a high-level view on the relationships of the equations within the detailed model and illustrates the use of the DSS (5.3).

5.1 Modelling Approach

The model aim is to provide the smallest buffer levels necessary and sufficient to ensure the desired Line Efficiency of an unreliable manufacturing line with limited repair capacity.

As stated within the literature review in section 3.2, the Lean Buffering approach is the most suitable approach to determine the buffer levels in the scope of this research. Unfortunately, the approach of Lean Buffering alone is not sufficient to cover all the conditions of the DSS, to fit within the research scope adaptions are necessary.

In 4.1.1.1 we found that the machines failure/repair characteristics are sometimes expressed in its components characteristics. The Lean Buffer approach needs the first two moments of the failure/repair distributions of each machine instead of the components characteristics. To comply with the Lean Buffering Approach, we need to aggregate the characteristics of all unreliable components j for a given machine i, into machine i's failure/repair distribution moments. The process is merely described in section 5.2.1.

The two moments of the repair distributions (i.e. the expected downtime and its variance) needed to calculate the Lean Buffer levels is dependent on the operator waiting times. Because our model has limited repair capacity, the number of operators determines the waiting times and therefore also the two moments of the downtimes. Approximations for the first and second moment of the waiting time to repair (WTTR) involves a cyclic queueing network and is extensively described in section 0.

The model has to be adapted to cope with Non-identical machines as discussed in the Literature survey on Lean Buffering (Section 3.2). Two approaches (LU and GU) are proposed and will be included in the Detailed Model in section 5.2.3.2 and 5.2.3.3

5.2 Detailed Model

This section starts with the general parameterization of the Detailed Model. Thereafter, the detailed model is treated in four sections: First: The approach for multiple unreliable components in a machine (5.2.1). Second: The approximation of the operator waiting times with a closed queueing network (5.2.2). Third: The calculation of the intermediate parameters used for the Lean Buffering approach (5.2.3). Fourth: The calculation of the Lean Buffer level with non-identical machines (5.2.4), including two approaches for non-identical machine efficiencies: the Local Upperbound (5.2.4.1) and Global Upperbound (5.2.4.1).

The general parameterization for the considered serial production lines, follows the same notation as shown in the block diagram in Figure 6.

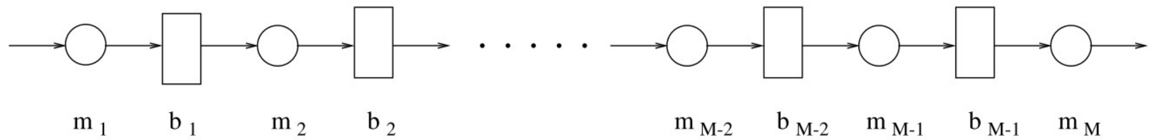


Figure 6: Block Diagram Serial Production Lines

Goods flow from the left to the right. The circles are the machines $m_i, i = 1, \ldots, M$, and the rectangles represents buffers $b_i, i = 1, \ldots, M-1$. The serial production line consists of M machines, where each pair of consecutive machines are separated buffers. In total there are $M-1$ buffers.

Each buffer b_i can store N_i parts, $i = 1, \ldots, M-1$ and $0 \leq N_i \leq \infty$. Then $N_i = 0$ implies that all product will be transferred from b_i to b_{i+1} directly and $N_i > 0$ implies that each product can be placed in a buffer.

5.2.1 Multiple unreliable components.

When a machine m_i has multiple unreliable components j, with $j \geq 2$. The aggregation of the uptime and downtime distributions for all components j of machine i will result in new aggregated general uptime and downtime distributions, characterized with is first two moments.

We use $E(U_{ij})$, $\text{var}(U_{ij})$, $E(R_{ij})$ and $\text{var}(R_{ij})$ for each $j \geq 2$ and a known type of distribution for each downtime and uptime of component j to calculate the aggregated values of $E(U_i)$, $\text{var}(U_i)$, $E(R_i)$ and $\text{var}(R_i)$.

$$E(R_i) = \text{Expected Repair time for machine } i$$
$$E(U_i) = \text{ Expected Uptime for machine } i$$
$$\text{var}(R_i) = \text{Variance Repair time for machine } i$$
$$\text{var}(U_i) = \text{Variance Uptime for machine } i$$

The procedure used for the machines in this research is explained in Appendix E

Merging multiple machines into one machine: a similar approach as described above, is pursued when the manufacturing layout limits the possible placement of a buffer between two consecutive machines m_i and m_{i+1}. In some cases, it is physically impossible or undesirable for other reasons to place a buffer between two machines. The uptime and downtime distributions must be aggregated over the machines in the same way as for unreliable components. However, this is only possible when the type of failure and repair distributions are known. We use $E(U_i)$, $\text{var}(U_i)$, $E(R_i)$ and $\text{var}(R_i)$ for both m_i and m_{i+1} and a known type of distribution for each downtime and uptime of machine m_i and m_{i+1} to calculate the values for values $E(U_i)$, $\text{var}(U_i)$, $E(R_i)$ and $\text{var}(R_i)$ Then machine m_i and m_{i+1} are merged to one machine m_i.

5.2.2 Cyclic Queueing Network for operator dependent repair times

To estimate the operator dependent repair time a cyclic queueing network (CQN) is used. The Operator/Workstation Interference Model, is introduced in a study from Kamath & Sanders (1991) and copes with the problem of operator induced waiting times due to limited repair capacity. Their machine repair-man model uses general uptime and downtime distributions. This makes it very applicable for our model. The model is described as a two-stage cyclic queuing network as shown in Figure 7.

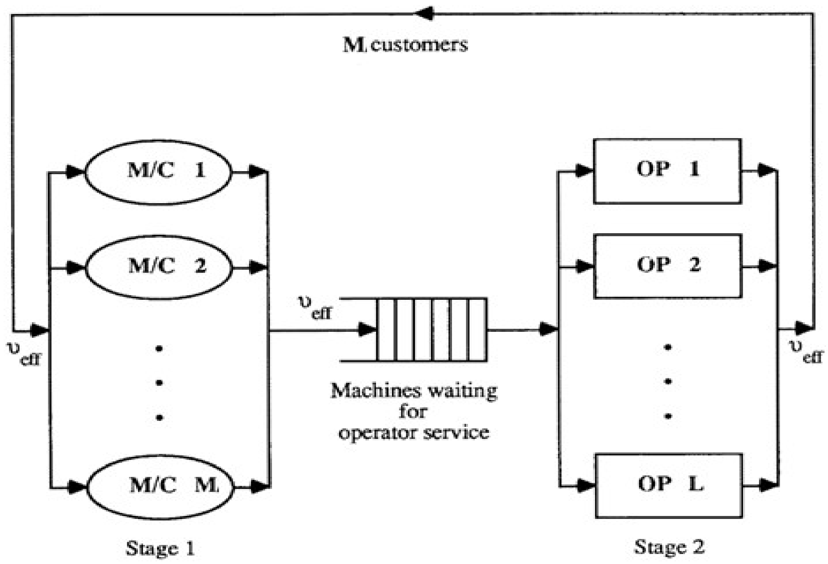


Figure 7: Cyclic Queuing Network (Kamath & Sanders, 1991)

The cyclic queueing network is closed; the number of customers within the system is fixed and equal to the number of machines. Stage 1 represent the number of running machines M. Stage 2 is a server node corresponding with the number of operators L in the pool, where $L < M$. Customers in the queue correspond with the failed machines which are waiting for an operator. When a customer moves from Stage 1 to the queue this means that the machine has a stoppage/breakdown and needs repair. When the repair is completed the customer moves from Stage 2 to Stage 1. By approximating the first and second moment of the waiting time for customers in the queue between stage 1 and 2 we obtain the first and second moment of the expected waiting time to repair.

Using the interference calculations, we can calculate the probability that multiple machines are down at the same moment. The formulas are based on the paper from Kamath & Sanders (1991).

The random variable $E[D_i]$, $i = 1, \ldots, M$ is the total expected down time, which is the total delay a product experiences from both the expected repair time $E[R_i]$ and the expected waiting time to repair $E[WTTR]$.

The total downtime for machine i is defined as

$$E[D_i] = E[R_i] + E[WTTR] \tag{7}$$

and assuming random variables R_i and $WTTR$ are stochastically independent we have:

$$\text{var}[D_i] = \text{var}[R_i] + \text{var}[WTTR]. \tag{8}$$

Let Pd_i be the probability that machine i is down, equals the expected time a machine is down $E(D_i)$ divided by the total time, which is the sum of the downtime $E(D_i)$ and the uptime $E(U_i)$:

$$Pd_i = \frac{E(D_i)}{E(U_i) + E(D_i)} = \frac{E(R_i) + E(I)}{E(U_i) + E(R_i) + E(I)} \tag{9}$$

and the expected number of machines in down state $E[K]$ is given by the sum of the probabilities that machine i is down for all $i \in M$:

$$E[K] = \sum_{i=1}^{M} Pd_i. \tag{10}$$

Let $p_k, k = 1,2 \ldots\ldots M$, be the probability that k machines are down at a certain moment. In addition, p_k is the steady state probability of k customers in stage 2 and $M - k$ customers at stage 1 (see figure 7). If we assume* that the status (up or down) of each machine is independent from the other machines, the probabilities can be expressed in recursive relationships for fast calculations. Proof of this recursive relationships can be found in Leung & Kamath (1991).

For $M \geq 1$ we have the following recursive relationships:

$$p_0^{(i)} = (1 - Pd_i)p_0^{(i-1)} \text{ for } k = 0 \tag{11}$$

$$p_k^{(i)}(1 - Pd_i)p_k^{(i-1)} + Pd_i p_{k-1}^{(i-1)} \text{ for } 1 \leq k \leq M - 1 \tag{12}$$

$$p_k^{(i)}(1 - Pd_i)p_k^{(i-1)} + Pd_i p_{k-1}^{(i-1)} \text{ for } 1 \leq k \leq M - 1 \tag{13}$$

where $p_0^{(0)} = 1$ and $p_k^{(0)} = 0$ for $k \geq 0$. The algorithm starts at $i = 0$ and $k = 0$ and subsequently calculates the probabilities for higher values of i until the given value of M is reached. The recursive calculation is applied in VBA, for the code see Appendix AAppendix R.

*remark: an evaluation on the assumption of independent machine downtimes can be found in Appendix F.

Now we can calculate the queue length, which is the expected number of failed machines waiting for operators $E[K_q]$ with:

$$E[K_q] = \sum_{k=L+1}^{M} (k - L)p_k, \tag{14}$$

this summation starts at $i = L + 1$ because there is no queue when there are equal or more operators L than machines M.

To calculate the operator service rate $\frac{1}{E(R)}$, which is later needed to calculate the mean arrival rate of failed machines to the queue of operators v_{eff} , we must first calculate an aggregate mean repair time $E(R)$ by combining the $E(R_i)$ for all $i = 1, \ldots, M$

$$E(R) \; = \sum_{i}^{M} \omega_i \, E[R_i], \tag{15}$$

with $E(R_i)$ being the total repair time for machine i and weights ω_i to take account for the probability that a repair activity (given a repair activity takes place) takes place on machine i, with $\omega_i, i = 1,2, \ldots, M$ such that $\omega_i \; \geq 0$ and $\sum \omega_i \; = \; 1$. The weights are calculated with:

$$\omega_i = \frac{Pf_i}{\sum_{i=1}^{M} Pf_i}, \tag{16}$$

where the calculation of Pf_i is the probability of a failure on machine i. The difference between Pd_i and Pf_i is exclusion of the expected operator waiting time E[WTTR] in Pf_i.

$$Pf_i = \frac{E[R_i]}{E[U_i] + E[R_i]} \tag{17}$$

We can also calculate the Aggregate Mean Downtime $E[D] = E[R] + E[WTTR]$.

To calculate the mean arrival rate of failed machines v_{eff} to the queue of operators, we multiply the average number of busy operators with the operator service rate as computed in Equation (15):

$$\begin{aligned} v_{eff} &= (E[K] - E[K_q]) * \; \frac{1}{E(R)} \\ &= \frac{E[K] - E[K_q]}{E[R]}, \end{aligned} \tag{18}$$

where the average number of busy operators is calculated by subtracting the expected number of failed machines waiting for operators $E(K_q)$ from the expected number of failed machine $E[K]$.

With Little's Law we can calculate expected waiting time in the queue: the expected waiting time to repair $E[WTTR]$:

$$E[WTTR] = \frac{E[K_q]}{v_{eff}}. \tag{19}$$

To calculate the variance of the mean interference time, the second factorial moment of the waiting time in the queue must be calculated. First, we calculate the second factorial moment of the queue length $E(K_q^2)$. This is done by approximations for the multiple server with poison arrivals and general service queueing model: M/G/c/∞ (Gross, Shortle, Thompson, & Harris, 2008, pp. 245) with

$$\begin{aligned} E[K_q^2] = &\ E[K_q(K_q - 1)] \\ = &\sum_{k=L+2}^{M} (k - L)(k - L - 1)p_k. \end{aligned} \tag{20}$$

Resulting in:

$$E[WTTR^2] = \frac{E[K_q^2]}{v_{eff}^2}, \tag{21}$$

with v_{eff}^2 being the square function of Equation (18)

$$v_{eff}^2 = \frac{(E[K] - E[K_q])^2}{1/E[R]^2}.$$

Finally, variance of the interference time var$[WTTR]$ can then be calculated:

$$\begin{aligned} \mathrm{var}[WTTR] = &\ E[WTTR^2] - (E[WTTR])^2 \\ = &\ \frac{E[K_q^2]}{v_{eff}^2} - (E[WTTR])^2. \end{aligned} \tag{22}$$

The calculation of Pd_i in Equation (9) uses $E[WTTR]$, while the calculation of $E[WTTR]$ needs the value of Pd_i. Therefore, the calculation is repeated until it convergences into a difference ε which is small enough, where $E[WTTR]^{old}$ is defined as the value obtained in the previous iteration.

$$\frac{\mathrm{abs}(E[WTTR]^{old} - E[WTTR])}{E[WTTR]} < \varepsilon \tag{23}$$

These formulas are congruent with the algorithm in the paper from (Kamath & Sanders, 1991). The used algorithm from Kamath & Sanders (1991) is shown in Appendix Q and is applied in VBA, which can be found in Appendix U. It also uses the calculations shown Appendix RAppendix S and Appendix T, where, respectively, formulas for the recursive calculations, the aggregated mean repair time and some general efficiency calculations are applied. It is adjusted for different clear times and only takes the heterogeneous case. For homogeneous lines the calculations simplifies, more information can be found in the original paper from (Kamath & Sanders, 1991).

*Remark: We calculated the expected waiting times $E[WTTR]$ when the machine failures are time dependent. Transfer lines typically have operation dependent failures: a failure cannot occur when the system is not producing. As a result, the real value of repair demands would be lower. However, a buffer increase would lead to an increase in the machine production time and therefore the number of repair demands could increase. Accordingly, an infinite buffer size approximates the value when using the time dependent failures.

Thus, it is given variables: $x_i = arrival\ repair\ demands\ for\ case\ i$

$$i = 1\ operation\ depenendent\ failures$$

$$i = 2\ time\ dependent\ failures$$

$$i = 3\ operation\ depenendend\ failures\ with\ buffers\ between\ stations$$

hypothesized that $x_1 < x_3 \leq x_2$. Therefore, we will calculate the value of time dependent failures, as this is easier to approximate, and it is the upper bound of the equation. A higher x_i leads to a higher $E[WTTR]$.

5.2.3 Lean Buffering

The uptime and downtime of each machine m_i is expressed in the average time in units of production: 1/ (machine cycle time) and is generally distributed with parameters: T_{up_i}, σ_{up_i}, T_{down_i} and σ_{down_i}, $i = 1, \ldots, M$.

Values from the machine interference model will be used as shown in Equation (24) and Equation (26). To express all up and downtime we use the relation: 1/ (machine cycle time), which equals the production speed: TH_{TBN}.

$$T_{down_i} = E[D_i] * TH_{TBN} \tag{24}$$

$$T_{up_i} = E[U_i] * TH_{TBN} \tag{25}$$

$$\sigma_{T_{down_i}} = TH_{TBN} * \sqrt{\mathrm{var}[D_i]} \tag{26}$$

$$\sigma_{T_{up_i}} = TH_{TBN} * \sqrt{\mathrm{var}[U_i]} \tag{27}$$

Subsequently the coefficient of variations for the uptime and downtime of each machine $m_i, i = 1, \ldots, M$ are:

$$\mathrm{CV}_{up_i} = \frac{\sigma_{up_i}}{T_{up_i}} \tag{28}$$

$$\mathrm{CV}_{down_i} = \frac{\sigma_{down_i}}{T_{down_i}} \tag{29}$$

and the machine efficiencies e_i including operator waiting times:

$$e_i = \frac{T_{up_i}}{T_{down_i} + T_{up_i}}. \tag{30}$$

5.2.3.1 Lean Buffering for non-identical machines

Enginarlar, Li, Meerkov, & Zhang, (2002) propose a rule for the calculation of the buffer capacity N_i between each pair of non-identical machines, which accommodates for the differences in downtime distributions between the two consecutive machines. Using the following parameterization:

The production Line Efficiency $E = \frac{TH_k}{TH_{bottleneck}}$, where TH_k, represents the throughput rate at the end of line with a normalized buffer capacity equal to k.

k denotes the level of buffering, expressed in the capacity of a buffer capable to store products during k downtimes.

The smallest k which ensures the aimed Line Efficiency E, is shown as k_E and referred to as lean buffer level (LB). A special case of k_E is the formula which is used when failures and repairs are assumed to be exponential, denoted by k_E^{exp}.

Equation (31) is the proposed by Enginarlar et al. (2002) for calculating the buffer capacity for non-identical lines under the assumption that all machine efficiencies e_i are identical and denoted by e

$$N_i = \; buffer\ capacity \;\; for \;\; i = 1, w, \dots M-1$$

$$N_i = \lceil \, k_E^{exp} * \max\{CV_{down_i}, CV_{down_{i+1}}\} * \max\{T_{down_i}, T_{down_{i+1}}\} \rceil, \tag{31}$$

For k_E^{exp} as a function of (M, E, e), we use the formulas as proposed by Enginarlar, Li, & Meerkov (2005a). This can be seen in Equation (32) .

$$k_E^{exp}(M, E, e) = Lean\ Buffer\ \ Levels.(exponential)$$

$$k_E^{exp}(M,E,e) = \begin{cases} \dfrac{e(1-Q)(eQ+1-e)(eQ+2-2e)(2-Q)}{Q(2e-2eQ+eQ^2+Q-2)} \times \\ \ln\left(\dfrac{E-eE+eEQ-1+e-2eQ+eQ^2+Q}{(1-e-Q+eQ)(E-1)}\right), & \text{if } e < E^{\frac{1}{M-1}} \\ 0, & \text{otherwise,} \end{cases} \tag{32}$$

with Q as shown in Equation (33):

$$Q = 1 - E^{\frac{1}{2}\left[1+\left(\frac{M-3}{M-1}\right)^{\frac{m}{4}}\right]} + \left(E^{\frac{1}{2}\left[1+\left(\frac{M-3}{M-1}\right)^{\frac{m}{4}}\right]} - \; E^{\frac{M-2}{M-1}}\right) \times exp\left\{-\left(\frac{E^{\frac{1}{M-1}}-e}{1-E}\right)\right\}. \tag{33}$$

Although this method overcomes the limitations of differing CV_{down_i} and T_{down_i}, it assumes that the efficiencies e_i of all machines are identical and denoted by e for the calculation of the level of buffering k_E^{ex}. The authors made this assumption because they argue that mostly all machines of a production line are roughly of the same efficiency.

We propose 2 solutions for non-identical machine efficiencies e_i, based on the findings in the literature review in Section 3.2: (1) The Local Upperbound approach and (2) the Global Upperbound approach.

5.2.3.2 Global Upperbound Approach

For different efficiencies among the machines in the line, we apply the Global Upper (GU) bound approach only for the machine efficiency (Chiang, Hu, & Meerkov, 2008):

$$\hat{e} := \min\{e_1, e_2, \dots, e_i\}$$

Substitution of $\hat{e}$ into all e in Equation (32) and (33) results in Equation (34) and (35):

$$\begin{aligned} k_E^{exp}(M, E, \hat{e}) = & \frac{\hat{e}(1-Q)(\hat{e}Q+1-\hat{e})(\hat{e}Q+2-2\hat{e})(2-Q)}{Q(2\hat{e}-2\hat{e}Q+\hat{e}Q^2+Q-2)} \\ & \times \ln\left(\frac{E-\hat{e}E+\hat{e}EQ-1+\hat{e}-2\hat{e}Q+\hat{e}Q^2+Q}{(1-\hat{e}-Q+\hat{e}Q)(E-1)}\right), \end{aligned} \tag{34}$$

with

$$\begin{aligned} Q = 1 - & E^{\frac{1}{2}\left[1+\left(\frac{M-3}{M-1}\right)^{\frac{m}{4}}\right]} \\ & + \left(E^{\frac{1}{2}\left[1+\left(\frac{M-3}{M-1}\right)^{\frac{m}{4}}\right]} - E^{\frac{M-2}{M-1}}\right) \times exp\left\{-\left(\frac{E^{\frac{1}{M-1}}-e}{1-E}\right)\right\}. \end{aligned} \tag{35}$$

Then, based on Equation (31), buffer sizes N_i , $i = 1, \dots, M-1$ are calculated using Equation (36). The result is rounded up the closest natural number N.

$$\begin{aligned} & N_i \\ & = \begin{Bmatrix} \left\lceil k_E^{exp}(M,E,\hat{e}) * \max\{CV_{down_i}, CV_{down_{i+1}}\} * \max\{T_{down_i}, T_{down_{i+1}}\}\right\rceil & \text{if } N_i > 0 \\ 0 & otherwise \end{Bmatrix} \end{aligned} \tag{36}$$

*Remark: For the Global Upperbound (GU) approach the calculation of the machine efficiency: $\hat{e} := \min\{e_1, e_2, \dots, e_m\}$ will result in the upperbound of the level of $k_E^{exp}(M, E, \hat{e})$, due to the monotonicity of the production rate with respect to the machine efficiency and buffer capacity. However, the degree of overestimation will be limited because the machine efficiencies are almost equal.

5.2.3.3 Local Upperbound Approach

Another way to calculate different efficiencies among the machines in the lines is to apply the Local Upper bound approach(Chiang et al., 2008). This method considers all pairs of consecutive machines m_i and m_{i+1}, and substitutes the $\hat{e}_i = \min\{e_i, e_{i+1}\}$ and $\hat{r}_i = \min\{r_i, r_{i+1}\}$.

$$\hat{e}_i = \min\{e_i, e_{i+1}\}, i = 1, \dots, M-1$$

The for each buffer place, the exponential level of buffering ${k_E^{exp}}_i(M, E, \hat{e}_i)$ can be calculated:

$$k_{E\ i}^{exp}(M, E, \hat{e}_i) = \frac{\hat{e}_i(1-Q_i)(\hat{e}_i Q_i + 1 - \hat{e}_i)(\hat{e}_i Q_i + 2 - 2\hat{e}_i)(2-Q_i)}{Q_i(2\hat{e}_i - 2\hat{e}_i Q_i + \hat{e}_i Q_i{}^2 + Q_i - 2)} \times \ln\left(\frac{E - \hat{e}_i E + \hat{e}_i E Q - 1 + \hat{e}_i - 2\hat{e}_i Q + \hat{e}_i Q^2 + Q}{(1 - \hat{e}_i - Q_i + \hat{e}_i Q_i)(E-1)}\right), \tag{37}$$

with:

$$Q_i = 1 - E^{\frac{1}{2}\left[1+\left(\frac{M-3}{M-1}\right)^{\frac{m}{4}}\right]} + \left(E^{\frac{1}{2}\left[1+\left(\frac{M-3}{M-1}\right)^{\frac{m}{4}}\right]} - \ E^{\frac{M-2}{M-1}}\right) \times exp\left\{-\left(\frac{E^{\frac{1}{M-1}} - \hat{e}_i}{1-E}\right)\right\}. \tag{38}$$

This results in the final buffer capacities N_i for $i = 1, \dots, M-1$ as shown in Equation (39). Similar to Equation (36), the result is rounded up the closest natural number N.

$$N_i = \begin{cases} \left\lceil k_E^{exp}(M, E, \hat{e}_i) * \max\{CV_{down_i}, CV_{down_{i+1}}\} * \max\{T_{down_i}, T_{down_{i+1}}\}\right\rceil & \text{if } N_i > 0 \\ 0 & otherwise \end{cases} \tag{39}$$

*Remark: The Lean Buffering model used in this research assumes time-dependent failures because this failure mode simplifies the analysis and results in just a small difference in comparison with operation- dependent failures (Enginarlar, Li, & Meerkov, 2005b). For transfer lines, it is shown that operation dependent failures results in a higher efficiencies compared to time dependent failures (Dhouib, Gharbi, & Mejri, 2010; Papadopolous, Heavey, & Browne, 1993). Therefore, we conclude that assuming time dependent failures will result in a lower bound for the real e_i. Consequently, the buffer capacities will be overestimated.

5.3 Total model

The total model minimizes the total buffer size $\sum_{i=1}^{M-1} N_i$, given a required Line Efficiency $E \in (0,..1)$ and number of operators $L \in (0,1,\ldots,M-1)$.

The total model can be seen in Figure 8 and is described briefly. A list of the inputs/decision variables and outputs can be found Appendix N. The steps of the DSS are briefly described and the necessary Equations with the corresponding Section of this document are stated.

Step 1: **Line Layout:** The layout of a machine line is, inter alia, characterized by the machines with multiple components and the possibility to place buffers between the machines. Based on this line layout information the multiple failure/repair distributions are aggregated. The calculation of these distributions is case specific, since every line is different, and therefore not included the DSS model. However, the aggregated failure distributions are inputs for the DSS model.

- Section: 5.2.1 Multiple unreliable components.
- Appendix E

Step 2: **Approximating the moments of the WTTR.** Using the CQN, we approximate the first and second moment of the waiting times to repair.

- Section 5.2.2
- Equations (7) to (23).

Step 3: **Calculate the total downtime**. Step 3 involves calculating the first two moments of the total downtime.

- Section
- Equation (7) and Equation (8).

Step 4: **Calculate the LB and the buffer levels $\boldsymbol{N_i}$**. The final step combines the information of the first three steps and calculates the buffer levels with Lean Buffer approach.

- Section 5.2.3 Lean Buffering
- Equation (24) to Equation (30)
- GU: Equation (34) to Equation (36)
- LU: Equation (37) to Equation (39)

Of course, Step 2, 3 and 4 can be recalculated for different numbers of operators and different line efficiencies to evaluate trade-offs.

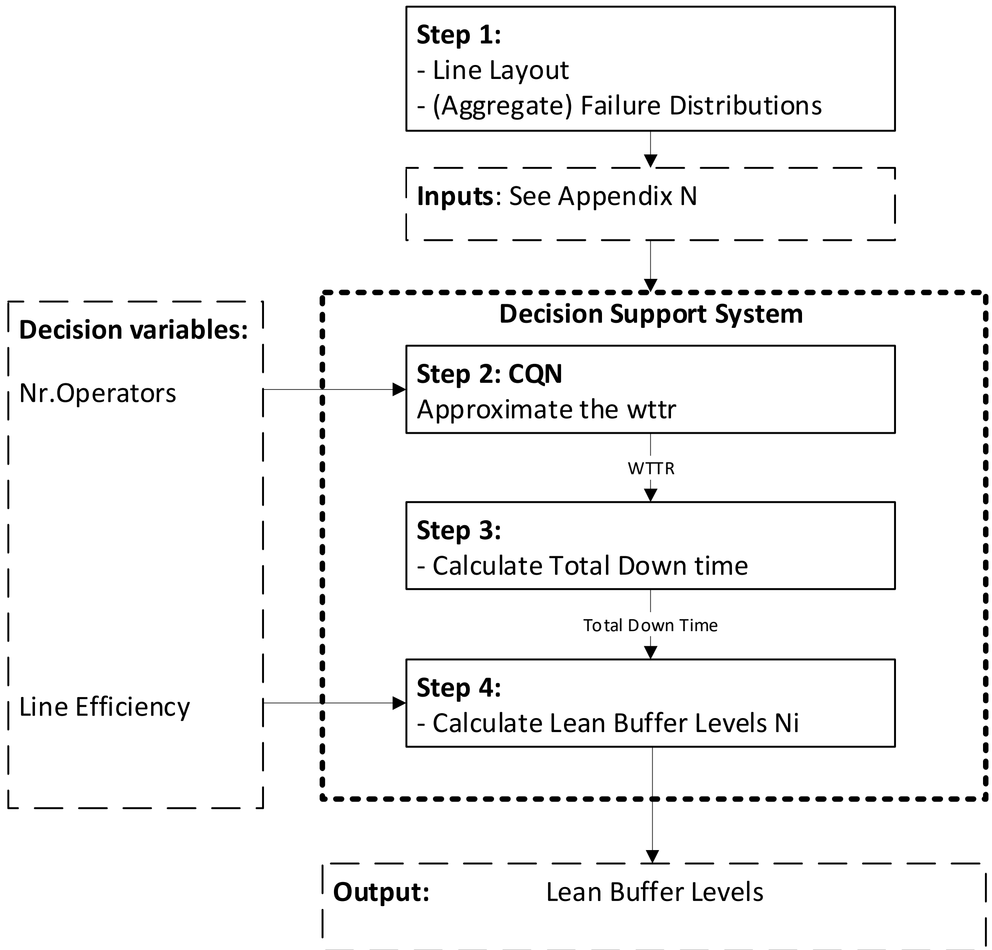


Figure 8: Decision Support System

6 Case study

In this chapter, the DSS will be tested with a case study. All results will be shown and validated with PacSi, which is Discrete Event Simulation software used by Bosch. We start with the validation of the DSS (6.1). Then, we do a Sensitivity Analysis (SA) on the number of operators the targeted Line Efficiencies and number of machines (6.2). We show the results for three scenarios', based on the layout of Omni-Trade, a customer from Bosch. (6.3). The last paragraph (6.4) provides a summary of our findings and results.

6.1 Validation

In this section, we validate the DSS in 4 phases, to see for each decision how it affects the performance of the system. This way we can assess the accuracy of the DSS for non-identical machines. First, we evaluate on the input for the validation of the DSS (6.1.1) Second, we will see which method we should use for non-identical machines, either GU or LU (6.1.2). Third, we will evaluate our relaxation of the model concerning time-dependent failures and operation-dependent failures (6.1.3). Fourth, the approach for multiple unreliable components is tested (6.1.4). Finally, we validate the influence of the cyclic queueing model and waiting times to repair on the model (6.1.5)

6.1.1 Input and validation approach

We generated input values for the $E[R_i]$ and $E[U_i]$ and their standard deviations. The domain for the values are chosen to be reasonable within these type of machine environments. The Expected value for the repair $E[R_i]$ is rounded in seconds and take values between 60 and 600 seconds, thus from the set $\{60, 61, \dots 600\}$. The standard deviation of the repair time R_i takes a value of $\sigma_{R_i} = E[R_i] * unif\{0.001; 0.2\}$. Then the machine efficiencies e_i take uniform distributed values between 0.95 and 1, thus $e_i = unif\{0.95; 1\}$. Then the $E[U_i]$ is calculated from the following relation: $E[U_i] = e_i * \frac{E(R_i)}{1-e_i}$. The standard deviation of the uptime U_i takes a value of $\sigma_{U_i} = E[U_i] * unif\{0.001; 0.2\}$. The data we used for validation of our model is found in Appendix G. The efficiency e_i is rounded on 3 decimals. The other variables the $E[R_i]$, $E[U_i]$, σ_{R_i} and σ_{U_i} are rounded to seconds to increase readability and to improve congruence with the DES system. In Appendix P we show the layout of the DSS.

To validate the DSS we followed the following approach: the DSS provided us with Lean Buffer sizes for all buffers N_i for a certain targeted Line Efficiency: E_T. Then, we build a packaging line in the simulation software with the same characteristics: inputs (including pooled operators) and obtained buffer levels as stated in the DSS. The we run the simulation for 20 replications of 10.000 minutes. The obtained Line Efficiency from the simulation E_S is used to check how accurate the output of the DSS is.

We check how close the relation between Simulation and the Target Line Efficiency is:

$$E_S = E_T$$

*Remark: Although, our DSS only needs the first two moment. The DES software needs a distribution to generate failure/repair data, based on our findings as explained in Appendix E.

Generally, we used normal distributions for both the repair and failure time. However, in Sections 6.1.4 and 6.3. we used different distributions, which are clearly stated in these sections.

6.1.2 GU and LU approach

We show the results of the GU and LU approach with a targeted Line Efficiency of $E_T = 0{,}97$. Table 2 shows the summations of the Buffer Sizes: $N = \sum_{\mathrm{i}=1}^{M-1} N_i$, for machine lines with a length $M = \{5, 10, 15\}$ machines. Table 3 shows the outcome of the simulation for the LU and GU approach with the buffer levels of Table 2.

$\boldsymbol{E_T = 0,97}$	M=5	M=10	M=15
N(LU)	1101	4399	7092
N(GU)	1424	5636	8581

Table 2: Sum of Buffer Sizes for E_T=0,87

$\boldsymbol{E_T}$= 0,97	M=5	M=10	M=15
$\boldsymbol{E_S}$(LU)	0,971	0,978	0,961
$\boldsymbol{E_S}$(GU)	0,979	0,985	0,967

Table 3: Simulations Outcomes LU and GU for E_T=0,97

We evaluate this by considering longer machine lines $M = \{10, 15\}$ and for different targeted Line Efficiencies $E_T = \{0{,}8; 0{,}85; 0{,}90; 0{,}95; 0{,}97\}$. Longer lines are chosen, because we expect to see larger differences in total buffer levels N. The results for $M = 10$ are shown in Table 4, and for M=15 in Table 5.

M=10	$\boldsymbol{E_T}$=0,85	$\boldsymbol{E_T}$=0,90	$\boldsymbol{E_T}$=0,95	$\boldsymbol{E_T}$=0,97
N(LU)	757	1426	2860	4399
$\boldsymbol{E_S}$(LU)	0,879	0,910	0,952	0,978
N(GU)	1219	1999	3709	5636
$\boldsymbol{E_S}$(GU)	0,900	0,929	0,968	0,985

Table 4: Simulations Results LU and GU for M=10

M=15	$\boldsymbol{E_T}$=0,80	$\boldsymbol{E_T}$=0,85	$\boldsymbol{E_T}$=0,90	$\boldsymbol{E_T}$=0,95	$\boldsymbol{E_T}$=0,97
N(LU)	1286	1915	2856	4903	7092
$\boldsymbol{E_S}$(LU)	0,835	0,865	0,899	0,939	0,961
N(GU)	1800	2491	3544	5876	8581
$\boldsymbol{E_S}$(GU)	0,858	0,884	0,914	0,946	0,967

Table 5: Simulations Results LU and GU for M=15

Looking at Table 4 and Table 5, we conclude that both the LU and GU generally provide sufficient buffer levels for lower levels of E_T. For both the LU and GU approach: simulation resulted in an output/efficiency which was too low for the cases of $M = 15$ & E_T= $\{0{,}95; 0{,}97\}$. We argue that this difference is small, only 1% from the targeted value. When looking at the Buffer Size, the LU approach has a big advantage over the GU. The $N(LU)$ being on average 24% smaller then $N(GU)$.

It was expected that the Global Upperbound method would result in more buffer space and higher E_S levels, compared to the Local Upperbound approach. However, since the difference in N is significantly large, while the difference in performance in terms of E_S is rather small. In conclusion, we use the Local Upperbound method from now onwards.

6.1.3 Operation Dependent Failures and Time Dependent Failures

Since Lean Level Buffering assumed time dependent failures, we want to see if operation dependent failures would influence the performance significantly. In the simulations software, we changed the time dependent failures to operation dependent for a $M = \{5{,}10, 15\}$ line with targeted efficiencies of $E_T = \{0.8; 0.85; 0.90; 0.95; 0.97\}$. The results are shown in Table 6, where empty cells correspond with the situation that no buffers were needed to obtain the targeted Line Efficiency. As expected TDF results in higher efficiencies compared to ODF. We evaluate the difference between the two: $Delta = ODF - TDF$.

	M=5			M=10			M=15		
	ODF	TDF	Delta	ODF	TDF	Delta	ODF	TDF	Delta
$\boldsymbol{E_T}$=0.80	-	-	-	-	-	-	0,851	0,835	0,016
$\boldsymbol{E_T}$=0.85	-	-	-	0,888	0,879	0,009	0,876	0,865	0,010
$\boldsymbol{E_T}$=0.90	-	-	-	0,916	0,910	0,006	0,906	0,899	0,007
$\boldsymbol{E_T}$=0.95	0,956	0,954	0,002	0,954	0,952	0,002	0,942	0,939	0,003
$\boldsymbol{E_T}$=0.97	0,971	0,971	0,001	0,979	0,978	0,001	0,962	0,961	0,001

Table 6: Simulations Results E_S for ODF and TDF

Table 6 shows that the difference between operation dependent and time dependent failures are small. In addition, we see that for longer lines the difference slightly increases. Moreover, we see that for higher targeted Line Efficiency the difference becomes lower. This can be explained by the fact that the manufacturing lines in those cases are designed to reduce the impact of failures in the line, consequently the impact of the operation dependent/time dependent failures will be reduced. $Delta$ is calculated as an absolute value, this could be somehow misleading. However, taking relative values $Delta_{rel} = \frac{ODF-TDF}{ODF}$ (Appendix H) results in the same conclusions.

Finally, we can conclude that time dependent failures slightly underestimate the performance compared to operation dependent failures. Using time dependent failures provides a lower bound on the line performance, and therefore increases the certainty of achieving the targeted Line Efficiency levels as used DSS.

6.1.4 Multiple Unreliable Components

In this chapter, we check for multiple the failures for one machine. We try to stay as close to the practice as possible, therefore we use the data from a vertical packer from Bosch. The data is used from the vertical packer OEE estimations. The vertical packer is, in this case, the bottleneck station and the second machine in line $i = 2$.

The packer is subject to six different failures/changeovers:

(1) Film reel Changeover (Constant)
(2) Zip reel Changeover (Constant)
(3) Print reel Changeover (Constant)
(4) Cleaning Cycle (Normally Distributed)

(5) Product Blocking in Cross Jaws (Exponentially Distributed)
(6) Product Blocking in Funnel (Exponentially Distributed)

We recall: $U_{ij} = Uptime\ for\ component\ j\ on\ machine\ i$. Machine 2 has $j = 6$ unreliable components, with U_{2j} and similarly, R_{2j} for $j = \{1,2,..6\}$.

Table 7 shows the expected repair- and uptime distribution of each unreliable component, these are both expressed in minutes.

	$\boldsymbol{j = 1}$	$\boldsymbol{j = 2}$	$\boldsymbol{j = 3}$	$\boldsymbol{j = 4}$	$\boldsymbol{j = 5}$	$\boldsymbol{j = 6}$
$\boldsymbol{U_{2j}(\mu, \sigma)}$	Cons[277]	Cons[291]	Cons[3962]	Norm[120;12]	Exp[480]	Exp[480]
$\boldsymbol{R_{2j}(\mu, \sigma)}$	Norm[5;1]	Norm[5;1]	Norm[2;0,4]	Norm[3;0,6]	Norm[10;2]	Norm[3;0,6]

Table 7: Uptime and Repair time distributions for the 'Worst Case' estimations.

Combining these failure, for the long run case resulted in a distribution of uptime U_2 as shown in Figure 9, with an average of 48,7055 and a standard deviation of 40,8049 in minutes.

$$\sigma_{U_2} = 40{,}8049$$

$$E(U_2) = \ \mu_{U_2} = 48{,}7055$$

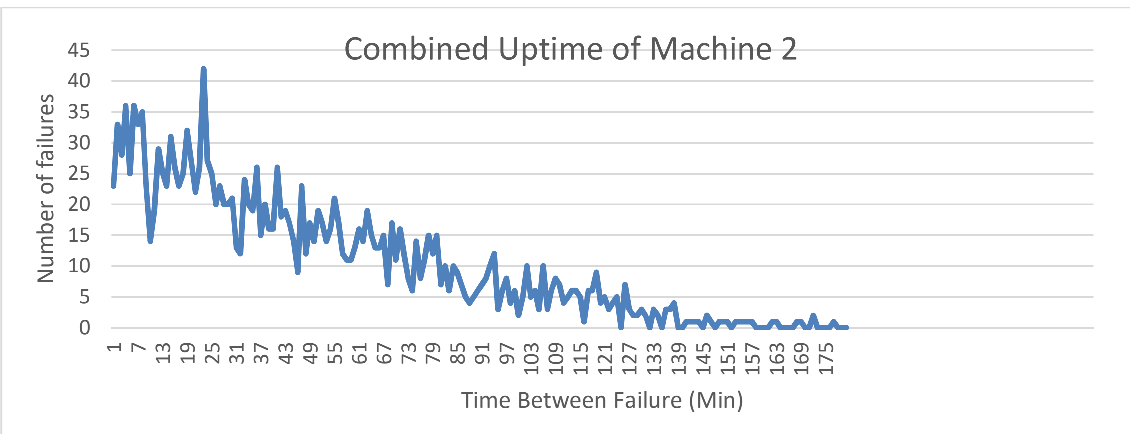


Figure 9: Long Run Time Between Failures Distribution.

Similarly, the combined Repair Time distribution is shown in Figure 10, with an average of 4,3970 and a standard deviation of 2,3346. Fitting a distribution on either the repair- or uptime was not possible without rejecting the 0 hypothesis. Still, both graphs give a good visual representation.

$$\sigma_{R_2} = 4{,}3970$$

$$E(R_2) = \ \mu_{R_2} = 2{,}3346$$

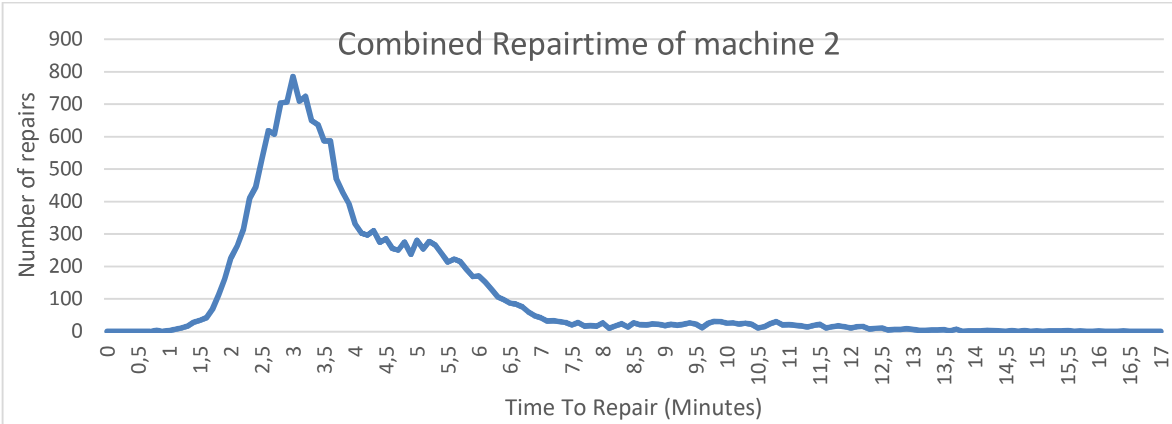


Figure 10: Long Run Time To Repair distribution.

Further explanation on how these repair and uptimes are calculated can be found in Appendix E. We will provide a new machine line where this machine will be the bottleneck. It will be placed as second machine. This makes sense since, mostly, only a conveyor is in front of this machine. Except for this value on the second machine, the same values are used for the others. We will start validation with a 5-machine line, with values as shown in dataset 2 in Appendix K, where machine 2 is the bottleneck of the system. This corresponds with findings within Bosch, as they reflect that the vertical packer is the bottleneck in most systems.

Due to the high values for the CV_{down_2}, Buffer Levels N_1 and N_2 around machine $i = 2$ are very high, as can be seen in Table 8.

M=5	N_1	N_2	N_3	N_4	N
E_T=0,94	2491	1203	0	146	3840
E_T=0,95	3022	1459	0	197	4678
E_T=0,96	3807	1838	0	268	5913
E_T=0,97	5102	2463	10	377	7952

Table 8: Buffer Sizes for M=5 with Multiple Failures

The buffer setups as shown in Table 8, were the input for the simulations, which resulted in obtained line efficiencies as shown in Table 9.

M=5	E_T=0,94	E_T=0,95	E_T=0,96	E_T=0,97
N	3840	4678	5913	7952
E_S	0.9978	0.9991	0.9988	0.9993
Difference	0.0578	0.0491	0.0488	0.0493

Table 9: Simulations Results for M=5 with Multiple Failures.

Unfortunately, the results of the simulation are not close to the targeted Line Efficiency. However, it shows that the Lean Buffering method provides high buffer levels and the increase in buffer levels between the E_T=0,94 and E_T=0,97 has no significant impact on the Simulated Line Efficiency E_S. We expect that the model is very sensitive to the change in CV_{down_i} and overestimates the Lean Buffer levels for a higher CV_{down_i}

6.1.5 Waiting times to repair

In this section, the influence of operators (the WTTR) will be added to the model. This will have an impact on the buffers. A decrease in operators leads to an increase in buffer size, and in opposite direction: and increase in operators will lead to a decrease in buffer size, this buffer size will approach the level of the model with 0 operators. Table 10 shows the output of the DSS for a M=15 machine line with a targeted efficiency E_T=0,95. The Expected Waiting Time to Repair $\mathsf{E}[WTTR]$, its standard deviation $\sigma_{WTTR} = \sqrt{\text{var}[WTTR]}$ and the Total Lean Buffer size $N = \sum_{\text{i=1}}^{M-1} N_i$ calculated with the Local Upper bound(LU) method.

M = 15	$\mathbf{E}[\boldsymbol{WTTR}]$	$\boldsymbol{\sigma_{WTTR}}$	$\boldsymbol{N}$
$\boldsymbol{L=0}$	0	0	4909
$\boldsymbol{L=1}$	83,31	119,50	22532
$\boldsymbol{L=2}$	5,63	27,74	6989
$\boldsymbol{L=3}$	0,37	6,03	4969
$\boldsymbol{L=4}$	0,02	6.03	4910

Table 10: Buffer Levels and expected Waiting time for M=15

From the result as showed in Table 10, we can conclude that the Lean Buffer size N decreases with an extensive amount, when increasing the number of operators from one to two. However, a further increase in the number of operators $L > 2$, results in less extreme reductions in N. As expected, the four-operator case, $L = 4$, almost equals the operator case $L = 0$. We have seen similar results with shorter lines, which are shown in similar format in Appendix J

6.2 Sensitivity analysis

In 6.2.1 we analyze the performance of the DSS for different line lengths and for different levels of Line Efficiency. Then, the number of operators are added to the model, to do a sensitivity analysis on the number of operators (6.2.2).

6.2.1 SA: Line Length & Line Efficiency

Figure 11, Figure 12 & Figure 13 are visual representations of the data in Appendix I. The purple line shows the targeted Line Efficiency E_T, the red points shows the Line Efficiency outcome of the simulation, $E_S(LU)$, with use of the Buffer size N_i as obtained from the LU-approach in the DSS. We check for different levels of targeted Line Efficiency $E_T = \{0{,}8; 0{,}85; 0{,}90; 0{,}95; 0{,}97\}$ and for 3 lengths of manufacturing lines $M = \{5, 10, 15\}$ how accurate the DSS Buffer Levels are.

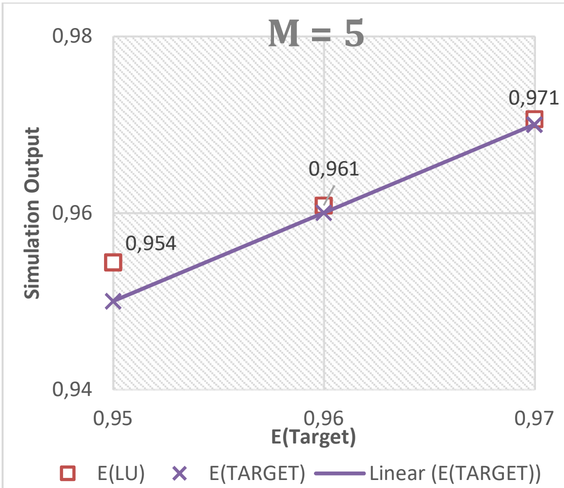


Figure 11: Simulations Results for LU and M=5

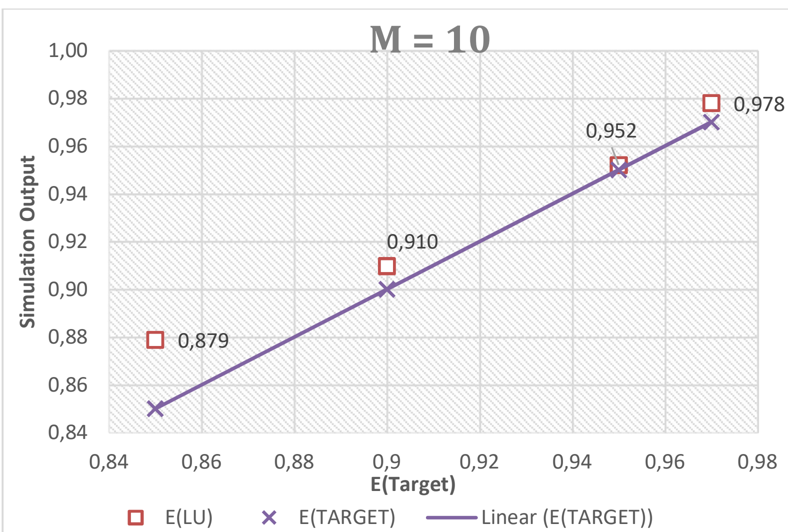


Figure 12: Simulations Results for LU and M=10

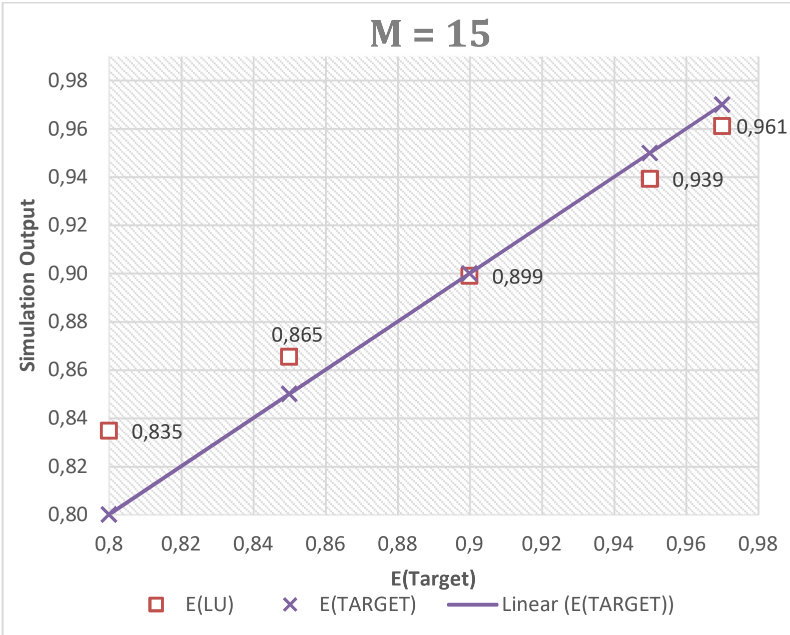


Figure 13: Simulations Results for LU and M=15

From these figures, we can conclude see that the DSS overestimates the required Buffer Levels on lower targeted Levels. Further, we see that for the longer machine line $M = 15$ the method provides too small Buffer Levels for $E_T \geq 0{,}95$. However, this difference is small: $E_T - E_S \leq 0{,}011$.

6.2.2 SA: Number of operators

For the model including operators, again we simulate the performance of the manufacturing line with the DES software and check if the Line Efficiency outcome coincides with the Targeted Line Efficiency. Now, we have an additional variable: Number of Operators L. In the simulation software, the pool of operators equals the value L.

Again, we considered three different manufacturing line sizes: $M = \{5, 10, 15\}$. We changed the number of operators L and checked for different levels of targeted E how the model performs.

Figure 14, Figure 15 and Figure 16 show that for the 1 operator case $L = 1$, the model consistently overestimates the Lean Buffer levels, resulting in too high Line Efficiencies.

For the short five machine line $M = 5$ as shown in Figure 14, the difference between E_S and the targeted E_T, stays almost the same for all levels of E. However, for longer lines $M = 10$ (Figure 15) and $M = 15$ (Figure 16), the differences tend to be larger at lower targeted levels of efficiencies E_T.

For all lines, the two-operator, $L = 2$, case shows very good Buffer Level estimations. Furthermore, for the $M = 15$ and $L = 3$ case the Line Efficiency is slightly below targeted as can be seen in Figure 16. This is a small deviation which may be caused by the simulation. We conclude that this is not a major problem in practice, because this hypothetical case will not occur: 2 operators would be a more efficient choice since the difference in waiting time is only ± 5 seconds (see Table 10).

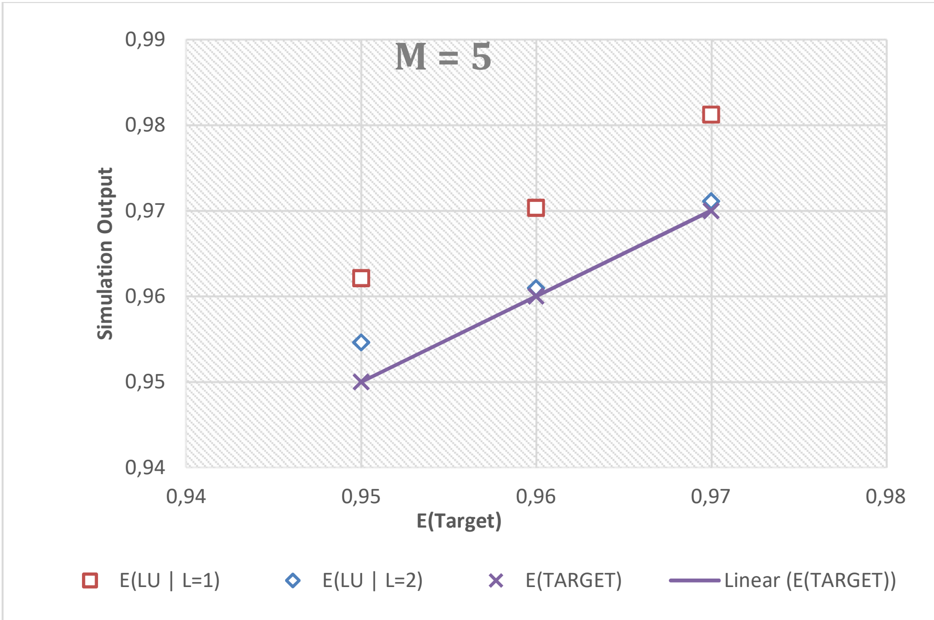


Figure 14: Simulations Results on Operator Influence and M=5

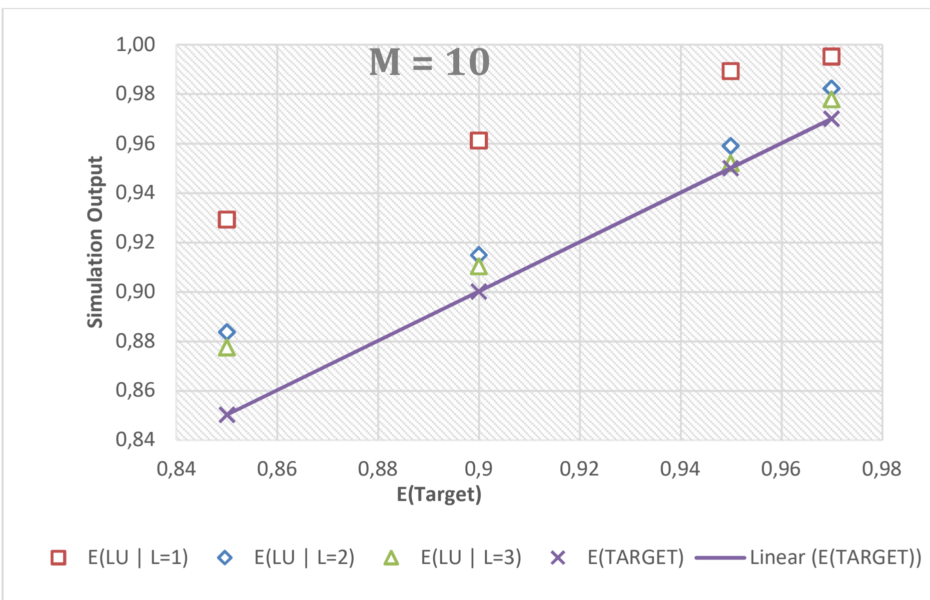


Figure 15: Simulations Results on Operator Influence and M=10

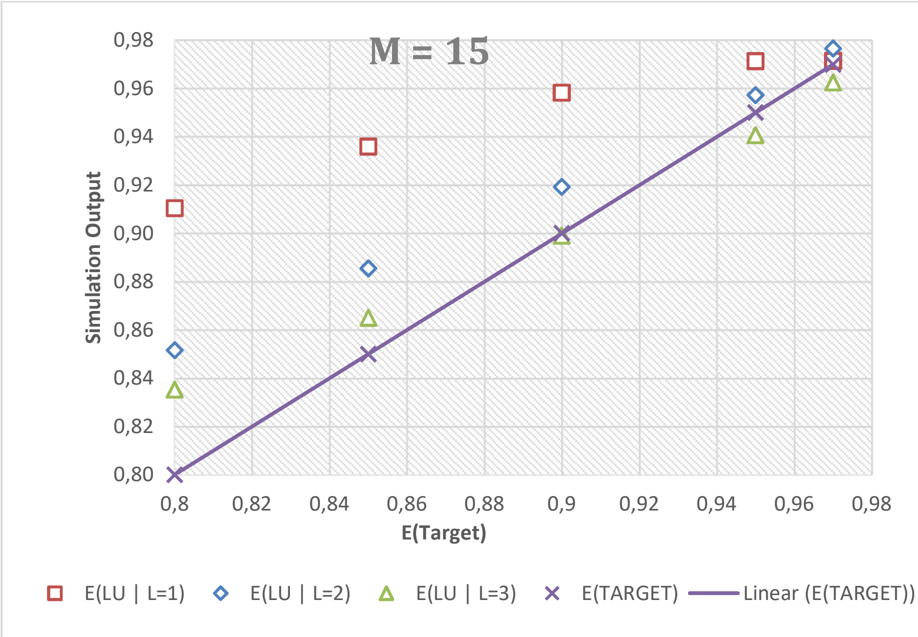


Figure 16: Simulations Results on Operator Influence and M=15

The results for the three-operator case were expectable when looking at Figures 15 and 16, because the three-operator case approaches the case of 0 operators.

We expect that the substantial overestimations for the 1 operator case is due to the increase in CV of downtime CV_{down_i}: one operator results in an increase in var[$WTTR$] and E[WTTR]. However, the impact of the $WTTR$ on the downtime is higher for the variance, var[D], than on the expected downtime, E[D], and thus results in an increased CV_{down_i}

In conclusion, an increase in waiting time, due to less operators, results in a much higher increase in the total variance in downtime var(D) relative to the expected total downtime E(D), which results in much higher CV_{down_i} values.

6.3 Omni-trade Scenario analysis

The use-case is based on the layout of a customer from Bosch. In the manufacturing facility there are six identical long lines of 7 machines and two identical short lines consisting of 3 machines in the hall. In total there are 48 machines in the hall. Furthermore, the first three machines of all lines are identical with machine 2 being the Vertical Packaging machine, combined with the multihead-weigher, the MHW/VVS. We have some data available for this machine, which is almost the same as used "multiple failures" case, although the production rate is adjusted to 70 bags per minute. For the multihead-weigher, there are some estimations about its performance, these estimations are categorized in three categories (worst case, realistic, theoretical). The used machine characteristics as estimated for this use-case by Bosch can be found in Appendix M.

In section 6.1.4 we calculated the aggregate failure data for the worst-case scenario, see Table 7. We followed the same procedure to calculate the "realistic" and 'theoretical"

U_2 and R_2 (explanation can be found in Appendix E). Table 11 and Table 12 show the used distributions for each failure j on machine 2 for the realistic and theoretical case respectively. The aggregate U_2 and R_2 results are shown in Table 13 and will be used as input for the DSS.

	$\boldsymbol{j=1}$	$\boldsymbol{j=2}$	$\boldsymbol{j=3}$	$\boldsymbol{j=4}$	$\boldsymbol{j=5}$	$\boldsymbol{j=6}$
$\boldsymbol{U_{2j}(\mu,\sigma)}$	Cons[277]	Cons[291]	Cons[3962]	Norm[240;24]	Exp[480]	Exp[480]
$\boldsymbol{R_{2j}(\mu,\sigma)}$	Norm[4;0,8]	Norm[4;0,8]	Norm[2;0,4]	Norm[3;0,6]	Norm[5;1]	Norm[2;0,4]

Table 11: Repair and Downtime distributions for the 'realistic' estimations.

J=	$\boldsymbol{j=1}$	$\boldsymbol{j=2}$	$\boldsymbol{j=3}$	$\boldsymbol{j=4}$	$\boldsymbol{j=5}$	$\boldsymbol{j=6}$
$\boldsymbol{U_{2j}(\mu,\sigma)}$	Cons[277]	Cons[291]	Cons[3962]	Norm[120;12]	Exp[480]	Exp[480]
$\boldsymbol{R_{2j}(\mu,\sigma)}$	Norm[3;1]	Norm[3;1]	Norm[2;0,4]	Norm[3;0,6]	Norm[2;1]	Norm[1;0,4]

Table 12: Repair and Downtime distributions for the 'theoretical estimations.

	Worst-Case	Realistic	Theoretical
$\boldsymbol{E(U_2)}$	48,71	66,36	77,20
$\boldsymbol{\sigma_{U_2}}$	40,80	50,78	60,16
$\mathbf{CV}_{\boldsymbol{u_2}}$	0,84	0,77	0,78
$\boldsymbol{E(R_2)}$	4,40	3,56	2,58
$\boldsymbol{\sigma_{R_2}}$	2,33	1,15	0,89
$\boldsymbol{CV_{r_2}}$	0,53	0,32	0,34

Table 13: Aggregate Uptime and Repair time distributions for MHW/VVS

Using the values as showed in Table 13, resulted in a data set 3 as can be found in Appendix L. This is a new data set i.e. newly randomized numbers. This dataset was used in the DSS, buffer sizes were calculated, and simulations were performed for the a 2, 3 and 4 operators pool. 1 Operator was not possible, this resulted in an operator utilization higher than 1.

Again, the total Lean Buffer size $N = \sum_{i=1}^{M-1} N_i$ is calculated with the Local Upperbound approach and simulation was performed to validate the DSS for this Use Case. The results are shown in Table 14.

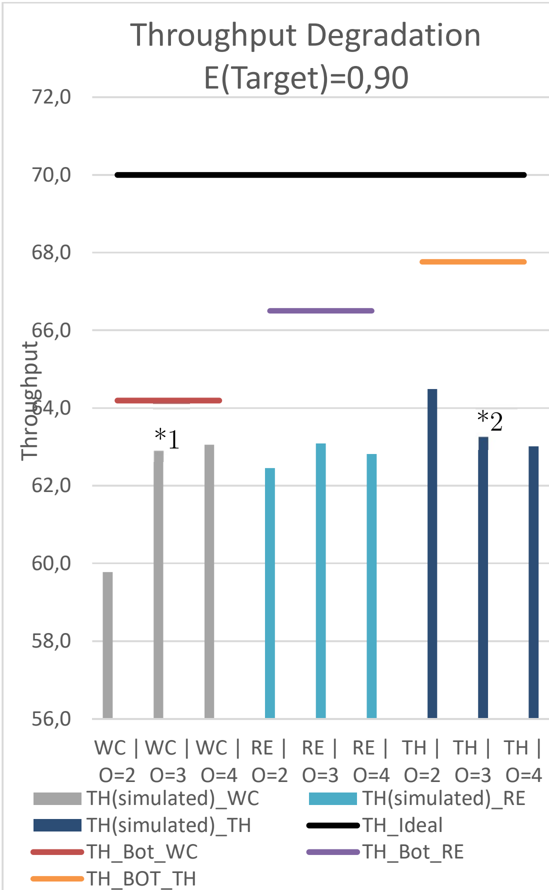
		E_T= 0,9		E_T= 0,95	
Use-Case Scenario:	Number of Operators	E_S	N	E_S	N
Worst Case	L=2	0,931	2459	0,946	5607
	L=3	0,980*1	1912	0,990	4251
	L=4	0,982	1675	0,999	3598*3
Realistic	L=2	0,939	1548	0,967	3700
	L=3	0,949	958	0,989	2361
	L=4	0,945	762	0,986	1829
Theoretical	L=2	0,952	1230	0,975	3215*4
	L=3	0,934*2	680	0,979	1908
	L=4	0,930	514	0,973	1453

Table 14: Total Lean Buffer Size and Simulation Results Omnitrade.

Table 14, shows that the DSS provided safe estimations again. Only one case was marginally too low (Worst Case, E_T =0,95 and L=2). All the other cases performed as expected and exceeded the targeted Efficiency.

More importantly, it shows the impact of the uncertainty of the estimations, i.e. the difference between the three use-cases. For example: in the three-operator case, a possible total buffer size N reduction of up to $\frac{1912-680}{1912} * 100\% = 64\%$ is possible, while still producing around 63 units per minute on average. Figure 17, column *1(worst case) and *2(theoretical) show the realized throughput in simulation, corresponding to the used buffer values as shown in Table 14 (see subscript).

Similarly, for column *3(worst case) and *4(theoretical), in Figure 18 we see that an increase in throughput of 2/bags per minute is possible with a slightly lower total Buffer Size N (see Table 14 last column), and only two operators instead of four.



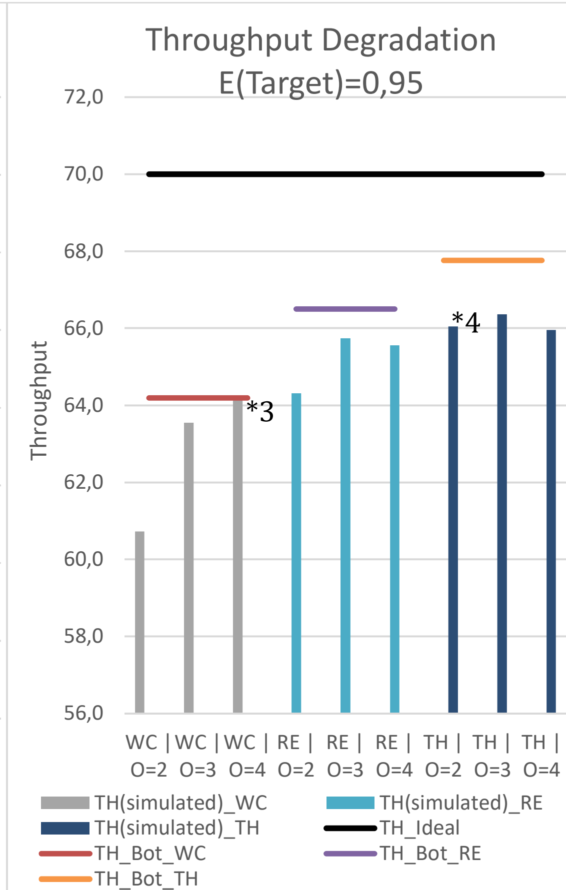


Figure 17: Throughput Degradation of the scenario's, with E_T=0,90

Figure 18: Throughput Degradation of the scenario's, with E_T=0,95

The scenario analysis shows the importance of measuring the failure and repair characteristics on the vertical packer. Even for three estimated cases, which are relatively close to each other, changes in the failure characteristics have sometimes more impact on the required buffer size and Line Efficiency, than the number of operators.

6.4 Summary of Results

We can conclude that the model copes very well with non-identical machines. Of course, our model assumed the machine efficiencies to be within the range of $e_i = unif\{0.950; 0{,}999\}$. Although the difference in efficiencies is rather small, the differences in downtime is large (up to a factor 10), which underlines the potential of the DSS. Furthermore, the assumption on the domain of e_i is defendable by the fact that in practice the efficiency of machines is not much lower than 0,95. And, when efficiency is much lower, this should result in improvement initiatives towards this bottleneck station, instead of focusing on Line Efficiency.

Also, we have seen that the model overestimates the Lean Buffer levels when 1 operator was used for a manufacturing line. We expect that this is a result of an increase in CV of downtime, CV_{down_i}, when working with a few operators. Similarly, when we evaluated the case of multiple unreliable components we found that the model highly overestimated the Lean Buffer Levels, possibly also due to this increase in CV_{down_i},

In conclusion, although in some cases the model tends to overestimate the level of buffer, it still provided a level of buffering "necessary and sufficient" to ensure the desired Line Efficiency of manufacturing line. When the CV_{down_i}, is high due to a low amount of operators we expect that the DSS does not provide the smallest level of buffering but a still feaseable and futher simulation will be necessarry to search for possible buffer size reductions.

Only for long machine lines $M = 15$ machines and a targeted Line Efficiency of $E_T \geq 0{,}95$ a rather small underestimation of $E_T - E_S = 0{,}011$ was found.

*Remark: In this research we used the variance of uptime $\text{var}[U_i]$ as input parameter. However, the buffer size N_i in our model is not dependent on the variance of uptime. We tested some other model which are not included in this thesis who included the CV of uptime CV_{up_i}, therefore this was of importance of the research. Besides that, the information of the variance of the uptime is still needed to use in the discrete event simulation software as a parameter. Also, the models used assume General distributed downtimes but is focused on non-exponential distributed uptimes, therefore it is important to check how big the variance is and if the CV of uptime does not exceed 1 within the scope of this research.

7 Conclusion

This chapter starts with a summary of the findings and results on the research assignment and deliverables (7.1). Then we state the limitations of the research (7.2) and provide recommendations for the use of this model in context of the company problem (7.3). We will end with stating the academic relevance of the research (7.4) and provide suggestions for directions for further research in this area (7.5).

7.1 Research Assignment

The research assignment defined in Section 3.3 was the following:

"Develop a Decision Support System (DSS) to provide the smallest buffer levels necessary and sufficient to ensure the desired Line Efficiency of an unreliable manufacturing line with limited repair capacity."

The research assignment was divided in three objectives to design a suitable DSS. Next, we will discuss each objective.

7.1.1 Deliverable 1

"Define a measure for evaluating the performance of a manufacturing line."

In the literature review on OEE for manufacturing lines, we found that OEE provides a good measure for descriptive statistics of a single machines performance. However, applying the OEE metric on a whole manufacturing line results in complexity due to differing definitions and limitations when calculations. OEEML, an OEE measure specifically designed for manufacturing lines is suggested, although this measure is also best used in a descriptive way (i.e. when a machine line is already producing). For prescriptive use of efficiency measures and to predict the outcome in advance, the complexity must be reduced, and a more general efficiency measure is suggested: Line Efficiency. Line Efficiency is less complex compared to OEEML, while still provides the necessary information regarding the line throughput and to both the machine manufacturing and the customer.

7.1.2 Deliverable 2

"Design a Decision Support System to facilitate new manufacturing lines design with providing Lean Buffer levels"

The Decision Support System uses a combination of theory from Chiang et al. (2008) and Enginarlar et al. (2002) to provide Lean Buffer levels under Line Efficiency constraints for serial manufacturing lines with non-identical unreliable machines. It is chosen to use a Local Upperbound approach for evaluating the buffer size between two non-identical machines. The model is designed to cope with general failure and repair distributions to increase the applicability of the model. Unfortunately, the increase in generality might compromise the accurateness compared to exponential queueing models.

An addition to the model is made to make the model feasible with limited repair capacity due to a pool of operators. These operators are a resource for the repairs of the unreliable machines. For this problem, we wanted to know the expected WTTR and the variation of the WTTR to use for the Lean Level Buffering model. To make estimations for the WTTR, we modelled it as a two-stage cyclic queuing network based on the approximations from Kamath & Sanders (1991). This approximation needs the same input as the Lean Level of Buffering methods and thereby limits the needed data for the DSS.

In conclusion, the DSS inputs are the first and second moment of each machines failure distribution, the lines ideal throughput rate, number of operators and a Line Efficiency target. The output of the decision support systems includes, among other things, the WTTR and most importantly the required buffer sizes necessary and sufficient to ensure the desired Line Efficiency of manufacturing line.

7.1.3 Deliverable 3

"Assess the applicability and validity of such a Decision Support System by a case study at Bosch"

The Decision Support System has some advantages over the simulation software used at Bosch. The DSS:

- Gives directions about the required buffer size.
- Shows the trade-off between the number of operators and required buffer size.
- Is much faster than simulation, due to the closed formula approach. This makes it a usable tool for quick calculations on different scenarios. Which is ideal for decision makers.

The simulations software can provide an estimation on the output of a system with certain manufacturing layout, but does not provide optimization or quick decision support functions. Therefore, it is suggested to use the DSS tool first and then validate with the simulation software, therewith reducing the amount of time spent on simulating unnecessary options.

For the validation of the DSS we recall chapter 8.4 Summary of Results and report that the model:

- Copes very well with non-identical machines with an efficiency $e_i \in \{0.950; 0{,}999\}$
- Tends to overestimate the Lean Buffer levels when the CV_{down_i}, is high. In the cases of 1 operator, or multiple unreliable components.
- Slightly underestimated the Lean Buffer levels only in the case of $M = 15$ and $E \geq 0{,}95$.

7.2 Limitations

Unfortunately, there was limited data available at Bosch. Consequently, we had to make assumption on the failure and repair distributions and we had limited possibilities to validate the DSS.

Aggregating multiple failure/repair distributions resulted in less accurate results. This limits the potential of the study and underlines the importance of measured uptime and downtime values, instead of the currently estimated values.

Another limitation is that the Lean Buffer method only works for serial production lines. Although, these lines are the by far the most common lines in flow lines manufacturing, for the special cases of parallel systems, simulation is advised. The Cyclic Queueing Network is not limited to serial machines and therefore will remain usable.

The most important limitation of the model is that it tends to overestimate the Lean Buffer levels when the CV_{down_i}, is high: occurring with a low level of operators and/or multiple unreliable components on machines.

7.3 Recommendations

The complexity and differing definitions make OEE a complex measure. To cope with this problem, it is recommended to provide good internal education on OEE and other efficiency measures. Internal education to reduce ambiguity, and limit the possibility of providing promises to customers which are not attainable. Be comfortable with your own measures: choose the OEE, following the DIN standard. Use Line Efficiency in addition to the bottlenecks OEE, when expanding to production lines. It recommended to focus on throughput of the bottleneck machine. The bottleneck machine has the largest improvements opportunity.

Standardize the use of OEE for single machines and Line Efficiency for line solutions throughout the organization. After the performance measures are in a standardized format, data from the companies own machines and from suppliers (machines from other manufactures which are in the lines) must be collected and stored in a database. In the current situation for each new project all data is obtained again, which is a waste of time and resources. In the future situation, a database of machines and their efficiencies can support the choice of a certain machine, providing the customers with choices in trade-offs between efficiency and costs. The importance of measure failure data on the machines is substantiated by the results for the Use-case in section 6.3 failure characteristics are more important than the number of operators.

In addition, caution is advised: the DSS provides good initial buffer levels. However, after a combination is chosen it is advised to perform simulation to assure the performance of the production line.

7.4 Academic relevance

This research showed how OEE related efficiency measures should be applied for manufacturing lines. It shows the relation between OEEML and Line Efficiency and provides clear directions to use Line Efficiency as a measure in the Design phase of a manufacturing line.

The DSS based on the rule-based approach of Lean Buffering provides sufficient buffer levels to attain a targeted Line Efficiency. It is shown that for non-identical machines the Local Upperbound method provides fast and accurate results for buffer sizes. Additionally, the Local Upperbound Method applied on non-exponential machines resulted in a sufficient performance.

Our main contribution is closing the Gap for Non-identical and Non-Exponential Lean Buffering approaches.

The addition of limited repair capacity to the Lean Buffering model is academically relevant, since the repair models are, usually, resource dependent in practice. Merely successfully combining these two fields of Lean Buffering and limited repair capacity provides sufficient results to perform more research in this area.

7.5 Suggestions for further research

In further research, the DSS and related Lean Buffering models should be validated with real (measured) data obtained from production lines.

This research primarily validated with normal distributed up and repair times. It is suggested to do more research on applying "Lean Buffering for Non-identical machines with general distributions", by validation of the model with the use of differing distributions in simulations software.

Since this research convolutes that the CV of downtime strongly influences the Lean Buffering, and could lead to strong overestimations. It is suggested to do a profound analysis on the influence of CV_{down_i}, when working general distributions. Eventually, more insights in this topic could be beneficial to the addition of limited repair capacity in the Lean Buffering model.

Although the impact of using time dependent failure models for an operation dependent failure case showed minor difference, future research in adapting the model to cope with operation dependent failures could reduce the level of overestimation of the model, especially useful when machine efficiencies are lower.

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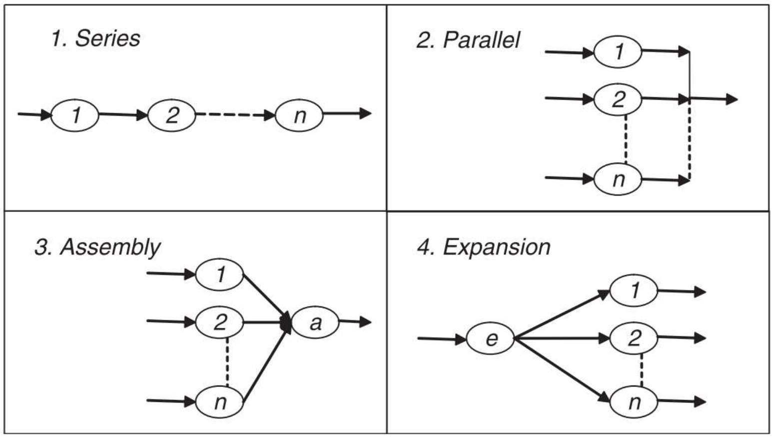
Appendix

Appendix A. List of abbreviations

Abbreviation	Definition
B2B	Business to Business
CV	Coefficient of Variance
DES	Discrete Event Simulations
DIN	Deutsches Institut für Normung
DSS	Decision Support System
EIL	Equipment Independent Losses
GU	Global Upperbound
LB	Lean Buffering
LU	Local Upperbound
MHW/VVS	MultiHead Weigher and Vertical Packer Machine
MTBF	Mean Time Between Failures
MTTF	Mean Time to Failure
MTTR	Mean Time to Repair
ODF	Time-Dependent Failures
OECL	Overall Equipment Cost Loss
OEE	Overall Equipment Efficiency
OEEML	Overall Equipment Effectiveness of a Manufacturing Line
OLE	Overall Line Effectiveness
OTE	Overall Throughput Efficiency
TDF	Operation-Dependent Failures
WIP	Work In Progress
WTTR	Waiting Time to Repair

Appendix B. Figures and Tables

Appendix C. OTE equations



Four subsystems (Muthiah & Huang, 2007)

Subsystem	OTE
Series	$\frac{\min\left\{\min_{i=1,2,\ldots,n-1}\left\{\mathrm{OEE}_{(i)} \times R_{\mathrm{th}(i)} \times \prod_{j=i+1}^{n} Q_{\mathrm{eff}(j)}\right\}, \mathrm{OEE}_{(n)} \times R_{\mathrm{th}(n)}\right\}}{\min_{i=1,2,\ldots,n}\{R_{\mathrm{th}(i)}\}}$
Parallel	$\frac{\sum_{i=1}^{n} (\mathrm{OEE}_{(i)} \times R_{\mathrm{th}(i)})}{\sum_{i=1}^{n} R_{\mathrm{th}(i)}}$
Assembly	$\frac{\min\left\{\min_{i=1,2,\ldots,n}\{\mathrm{OEE}_{(i)} \times (R_{\mathrm{th}(i)}/k_{A(i)}) \times Q_{\mathrm{eff}(a)}\}, R_{\mathrm{th}(a)} \times \mathrm{OEE}_{(a)}\right\}}{\min\left\{\min_{i=1,2,\ldots,n}\{R_{\mathrm{th}(i)}/k_{A(i)}\}, R_{\mathrm{th}(a)}\right\}}$
Expansion	$\frac{\sum_{i=1}^{n} \min\{R_{\mathrm{th}(e)} \times \mathrm{OEE}_{(e)} \times k_{E(i)} \times Q_{\mathrm{eff}(i)}, R_{\mathrm{th}(i)} \times \mathrm{OEE}_{(i)}\}}{\sum_{i=1}^{n} \min\{R_{\mathrm{th}(e)} \times k_{E(i)}, R_{\mathrm{th}(i)}\}}$

OTE calculations of subsystems (Muthiah & Huang, 2007)

And the Bottleneck Indicator as interpreted from Muthiah & Huang (2007). Pick equipment i with the lowest outcome: $B_i = OTE_{(i)} \times R_{th(i)} \times \prod_{j=i+1}^{n} Q_{eff(j)}$

Appendix D. OLE equations

$$OLE = LA \times LPQP$$

with,

$$LA = \ Line\ Availability$$

$$LA = \frac{OT_n}{[LT]}$$

$$OT_n = Operating\ time\ at\ the\ n-\text{th process}$$

$$LT = Line\ Loading\ Time$$

$$LPQP = \ \text{Line Quality and Line Performance}$$

$$LPQP = \frac{(G_n \ \times CYT)}{OT_1}$$

$$CYT = \text{largest bottleneck cycle time}$$

$$OT_1 = \text{Operating time of the first process}$$

$$G_n = \text{the ratio of good products at the } n-\text{th process}$$

OLE provides good results only when it is applied to a continuous production line, however when buffers or decouples are placed between machines, the premise made to evaluate OT_i does not hold anymore (Braglia et al., 2009). For example: when there is a buffer between machine i and downstream station $i+1$, the downstream station $i+1$ can continue producing if machine i is in downtime state. OLE would underestimate the efficiency of the production line due to this missing buffering function (de Groote, 2017)

Appendix E. Approach on Aggregate Uptimes and Repair times

The table as shown beneath is equal to Table 7 in Section 6.1.4 and is showed here just for clarification purposes.

Const: Constant means that the failure occurs at a certain constant operation time, for example a material change (glue or packaging material)

Norm: Normally distributed. For the repairs and for the time between cleaning cycles

Exp: Exponentially distributed for randomly occurring events: for example a product stuck in the mechanism.

	$j = 1$	$j = 2$	$j = 3$	$j = 4$	$j = 5$	$j = 6$
$U_{2j}(\mu, \sigma)$	Cons[277]	Cons[291]	Cons[3962]	Norm[120;12]	Exp[480]	Exp[480]
$R_{2j}(\mu, \sigma)$	Norm[5;1]	Norm[5;1]	Norm[2;0,4]	Norm[3;0,6]	Norm[10;2]	Norm[3;0,6]

$U_2(\mu, \sigma)$:

To reduce the computer processing time, the domain to calculate the $U_2(\mu, \sigma)$:

is set to 100.000 minutes. For each failure j, values up to 100.000 were generated according to their $U_{2j}(\mu, \sigma)$: distributions. For constants, this would result in: 277, 554, … and so on. For other distributions, a new time value was generated and added to the previous summed failure time. Continuing this approach for all j resulted in all failure times within 1.000.000 minutes. Then, we calculated the time between each pair of consecutive failures to determine the aggregated time between failure. This data set was then checked for a mean and a standard deviation.

$R_2(\mu, \sigma)$:

For the $R_2(\mu, \sigma)$:the domain was: 1.000.000 minutes. So, for each failure j we knew the number of failures which would happen within 1.000.000 minutes: $\frac{1.000.000}{U_{2j}(\mu,\sigma)}$. For example: failure number one, $j = 1$, occurs 1000000/277= 3610 times on average. Then we generated 3610 values randomly from the $R_{2,1}(\mu, \sigma)$ distribution, which is normally distributed with a mean of 5 minutes and a standard deviation of 1 minute. We followed this procedure for each j=1, 2, …, 6. This resulted in a set with repair times, which were then checked for a mean and a standard deviation. This way, all the $R_{2,j}(\mu, \sigma)$ are averaged and adjusted for frequency of their occurrence regarding to their respective $U_{2j}(\mu, \sigma)$.

Appendix F. Evaluation on independence assumption for $\boldsymbol{R_i}$ and WTTR

The assumption of independence is not totally true, as machines interact among each other through the pool of operators. However, in our model we take account for that interaction because they interact via the WTTR and thus the mean downtime. Still, we assume this to be limited as isolated efficiencies of the machines are generally high. For more information see Kamath & Sanders (1991, p.102)

Appendix G. Dataset (1): Non-Identical Machines

The domain for the values are chosen to be reasonable within these type of machine environments:

$E[R_i]$ in seconds $\in \{60, 61, \ldots 600\}$

$\sigma_{R_i} = \quad E[R_i] * unif\{0.001; 0.2\}$

$e_i = unif\{0.950; ,999\}$ The efficiency e_i is rounded on 3 decimals.

Then the uptime $E[U_i]$ is calculated from the following relation:

$E[U_i] = e_i * \frac{E[R_i]}{1-e_i}$.

$\sigma_{U_i} = \quad E[U_i] * unif\{0.001; 0.2\}$.

i=	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
$\boldsymbol{e_i}$	0,977	0,972	0,994	0,992	0,971	0,960	0,994	0,976	0,967	0,974	0,967	0,959	0,999	0,971	0,960
$\boldsymbol{E[U_i]}$	23236	16246	40423	36332	12087	11832	17229	19520	8674	17757	7677	9216	359640	9342	2880
$\boldsymbol{\sigma_{U_i}}$	127	274	2135	4856	1217	1805	1739	1514	920	2931	319	1116	18160	1643	329
$\boldsymbol{E[R_i]}$	547	468	244	293	361	493	104	480	296	474	262	394	360	279	120
$\boldsymbol{\sigma_{R_i}}$	72	42	10	47	4	55	4	73	12	22	13	37	25	45	1

Appendix H. Relative Delta (ODF &TDF)

This table shows the results of simulation for a relative delta between the Operation Dependent Failures (ODF) and Time Dependent Failures TDF. The deviation is calculated relative to the Operation Dependent Failure case: $Delta_{rel} = \frac{ODF-TDF}{ODF}$

	ODF	**TDF**	$Delta_{rel}$	**ODF**	**TDF**	$Delta_{rel}$	**ODF**	**TDF**	$Delta_{rel}$
E_T**=0,80**	-	-	-	-	-	-	0,851	0,835	0,019
E_T**=0,85**	-	-	-	0,888	0,879	0,010	0,876	0,865	0,011
E_T**=0,90**	-	-	-	0,916	0,910	0,007	0,906	0,899	0,007
E_T**=0,95**	0,956	0,954	0,002	0,954	0,952	0,002	0,942	0,939	0,003
E_T**=0,97**	0,971	0,971	0,001	0,979	0,978	0,001	0,962	0,961	0,001

Appendix I. Results for Non-Identical Machines

Data from the DSS and simulation software, this data is plotted in the graphs for the sensitivity analysis in Section 6.2.1. The results for different line lengths are shown in the tables beneath for respectively $M = 5, 10$ & 15. The Local Upperbound approach is used

M = 5			
$\boldsymbol{E_T}$	0,95	0,96	0,97
$\boldsymbol{E_S}$	0,954	0,961	0,971
Difference: $\boldsymbol{E_S}$ - $\boldsymbol{E_T}$	0,004	0,001	0,001

M = 10				
$\boldsymbol{E_T}$	0,85	0,9	0,95	0,97
$\boldsymbol{E_S}$	0,879	0,910	0,952	0,978
Difference: $\boldsymbol{E_S}$- $\boldsymbol{E_T}$	0,029	0,010	0,002	0,008

M = 15					
$\boldsymbol{E_T}$	0,8	0,85	0,9	0,95	0,97
$\boldsymbol{E_S}$	0,835	0,865	0,899	0,939	0,961
Difference: $\boldsymbol{E_S}$- $\boldsymbol{E_T}$	0,035	0,015	-0,001	-0,011	-0,009

Appendix J. Operator Influence for E(target) = 0,95

Total Buffer Levels N and first two moments of the waiting time to repair for differing number operators and line lengths.

M = 5	$\mathrm{E}[WTTR]$	σ_{WTTR}	N
$L = 0$	0	0	566
$L = 1$	15,79	46,18	878
$L = 2$	0,23	3,83	569

M = 10	$\mathrm{E}[WTTR]$	σ_{WTTR}	N
$L = 0$	0,00	0,00	2865
$L = 1$	48,48	96,98	10605
$L = 2$	2,18	17,18	3280
$L = 3$	0,08	2,61	2868

M = 15	$\mathrm{E}[WTTR]$	σ_{WTTR}	N
$L = 0$	0	0	4909
$L = 1$	83,31	119,50	22532
$L = 2$	5,63	27,74	6989
$L = 3$	0,37	6,03	4969
$L = 4$	0,02	6.03	4910

Appendix K. Data Set (2): Multiple Failures on Machine 2

This dataset is the dataset used for section 6.1.4, where machine 2 is subject to multiple unreliable components.

i=	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
$\boldsymbol{e_i}$	0,977	0,917	0,994	0,992	0,971	0,960	0,994	0,976	0,967	0,974	0,967	0,959	0,999	0,971	0,960
$\boldsymbol{E}[\boldsymbol{U_i}]$	23236	2922	40423	36332	12087	11832	17229	19520	8674	17757	7677	9216	359640	9342	2880
$\boldsymbol{\sigma_{U_i}}$	127	2449	2135	4856	1217	1805	1739	1514	920	2931	319	1116	18160	1643	329
$\boldsymbol{E}[\boldsymbol{R_i}]$	547	264	244	293	361	493	104	480	296	474	262	394	360	279	120
$\boldsymbol{\sigma_{R_i}}$	72	140	10	47	4	55	4	73	12	22	13	37	25	45	1

Appendix L. Data Set (3): Use-Case

For the use case, we have six identical 7-machine lines and there are two identical 3-machine lines which consists of the same first three machines as the 7-machine line. The six long machine lines account for machine 1 to 42. And the two short lines are machine 43 to 48. In total, there are 48 unreliable machines in this system. The table below shows all machine numbers and their corresponding failure and repair data in seconds, used in our simulations.

	Machine number i						
Machine line 1	1	2	3	4	5	6	7
Machine line 2	8	9	10	11	12	13	14
Machine line 3	15	16	17	18	19	20	21
Machine line 4	22	23	24	25	26	27	28
Machine line 5	29	30	31	32	33	34	35
Machine line 6	36	37	38	39	40	41	42
Machine line 7	43	44	45				
Machine line 8	46	47	48				
Efficiency Ei	0,971	0,949	0,981	0,984	0,994	0,986	0,966
MTBF	11719	3981	22615	21894	54836	7747	15428
Sigma MTBF	1349	3047	3659	2388	221	177	3009
MTTR	350	214	438	356	331	110	543
Sigma MTTR	33	69	70	16	4	19	59

The third column, representing the second machine in each line is the column of interest. There we change the values for three cases: Worst-case, realistic and theoretical. Changed according to the values obtained in the aggregation procedure. Similar to the data in Table 13 in chapter 6.3 we show it in seconds in the table on the next page:

	Worst-Case	Realistic	Theoretical
$\boldsymbol{e_2}$	0,917	0,949	0,968
$\boldsymbol{E}(\boldsymbol{U_2})$	2922	3981	4632
$\boldsymbol{\sigma_{U_2}}$	2449	3047	3610
$\boldsymbol{E}(\boldsymbol{R_2})$	264	214	155
$\boldsymbol{\sigma_{R_2}}$	140	69	53

Appendix M. Vertical Packer and Multihead-weigher OEE information

Subsystem: MHW / VFFS		Worse Case	Realistic	Theoretical
Working time				
Shifts / day	[#]	3,00	3,00	3,00
Working days / week	[#]	7,00	7,00	7,00
Machine working time for 1 shift = measuring interval	[hours]	8,00	8,00	8,00
Production Parameters				
Output: Set Performance (Realised Value)	[bpm]	70,00	70,00	70,00
Draw off length (for Filmreel and Zipreel)	[mm]	160,00	160,00	160,00
Filmreel content	[m]	3100,00	3100,00	3100,00
Zipreel content	[m]	3250,00	3250,00	3250,00
TTO printreel content	[m]	5000,00	5000,00	5000,00
TTO print height	[mm]	20,00	20,00	20,00
Filmreel run time	[min]	276,79	276,79	276,79
Zipreel run time	[min]	290,18	290,18	290,18
Printreel run time	[min]	3571,43	3571,43	3571,43
Planned Downtime (per 8 hour shift)				
Filmreel changeover time / filmreel	[min]	5,00	4,00	3,00
Zipreel changeover time / zipreel	[min]	5,00	4,00	3,00
TTO printlint changeover time /printlint	[min]	2,00	2,00	2,00
Cleaning time / cleaning cycle	[min]	3,00		
Cleaning cycles per shift	[n]	4,00	3,00	3,00
Unplanned Downtime (per 8 hour shift)			2,00	1,00
Product between cross jaws	[min]	3,00	2,00	1,00
Product blocking in funnel	[min]	10,00	5,00	2,00

Appendix N. Model Parameters

List of model parameters, which are inputs/decision variables or output of the model.

Description	parameter	Type
Number of Operators	$\boldsymbol{L}$	Decision Variable
Line Efficiency	$\boldsymbol{E}$	Decision Variable
Number of Serial Machines in the packaging lines	$\boldsymbol{M1}$	Input
Number of Machines under responsibility of the operator pool	$\boldsymbol{M2}$	Input
Expected Repair time for machine $\boldsymbol{i}$	$\boldsymbol{E(R_i)}$	Input
Expected Uptime for machine $\boldsymbol{i}$	$\boldsymbol{E(U_i)}$	Input
Variance Repair time for machine $\boldsymbol{i}$	$\mathbf{var}(\boldsymbol{R_i})$	Input
Variance Uptime for machine $\boldsymbol{i}$	$\mathbf{var}(\boldsymbol{U_i})$	Input
Production speed. Equals the Throughput rate of the Theoretical Bottleneck.	$\boldsymbol{TH_{TBN}}$	Input
Expected Buffer Capacity for buffer $\boldsymbol{i}$	$\boldsymbol{N_i}$	Output

In the thesis M is used for both M1 and M2 to increase readability. However, there is a difference between M1 and M2. The DSS supports up to 60 machines for the cyclic queueing network to calculate the WTTR, which is represented by M2. For buffer sizes the DSS supports up to 15 machines, equivalent to 14 buffer places, represented by M1.

Appendix O. Calculating variables

List of variables which are calculated within cyclic queueing network model:

Description	Parameter
Expected Mean Waiting Time to Repair	$E[WTTR]$
Expected Mean Waiting Time to Repair of the previous iteration	$E(WTTR)^{old}$
Variance Waiting Time to Repair	$\mathrm{var}[WTTR]$
Aggregate Mean repair time	$E(R)$
Aggregate Mean down time	$E(D)$
Probability that machine i is down	Pd_i
Probability of a failure on machine i	Pf_i
probability that a repair activity (given a repair activity takes place) takes place on machine i	ω_i
expected number of machines in down state	$E[K]$
expected number of failed machines waiting for operators. (queue length)	$E[K_q]$
Second moment of $E[K_q]$.	$E(K_q^2)$
Mean arrival rate of failed machines to the queue of operators	v_{eff}
Long Run Operator Busy time	$E[O]$

With

$$E[O] = \frac{1}{L}\sum_{i=1}^{M}\frac{E[R]}{E[Ui] + E[D]}$$

List of variables which are calculated within Lean Buffering Model

Description	Parameter
Production Speed	TH_{TBN}
Downtime in produced units (cycles)	T_{down_i}
Uptime in produced units (cycles)	T_{up_i}
Standard deviation of the downtime in produced units (cycles)	$\sigma_{T_{down_i}}$
Standard deviation of the uptime in produced units (cycles)	$\sigma_{T_{up_i}}$
Coefficient of variation of the downtime	CV_{down_i}
Coefficient of variation of the uptime	CV_{up_i}
Throughput rate at the end of line with a normalized buffer capacity equal to k	TH_k
level of buffering = capacity of a buffer capable of storing products during k downtimes.	k
Lean Buffer level (LB)	k_E
Lean Buffer level (LB) when uptime/downtime is assumed to be exponential	k_E^{exp}
Machine efficiencies	e_i
Global Upperbound of machine efficiencies	$\hat{e}$
Local Upperbound of machine efficiencies	$\hat{e}_i$
Line Efficiency	E
Targeted Line Efficiency	E_T
Line Efficiency as outcome from Simulation	E_S

Appendix P. DSS overview

The Excel file has a dashboard page.

The first picture shows the Input Boxes, where the correct parameters must be filled in. The Output box, where all necessary output needed is showed. Clicking the blue button runs the VBA script (Main algorithm).

Input			
	Scientific Notation		
Line Efficiency Requirement	E	85%	
Bags per minute	TH(ideal)	120	
Nr. Serial Machines	M1	15	(Max 15)
Nr. Total Machines	M2	15	(Max 60)
Nr. Operators	m	2	
Delta	deltaei	0,0000001	

Update Downtime and Effiencys.

Output		
Total Buffer Space (Local Upperbound)	[products]	2731
Expected Mean Waiting Time	EWTTR [seconds]	5,43
Sigma Mean waiting time	SQRT(WTTR) [secon	27,25
Aantal iteraties		4
Expected MTTR	ER [seconds]	359,6
Expected Mean downtime	ED [seconds]	365,0
Expected mean number of failed machines	EK	0,4
Expected Long run operator busy time	EO	0,22
Line Efficiency Without buffers		71,33%
Bottleneck machine efficiency	ei	0,958
Bottleneck efficieny excl operators	ei	0,959
Steady state production rate	Lampda	97,743

The second picture shows where all machines (up to 60) failure characteristics must be filled in (Repair time, uptime and deviations must be filled in as well. This is also done on the dashboard page). Below, the calculated buffer size for each buffer place is shown.

	(Machines fo which buffers need to be calculated. Maximum number of machines =15)														
	Machine 1	Machine 2	Machine 3	Machine 4	Machine 5	Machine 6	Machine 7	Machine 8	Machine 9	Machine 10	Machine 11	Machine 12	Machine 13	Machine 14	Machine 15
E(Ui)	23236	16246	40423	36332	12087	11832	17229	19520	8674	17757	7677	9216	359640	9342	2880
Sigma E(Ui)	127	274	2135	4856	1217	1805	1739	1514	920	2931	319	1116	18160	1643	329
E(Ri)	547	468	244	293	361	493	104	480	296	474	262	394	360	279	120
Sigma E(Ri)	72	42	10	47	4	55	4	73	12	22	13	37	25	45	1

Buffer size for buffers Ni required to obtain line effiency E

Buffer 1	Buffer 2	Buffer 3	Buffer 4	Buffer 5	Buffer 6	Buffer 7	Buffer 8	Buffer 9	Buffer 10	Buffer 11	Buffer 12	Buffer 13	Buffer 14
199	143	0	179	217	444	264	237	144	165	166	166	183	224

A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q
	Scientific Notation															
	MachineNr. (J)	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
In seconds	Mu up	23236	16246	40423	36332	12087	11832	17229	19520	8674	17757	7677	9216	359640	9342	2880
	Sigma up	127	274	2135	4856	1217	1805	1739	1514	920	2931	319	1116	18160	1643	329
	Mu down	547	468	244	293	361	493	104	480	296	474	262	394	360	279	120
	Sigma Down	72	42	10	47	4	55	4	73	12	22	13	37	25	45	1
In cycles	Expected (MTTR+WTTR) in cycle	1104,86	946,861	498,861	596,861	732,861	996,861	218,861	970,861	602,861	958,861	534,861	798,861	730,861	568,861	250,861
	Sigma (MTTR+WTTR) in cycles	153,966	100,128	58,0476	108,653	55,0774	122,758	55,0774	155,838	59,5443	70,0394	60,3781	91,8995	73,9562	105,212	54,53
	$\hat{e}$i	0,97678	0,97168	0,99387	0,99185	0,97058	0,95958	0,99369	0,97574	0,96642	0,97371	0,96634	0,95846	0,99898	0,97045	0,95827
	ei	0,977	0,972	0,994	0,992	0,971	0,96	0,994	0,976	0,967	0,974	0,967	0,959	0,999	0,971	0,96
	CV up	0,00547	0,01687	0,05282	0,13366	0,10069	0,15255	0,10093	0,07756	0,10606	0,16506	0,04155	0,12109	0,05049	0,17587	0,11424
	CV down	0,13935	0,10575	0,11636	0,18204	0,07515	0,12314	0,25165	0,16052	0,09877	0,07304	0,11289	0,11504	0,10119	0,18495	0,21737

Min $\hat{e}$	0,9583	<Bottlenceck efficiency including operators
Min (ei)	0,9590	<Bottlenceck efficiency excluding operators

minei	0,97168	0,97168	0,99185	0,97058	0,95958	0,95958	0,97574	0,96642	0,96642	0,96634	0,95846	0,95846	0,97045	0,95827
minri	0,00091	0,00106	0,00168	0,00136	0,001	0,001	0,00103	0,00103	0,00104	0,00104	0,00125	0,00125	0,00137	0,00176
Qi	0,13786	0,13786	0,14055	0,13772	0,13641	0,13641	0,13837	0,13721	0,13721	0,1372	0,13628	0,13628	0,13771	0,13626
Local upperbound approach	199	143	-60	179	217	444	264	237	144	165	166	166	183	224

From Dashboard		
Input	Notation	Value
Line Efficiency requirement	E	85%
Bags per minute	TH	120
Steady state production rate	Lampda	97,7431
Nr. Serial Machines	M1	15
Nr. Total Machines	M2	15
Nr. Operators	L	2
Delta	deltaei	1E-07

Calculated WTTR Variables		
Expected Mean Interference time		5,43061
Variance Interference Time		742,38
Aantal iteraties		4
Expected Repair time		359,588
Maximum Repairtime		547
Expected Mean downtime		365,019
Expected number of failed machines		0,36678
Expected Long run operator busy time		0,22155
Line Efficiency Without buffers		0,71332
Bottleneck machine efficiency	ei	0,9583
Bottleneck efficieny excl operato	ei (operato	0,9590
Steady state production rate		97,7431

Appendix Q. Cyclic Queueing Network Algorithm

The algorithm of the Operator Interference Model is applied in VBA and can be found in Appendix U. It also uses the calculations as shown in Appendix R, Appendix S and Appendix T, where, respectively, formulas for different clear times and some general efficiency calculations are applied. The main algorithm is simplified to:

```
{Input}
input(L);                                    {No. of operators}
input(M);                                    {No. of machines}
for i = 1 to M
        input (E(U_i));
        input (Sigma E(U_i));
        input (E(R_i));
        input (Sigma E(U_i));
input (ε);                                   {stop criterium}
{initialize} E(I) = 0;
Calculate aggregate E(R)= Weighted sum of E(R_i) for all i

{Main Loop}
Repeat
E(WTTR)^old = E(WTTR);     E(D) = E(R) + E(WTTR)
begin
for i = 1 to M do
        Pd_j = E(D) / (E(U_i)+E(D));
for k = 1 to M do
        calculate pd_k using the recursive relationships;
E(K) = 0;
for i = 1 to M do
        E(K) = E(K)+ P_i
E(K_q) = 0;
for k = L + 1 to M do
        E(K_q) = E(K_q) + (k − L)p_k
        E(WTTR)= E(K_q)E(R) / (E(K)−E(K_q))
Until abs(E(WTTR)^old−E(WTTR)) / E(WTTR) < ε;
{calculate var(WTTR)}
        E(K_q^2) = 0;
For k=L+2 to J do
        E(K_q^2) = E(K_q^2) + (k − L)(K − L − 1)p_k
        Var(WTTR) = E(K_q^2)(E(R))^2 / (E(K)−E(K_q))^2 − [E(WTTR)]^2
```

Appendix R. Recursive Relations VBA code

```
Sub RecursiveRelations(M2)
ActiveWorkbook.Worksheets("Recursive Calculations").Select
Dim k As Double
Dim i As Double
Dim pki As Double
'Start
k = 0
i = 1

'For P0(i) Equation(11)
Do While i <= M2
    pki = (1 - ActiveWorkbook.Worksheets("Recursive Calculations").Cells(3 + i, 3).Value) *
ActiveWorkbook.Worksheets("Recursive Calculations").Cells(3 + i - 1, 4 + k).Value
    Cells(3 + i, 4 + k).Value = pki
    i = i + 1
Loop
k = 1
'For pk(i) Equation(12)
Do While k <= M2 - 1
    i = 1
    Do While i <= M2
    pki = (1 - Cells(3 + i, 3).Value) * Cells(3 + i - 1, 4 + k).Value + Cells(3 + i, 3).Value * Cells(3 + i
- 1, 4 + k - 1).Value
    Cells(3 + i, 4 + k).Value = pki
    i = i + 1
    Loop
k = k + 1
Loop
i = 1
'For pk(i)=Pi(i)Equation(13)
Do While i <= M2
    If (k = i) Then
    pki = Cells(3 + i, 3).Value * Cells(3 + i - 1, 4 + i - 1).Value
    Cells(3 + i, 4 + k).Value = pki
    Else
    Cells(3 + i, 4 + k).Value = 0
    End If
i = i + 1
Loop
End Sub
```

Appendix S. Expected Mean Repair Time VBA code

```
Sub ExpectedMeanRepairTime(M2)
Dim wi As Double
Dim pfi As Double
Dim sumpf As Double
Dim ER As Double
i = 1
    Do While i <= M2 'Equation 17
        pfi = (ActiveWorkbook.Worksheets("Inc Operators").Cells(5, 2 + i).Value) /
(ActiveWorkbook.Worksheets("Inc Operators").Cells(3, 2 + i).Value +
ActiveWorkbook.Worksheets("Inc Operators").Cells(5, 2 + i).Value)
        ActiveWorkbook.Worksheets("Recursive Calculations").Cells(3 + i, 67).Value = pfi
        sumpf = sumpf + pfi
        i = i + 1
    Loop
i = 1
    Do While i <= M2 'Equation 16
        ActiveWorkbook.Worksheets("Recursive Calculations").Cells(3 + i, 68).Value =
ActiveWorkbook.Worksheets("Recursive Calculations").Cells(3 + i, 67).Value / sumpf
        i = i + 1
    Loop
i = 1
    Do While i <= M2 'Equation 15
        ER = ER + ActiveWorkbook.Worksheets("Inc Operators").Cells(5, 2 + i).Value *
ActiveWorkbook.Worksheets("Recursive Calculations").Cells(3 + i, 68).Value
        i = i + 1
    Loop
    ActiveWorkbook.Worksheets("Inc Operators").Cells(39, 4).Value = ER
End Sub
```

Appendix T. Efficiency calculations VBA code

```
Sub MinimumEfficiency()
Dim BotEffIncOperator As Double
Dim BotEffExcOperator As Double
Dim LineEffWithoutBuffers As Double
Dim LineEfficiencyRequirement As Double
Dim i As Integer
ActiveWorkbook.Worksheets("Inc Operators").Select
'This Module calculates the efficiencys and throws an error when no buffers are needed

i = 1
M1 = ActiveWorkbook.Worksheets("Inc Operators").Cells(30, 4).Value
LineEfficiencyRequirement = ActiveWorkbook.Worksheets("Inc Operators").Cells(27, 4).Value

'Effiencys
BotEffIncOperator = Application.WorksheetFunction.Min(Range(Cells(9, 2 + i), Cells(9, 2 + M1)))
BotEffExcOperator = Application.WorksheetFunction.Min(Range(Cells(10, 2 + i), Cells(10, 2 + M1)))
Cells(15, 3).Value = BotEffIncOperator
Cells(16, 3).Value = BotEffExcOperator

'Line Efficiency Without buffers including operators
LineEffWithoutBuffers = Application.WorksheetFunction.Product(Range(Cells(9, 2 + i), Cells(9, 2 +
M1))) / BotEffExcOperator
Cells(44, 4).Value = LineEffWithoutBuffers

'throw error when No buffers are needed
If (LineEffWithoutBuffers >= LineEfficiencyRequirement) Then
MsgBox ("No Buffers Needed, Line Efficiency without buffer can go up-to: " & LineEffWithoutBuffers)
End If

ActiveWorkbook.Worksheets("Dashboard").Select
End Sub
```

Appendix U. Main CQN algorithm VBA code

```
Sub Algorithm1()
Application.ScreenUpdating = False
'Variables
Dim L As Double 'No. Repairman
Dim i As Double 'No. Machine
Dim ER As Double 'No. Mean repair time
Dim EWTTR As Double 'Expected Mean Waiting Time To Repair
Dim VWTTR As Double 'Variance Interference Time
Dim ED As Double 'Expected Mean total downtime
Dim EWTTR_old As Double 'Expected Mean Waiting time from previous loop
Dim EK As Double 'Expected number of failed machines
Dim dummieloopvariabele As Double 'MainLoop variable
Dim EKq2 As Double 'Number of failed machines waiting for operators Second moment
Dim EKq As Double 'Number of failed machines waiting for operators First moment
Dim EO As Double 'Long run operator busy time
Dim Epsilon As Double 'Stop Criterium
Dim M2 As Double 'Number of total machines

'Start
ActiveWorkbook.Worksheets("Recursive calculations").Range("C4:BN63").ClearContents
ActiveWorkbook.Worksheets("Inc Operators").Select
Range("D36:D44").ClearContents

'Inputvariables
L = ActiveWorkbook.Worksheets("Inc Operators").Cells(32, 4).Value
M2 = ActiveWorkbook.Worksheets("Inc Operators").Cells(31, 4).Value
M1 = ActiveWorkbook.Worksheets("Inc Operators").Cells(30, 4).Value
i = 1
Epsilon = ActiveWorkbook.Worksheets("Inc Operators").Cells(33, 4).Value

'Initialize
EWTTR = 0
ActiveWorkbook.Worksheets("Inc Operators").Cells(38, 4).Value = 0
ActiveWorkbook.Worksheets("Inc Operators").Cells(40, 4).Value =
Application.WorksheetFunction.Max(Range(Cells(5, 2 + i), Cells(5, 2 + M2))) 'returns maximum repair
time

'Initialize MeanExpectedRepairTime
Call ExpectedMeanRepairTime(M2)
ER = ActiveWorkbook.Worksheets("Inc Operators").Cells(39, 4).Value


'Main loop Repeats until delta is achieved
'Begin
Do While dummieloopvariabele < 1
'Pick right E(C)
```

```
    EWTTR_old = EWTTR
    ED = ER + EWTTR
    If (ActiveWorkbook.Worksheets("Inc Operators").Cells(32, 4).Value < 1) Then
        Call MinimumEfficiency
        Exit Sub
    ElseIf (ActiveWorkbook.Worksheets("Inc Operators").Cells(31, 4).Value -
ActiveWorkbook.Worksheets("Inc Operators").Cells(32, 4).Value <= 2) Then
        MsgBox ("To many operators") 'For the variance(k = L + 2)
        ActiveWorkbook.Worksheets("Dashboard").Select
        Application.ScreenUpdating = True
        Exit Sub
    End If

    'begin
    i = 1
    Do While i <= M2 'Equation 9
        ActiveWorkbook.Worksheets("Recursive Calculations").Cells(3 + i, 3).Value = (EWTTR +
ActiveWorkbook.Worksheets("Inc Operators").Cells(5, 2 + i).Value) /
(ActiveWorkbook.Worksheets("Inc Operators").Cells(3, 2 + i).Value + EWTTR +
ActiveWorkbook.Worksheets("Inc Operators").Cells(5, 2 + i).Value)
        i = i + 1
    Loop
    'calculate pk using the recursive relationships: Equations (11-13)
    Call RecursiveRelations(M2)
    EK = 0
    i = 1
    'Calculate Expected number of failed machines Equation(10)
    Do While i <= M2
        EK = EK + ActiveWorkbook.Worksheets("Recursive Calculations").Cells(3 + i, 3).Value
        i = i + 1
    Loop

    'Calculate long run operator busy time
    i = 1
    EO = 0
    Do While i <= M2
        EO = EO + (1 / L) * (ER / (ActiveWorkbook.Worksheets("Inc Operators").Cells(3, 2 + i).Value
+ ED))
        i = i + 1
    Loop
    If EO >= 1 Then
        MsgBox ("Operator utilizization is higher then one. Please increase the number of operator")
        ActiveWorkbook.Worksheets("Inc Operators").Cells(43, 4).Value = EO
        ActiveWorkbook.Worksheets("Dashboard").Select
        Application.ScreenUpdating = True
        Exit Sub
    End If
```

```
    'Part for EKq Equatuation(14)
    EKq = 0
    k = L + 1
    Do While k <= M2
        EKq = EKq + (k - L) * ActiveWorkbook.Worksheets("Recursive Calculations").Cells(3 + M2, 4
+ k).Value
        k = k + 1
    Loop
    EWTTR = EKq * ER / (EK - EKq) 'Equations(18)&(19)
    'stop criterium for main loop
    If (Abs(EWTTR_old - EWTTR) / EWTTR) < Epsilon Then 'Equation(23)
        dummieloopvariabele = 1
    End If
    ActiveWorkbook.Worksheets("Inc Operators").Cells(38, 4).Value = ActiveWorkbook.Worksheets("Inc
Operators").Cells(38, 4).Value + 1 'Counter for iterations
Loop
ActiveWorkbook.Worksheets("Inc Operators").Cells(36, 4).Value = EWTTR

'Calculate second factorial moment of the queue length
EKq2 = 0
k = L + 2
Do While k < M2 'Equation(20
    EKq2 = EKq2 + (k - L) * (k - L - 1) * ActiveWorkbook.Worksheets("Recursive
Calculations").Cells(3 + M2, 4 + k).Value
    k = k + 1
Loop
'calculate the variance Equation(22)
VWTTR = ((EKq2) * (ER ^ 2)) / ((EK - EKq) ^ 2) - EWTTR ^ 2

'Write Variables to excel
ActiveWorkbook.Worksheets("Inc Operators").Cells(43, 4).Value = EO
ActiveWorkbook.Worksheets("Inc Operators").Cells(37, 4).Value = VWTTR
ActiveWorkbook.Worksheets("Inc Operators").Cells(41, 4).Value = ED
ActiveWorkbook.Worksheets("Inc Operators").Cells(42, 4).Value = EK
'Calculates efficiencys for buffersizecalculations
Call MinimumEfficiency
'Finish
Application.ScreenUpdating = True
ActiveWorkbook.Worksheets("Dashboard").Select
End Sub
```