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IMPROVING PAPER MACHINE CLOTHING SUPPLIER'S INDUSTRIAL INTERNET OFFERING WITH ARTIFICIAL INTELLIGENCE

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ABSTRACT

Lasse Janhunen: Improving paper machine clothing supplier’s industrial internet offering with artificial intelligence
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Overall amount of data has grown exponentially during the last few years. The increase in the availability of data has driven companies and countries towards digitalization with growing pace. Therefore, the industrial internet applications have become more successful than ever. These applications provide companies more tools to utilize data-driven decisions. In paper industry, paper machine original equipment manufacturers have started to utilize the industrial internet capabilities with increasing pace. The increasing competition has led to the fact that today, utilization of the possibilities offered by industrial internet is part of target organization’s (Valmet) main strategies. Thus, the paper machine clothing (PMC) unit of Valmet has commissioned this thesis work.

The goal of this research was to improve Valmet’s PMC unit’s industrial internet offering. Improvement actions taken were to enhance the existing offering through customer feedback and to provide additional value with artificial intelligence. The approach towards the subject was to find out the existing theory behind the operational context of the fabrics, discover possible developmental actions through prototyping and by creating value-adding AI models to support the offering.

During this research process it came evidently clear that the initial industrial internet applications would have good applicability in pilot customer’s daily routines. Though good developmental points were discovered from the prototyping phase, the functionality issues of the initial industrial internet applications during the timeframe of this thesis limited the quality of the feedback. More thorough study for customer feedback should be conducted after the applications have been in daily use for solid amount of time.

This research provided two value-adding models for industrial internet applications. The idea for the models sprung from the hopes of the target company. Initially, fabric delivery cycles have been defined more or less by hand. Thus, the Monte Carlo simulation to optimize delivery cycles and to manage risk governing possible shortages was illustrated as the first model. The second model aimed to enhance the first model by conducting estimations of remaining fabric lifetime from customer’s mill’s process data. Neural network was chosen as the machine learning method for this model. Both models were tested with actual process data and the results of the case study were polarized. The simulation model provided valid results and first indications showed that it would bring true added value to the target organization. However, the results of the second model indicated that with available data valid results were not acquired. The results of this study indicate that the artificial intelligence models can be utilized to fabrics industrial internet but more emphasis should be pointed on the comparison of different machine learning methods and to enhance the quality and quantity of the available data.

Keywords: Paper machine clothing, Industrial internet, Artificial intelligence, Monte Carlo simulation, Reliability

TIIVISTELMÄ

Lasse Janhunen: Paperikonekudostoimittajan teollisen internetin tarjooman kehittäminen tekoälyn avulla
Diplomityö
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Olemassa olevan datan määrä on kasvanut eksponentiaalisesti viime vuosina. Datan saatavuuden kasvu on ajanut yhtiöitä ja valtioita kohti digitalisaatiota kasvavalla tahdilla. Tästä syystä teollisen internetin sovellukset ovat suositumpia kuin koskaan. Teollisen internetin sovellukset tarjoavat enemmän työkaluja datapohjaiseen päätöksentekoon. Paperikoneteollisuudessa laitetoimittajat ovat alkaneet hyödyntämään teollisen internetin mahdollisuuksia kiihtyvällä tahdilla. Tämä on johtanut esimerkiksi siihen, että nykyään teollisen internetin mahdollisuuksien hyödyntäminen on osa kohdeyrityksen (Valmet) strategiaa. Strategian painopisteen myötä paperikonekudosyksikkö (PMC) antoi toimeksiannon tälle diplomityölle.

Tutkimuksen tavoitteena on kehittää Valmetin paperikonekudosyksikön teollisen internetin tarjoomaa. Kehitysaskeleet koskivat lisäarvon tuottamista tarjoomaan asiakaspalautteen sekä tekoälysovellusten kautta. Aihetta lähestyttiin keräämällä vallitseva teoria paperikonekudosten toiminnallisuudesta, etsimällä kehityskohteita pilotoinnista asiakkaan kanssa sekä luomalla lisäarvoa tuovia sovelluksia teollisen internetin tarjooman tueksi.

Teollisen internetin tarjooman sovellusten mahdollinen lisäarvo asiakkaiden päivittäiseen toimintaan tuli selväksi tutkimusprosessin aikana. Keskustelut pilottiasiakkaan kanssa tuottivat monia kehityskohteita, mutta alkuperäisen tarjooman ongelmat kuitenkin rajoittivat asiakaspalautteen laatua. Syvempi tutkimus olisi hyvä toteuttaa sen jälkeen, kun sovellukset ovat olleet päivittäisessä käytössä riittävästi.

Diplomityössä löydettiin kaksi lisäarvoa tuottavaa tekoälymallia teollisen internetin sovelluksille. Alkuidea mallien luonnille lähti kohdeyrityksen toiveista. On tavallista, että kudosten toimitussyklit määritellään manuaalisesti. Tästä syystä ensimmäiseksi malliksi muodostui toimitussyklien optimoimiseksi sekä sitä ympäröivän riskin hallitsemiseksi Monte Carlo -simulaatiomalli. Toisen tekoälymallin tehtävänä oli tukea ensimmäistä mallia suorittamalla paperikonekudoksen jäljellä olevan eliniän ennustuksia prosessidatan avulla. Koneoppimismalliksi tälle mallille valikoitui neuroverkko. Molempien mallien toimivuus testattiin todellisen prosessidatan avulla ja testien tulokset olivat kahtiajakoiset. Simulaatiomalli tuotti erinomaisia tuloksia ja kohdeyrityksen ensimmäisten indikaatioiden pohjalta se voisi tuoda todellista lisäarvoa yritykselle. Toisen, neuroverkkoennustamiseen pohjautuvan, mallin tulokset olivat taas saataville olevasta datasta epäkelpoja. Tutkimuksen tulokset osoittavat kuitenkin sen, että tekoälymalleja voidaan soveltaa paperikonekudosten teollisen internetin palveluihin, mutta eri koneoppimistekniikoiden sopivuudesta vaaditaan enemmän tutkimusta. Lisäksi olemassa olevan datan laatua tulee parantaa toimivien mallien luomiseksi.

Avainsanat: Paperikonekudokset, teollinen internet, tekoäly, Monte Carlo -simulaatio, luotettavuustekniikka

PREFACE

Conducting this thesis was one of the most challenging and developing processes that I have completed. The goal, improving the initial industrial internet offering, was clear but the road towards it had many possibilities and challenges. And since the improvement was examined from multiple perspectives, the thesis process included multiple stakeholders. Thus, I would like to thank all participants because the completion of this thesis would not have been possible without excellent cooperation.

I would like to thank Valmet Technologies for commissioning my thesis work. Special thanks to my supervisor Tero Ylikoski and my colleague Juha Nieminen who both helped me tremendously during this project. Thanks also to my thesis supervisors from Tampere University, Jouko Laitinen and professor Kari Koskinen, who helped me in providing academical contribution in this research.

Last, but definitely not the least, I would like to present thanks to my wife Tuuli for continuous support during the process.

Tampere 28th of November 2019

Lasse Janhunen

CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF SYMBOLS AND ABBREVIATIONS

AI	Artificial intelligence
Alteryx	Data-analytics platform
CRM	Customer Relationship Management
CSV	Comma separated value
DCS	Distributed Control System
IIoT	Industrial Internet of Things
IoT	Internet of Things
KPI	Key Performance Indicator
LAN	Local Area Network
LSE	Least square error
Mathcad	Mathematical software
OEM	Original Equipment Manufacturer
PMC	Paper Machine Clothing
PMC Analytics	Valmet's paper machine clothing unit's industrial internet application
PMC Monitor	Valmet's paper machine clothing unit's industrial internet application
Q&A	Questions and answers
R&D	Research and Development
RUL	Remaining useful lifetime
RBAC	Role based access control

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1. INTRODUCTION

1.1 Thesis background

Digitalization and the need for data-driven businesses has grown substantially during the last few years. Neglecting the digitalization causes a major risk of losing business in today's extremely competitive markets (Tihinen, et al., 2016). It is reported that 92% of the surveyed companies have accelerated big data and AI investments and 88% report a greater urgency to invest even more (Bean & Davenport, 2019). The increase in this pace is a straight result from the increase of overall available data – in last two years alone 90 percent of the data in the world has been generated (Marr, 2018). Thus, industrial internet applications have become more successful than ever. In short, industrial internet is portrayed as a combination of intelligent machines, people and processes which automates and rationalizes operations, enables new business and improves decision-making through advanced data-analytics methods (Boyes, 2018; McClelland, 2016; Tihinen, et al., 2016).

The most desired quality of industrial internet analytics is it being almost instantaneous and automatic for users (Boyes, 2018). The data flows nowadays lightning fast so the processing and the analysis phases must be also made as fast as possible. The amount of data is usually vast and therefore it is too tedious and problematic to make deeper analysis by hand. With this problem at hand, the artificial intelligence (AI) has speeded the computing greatly (Nilsson, 1998). By choosing the correct technique will allow users to act with more precision and quickness in everyday decision-making.

Paper machine original equipment manufacturers (OEM) have started to utilize the industrial internet capabilities with increasing pace. Valmet's industrial internet initiative, Voith's papermaking 4.0 and Andritz's Metris are all good examples of using industrial internet to generate added value to customer through enhancing mill efficiency and profitability, optimizing the use of resources and optimizing asset reliability (Andritz, 2017; Valmet A, 2019; Voith, 2019). Thus, the competition is fierce in the field which leads to need for all units to develop their industrial internet offering further. With this goal in mind, the paper machine clothing (PMC) unit of Valmet has commissioned this thesis work.

The knowhow on industrial internet in target company grew in 2015 when the automation business unit was merged to company as a result of company acquisition. Thus today, the utilization of the possibilities offered by industrial internet is one of the main strategies in organization. Main emphasis of industrial internet initiative is the collection of data of machines and then processing and analyzing it. Therefore, the aim is to improve OEM customer's performance by adjusting actions and planning maintenance with the available data. (Valmet, 2019 C)

It takes many steps for the process data to be in easily readable form. The path of data to PMC unit's industrial offering is portrayed in Figure 1. The data flow begins in the customer's paper or board machine where the process parameters are being measured to automation system through sensors. Without this step the efficient of use of paper machine would be close to impossible with the amount of process parameters being thousand-fold. The essential process data is accessible to through servers which can be installed to customer's machine with customer's consent. Without a green light to extract the data, the path of data is disturbed. Therefore, in every possible case for industrial internet applications, the journey starts from customer's approval to give access to data. After successful extraction, the data is stored through secure paths to Amazon AWS cloud. The good connectivity between Amazon and other software's allows easy transformation of data to preprocessing phase where more complex analysis can be made (with Python for example) in addition of data preparation for business intelligence software. The processed data can now be processed with business intelligence tools and target company has chosen Tableau software for it. In Tableau, the dashboards are tailored to match customer's needs to bring additional value about their own process to them. This package is delivered to customer through specifically designed Valmet Customer Portal.

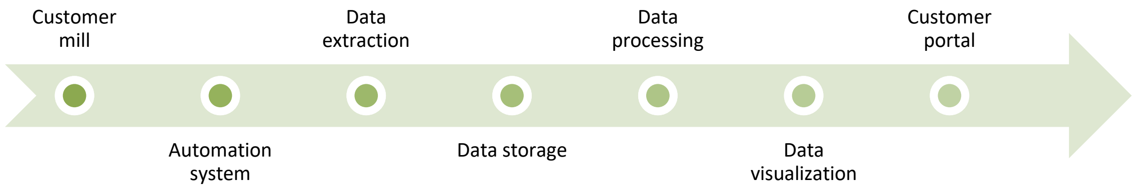

Figure 1. *PMC unit industrial internet ecosystem illustrating the process data flow from paper machine to industrial internet applications*

Industrial internet offering of target organization's PMC unit is cut into two applications: PMC Monitor and PMC Analytics. PMC Monitor is an application for customer to keep track of fabric stock amounts and manufacturing pipelines. The second application, PMC Analytics, is a fabric performance benchmarking tool through selected process key-performance indicators (KPI). With these KPI-values the previous same position products are being compared against each other.

The main assignment in this thesis work is to improve the industrial internet offering of PMC unit. The offering consists of two distinct applications and the first version of the industrial internet offering was constructed before the thesis so main emphasis will be to improve its current state. The improvement will be conducted with two main points of emphasis: taking advantage of relevant AI technologies and to ask customers what features the offering should have.

One goal of the industrial internet applications is to give additional value to customer. Thus, the developmental focus in this research moves intimately with customer feedback. A good method to bring customer into developmental loop is to conduct prototyping. Prototyping allows customer to participate in developmental phase through suggestions and the developers can see how the service meets customer needs (Räty, 2016). In this research, the prototyping is conducted via one pilot customer.

The customer feedback and prototyping process focus on modifying the existing industrial internet offering. To generate scientific contribution through this research, analytical improvements are presented. The new era which combines internet with artificial intelligence is gaining momentum by triggering changes in the models, means and ecosystem of the industries (Li, et al., 2017). Thus, the combination of industrial internet and AI will be studied and applied into the realm of paper machine clothing in this thesis work.

1.2 Goal and scope of the thesis

First and foremost, the goal of the thesis is to provide additional value to PMC unit's industrial internet offering. Since the main user-group of the application will be customer, the application will be improved through hopes and suggestions of the customer. The first version of the application was launched earlier so one major point of emphasis in thesis will be to present the application to customer, to get feedback from it and to act accordingly.

Research questions discuss following objectives:

1. What customer needs to know about the fabric's operational capability?
2. What are the key parameters which affect fabrics industrial internet AI applications?
3. What kind of AI models would benefit the company and the customer the most?

Though much can be made with customer collaboration, most of the work must be done beforehand. In effort to add state of the art research to the scope of this thesis, one goal will be to figure out whether AI could be used to give an edge for PMC unit's industrial internet application. In this thesis work two models, stock level simulations and fabric lifetime estimations with neural networks, are presented and their applicability and feasibility towards industrial internet applications studied.

One solution to add more intelligence in to the existing offering is to make probability calculations to optimize the customer fabric stock amounts and delivery timings. This is made possible by calculations used in reliability engineering where distribution will be fitted against the runtime pattern of the past fabrics from the same position and then used in Monte Carlo simulations. Simulations allow more flexibility compared to analytic models and therefore are more straight-forward (Matsuoka, 2013). In this thesis, the most fitting distribution will be chosen and used in a case study to evaluate optimal ordering intervals and reliability of supply.

Another part in possible improvements to industrial internet will introduce a deeper dive to artificial intelligence world – neural networks. In this thesis, the possibility to add neural network to make predictions from the process data gathered from the customer mills will be evaluated. The usage of neural networks will govern the possibility to estimate fabric lifetime with process parameters. This is where neural networks might prove to be useful tools because of their property to make use of all available data and to learn from it (Haykin, 1999). In case of paper and board mills they have hundreds of relevant process parameters which could be considered when trying to find correlations between them and the remaining fabric lifetime. These linkages between process parameters and fabric lifetimes will be studied for finding the most robust model for estimations. Neural network prediction model will be conducted with Alteryx software.

Scope of this thesis will be limited to making the groundwork for AI applications and by listing the customer demands and acting on them if possible. This means that this thesis work lays framework for possible improvement steps and discusses their feasibility. Press felt's will be used as a pilot product and other products will not be covered at this stage. However, with completed models the shift to another product group should not require extra steps. Things that change consist only different runtime sample distributions and different parameters to monitor.

1.3 Thesis structure

The thesis starts with a collection of relevant theories concerning the subject at hand. To generate valid models or begin the developmental work with the customer, the theory behind the operating context of the fabrics must be reviewed. This chapter also provides theory to back the framework creation for two presented models. For first model, stock level simulations, it is vital to understand how inventories are managed and how to generate valid simulation models. The second model revolves around artificial intelligence and neural networks which was pre-selected as the AI method due the nature of the operating context of fabrics containing hundreds of process variables. Hence the data is in the center of this research, the theory of the data flow from paper machine to industrial internet application is also discussed. Finally, the synthesis subchapter illustrates how this fragmented collection of theories intertwine. By laying this theoretical framework, the linkage between models could also be demonstrated.

Third chapter in this thesis work discusses the selected research methodology and process. Because the commission is to improve an existing industrial internet offering, the present state analysis of applications and overall introduction of Valmet's Industrial Internet are presented. Last subchapter of the third chapter collects the vital customer feedback regarding the industrial internet applications and possible improvements.

Customer feedback provides a valid starting point for the development of two presented models. Fourth chapter illustrates the steps behind the model development.

First model for stock level simulations is conducted with both Mathcad and Alteryx software. The second model about fabric lifetime estimations is created with Alteryx.

In a spirit of constructive research, case study was conducted in fifth chapter. It demonstrates the performance of generated models using real data. For stock level simulation model, the case study focuses on to compare different distribution fitting options and their applicability towards software Alteryx. Remaining fabric lifetime estimation model is divided into two different sets of parameters for neural network to use: theoretical selection of relevant signals and selecting all available signals. Process data of the case study is then fed to these to neural networks and the accuracy of predictions examined.

The sixth chapter of this thesis work discusses the results of the case compared to previous research. However, the exact research concerning paper machine clothing and industrial internet or artificial intelligence is nonexistent. Therefore, results are compared to previous research concerning the application of neural network or Monte Carlo simulation models. This chapter also discusses the applicability of presented models towards the PMC unit's industrial internet applications and makes suggestions about developmental steps for future. The final chapter presents the conclusions of this thesis work.

2. THEORETICAL FRAMEWORK

2.1 Paper machine clothing in the operational environment

Typical paper or board machine has three distinct sections containing paper machine clothing: forming, pressing and drying. In these sections, the fabrics are a vital part of the papermaking process because the paper web is in a continuous contact with a fabric (Paulapuro, 2008). Forming fabrics, press felts and drying fabrics alongside with shoe press belts all have important but very specific functions in the papermaking process. And since the paper grade, speed and size of the machine are different, all fabrics must be engineered distinctly to suit current situation (Adanur, 1997).

2.1.1 Forming fabrics

Papermaking processes follow similar pattern in the wet-end part of the paper or board machine. First, the mix of cellulose is prepared and then launched on to wire. In this point water is drained from the mix and wet web is formed (Paulapuro, 2008; KnowPap, 2019). There are in general two kinds of dewatering: filtration or thickening (Paulapuro, 2008). In the wire section, most of the dewatering comes by filtration and after all the free mix has been dewatered, remaining water will be removed by thickening (Holik, 2013). This is one reason why paper machine wet end is usually with similar composition: wire section first with better filtration and press section after where thickening effect of the mix is maximized (Paulapuro, 2008; Holik, 2013).

When comparing forming section to press or drying sections, the forming section is the most critical stage in the papermaking process by affecting the end-quality of final sheet the most (Adanur, 1997; Holik, 2013). If the sheet formation is insufficient in the forming section, it becomes virtually impossible to correct it in pressing or drying sections. Therefore, all parts of the forming section, from dewatering elements to rolls and fabrics, must be designed with precision (Adanur, 1997).

The first fabric in the papermaking process is called forming fabric. Their main objective is to filtrate water from the web so that the fibers don’t pass through (KnowPap, 2019; Adanur, 1997). This is the process which allows papermaking in the first place. In addition to filtration one objective is to transport and to support web from headbox to press section (Holik, 2013). Most of the dewatering during papermaking process occurs at the forming section which makes forming fabric an essential element in the process

(Pikulik, 2013). Water removal along paper machine sections is portrayed in Figure 2. As discussed earlier, the effect of forming section towards the end quality is huge. This applies to forming fabrics particularly well because multiple sources state that the goal of the rest papermaking process is to maintain the quality achieved at the forming section (Paulapuro, 2008; KnowPap, 2019; Adanur, 1997; Holik, 2013).

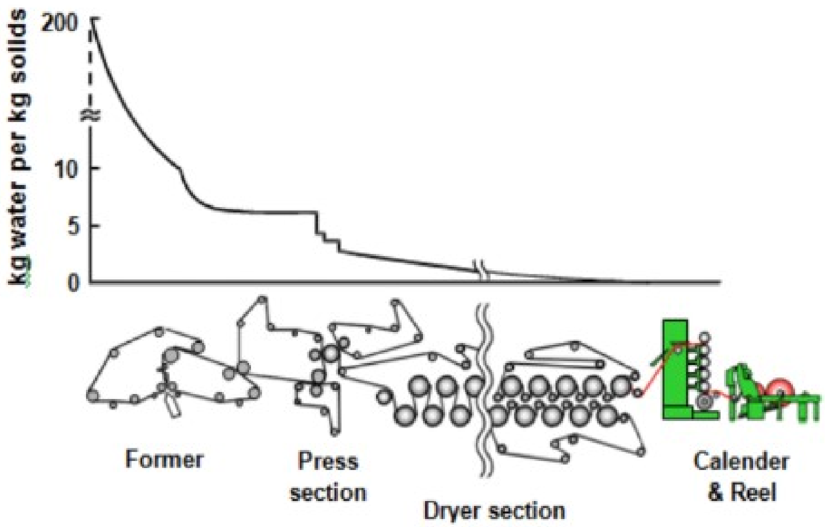

Figure 2. *Water removal along each section of the paper machine (Pikulik, 2013)*

Forming fabrics are used under differentiating conditions. Speeds range from 100 m/min to even 1900 m/min and different grammages of the web vary enormously (Häggblom-Ahnger & Komulainen, 2006). The selection of correct forming fabric is related to paper grade and the configuration of the wire section (Adanur, 1997) (KnowPap, 2019). One key choice in practice is that usually more dense forming fabrics are selected to paper machines running with lighter paper grades (Häggblom-Ahnger & Komulainen, 2006). To have a well-functioning forming section forming fabric must have stable structure, be wear resistant and have good qualities for dewatering (Häggblom-Ahnger & Komulainen, 2006; KnowPap, 2019).

European Paper Machine Clothing defines that there are five different standard types of forming fabrics: single layer (SL), double layer (DL), triple layer (TL), SSB (Self Support Binder) and triple weft (TW) wires (KnowPap, 2019; Häggblom-Ahnger & Komulainen, 2006). Compared to traditional double layer fabrics, SSB-fabrics offer better fabric stability and longer runtimes. On the other hand, triple weft forming fabrics are more rigid which offers better paper profiles in cross direction. Triple weft fabrics' more rigid and heavier structure is a disadvantage in some cases because it increases the water carried by the fabric which in contrast might lower the dry content after forming section. (KnowPap, 2019)

2.1.2 Press felts

Goal of the press section is to remove water from the web by pressing it in a nip. Traditionally nip is a compression where two rolls press against one another. In press section nips usually have one or two press felts supporting the web from crushing. As other fabrics press felts carry the web from one section to another and therefore, they have significant effect on the quality of the end-product. Press felts are also crucial part of the dewatering in a paper or board machine’s press section and like in the case of forming fabrics, they must be designed and tailored individually to every machine and position. (Holik, 2013; KnowPap, 2019; Paulapuro, 2008)

Press felts are generally split into types by their base structure. Different base structures define for example felt’s firmness and affect remarkably to dewatering abilities (Adanur, 1997; Paulapuro, 2008). Modern subtypes for felts are: 1) single-base woven felts, 2) woven laminate felts, 3) non-woven felts, 4) composite felts and 5) seamed felts (Adanur, 1997; KnowPap, 2019).

Three most coveted qualities of the press felts are long runtime, excellent dewatering and being non-marking (Valmet, 2019 B). Excellent dewatering means that in a nip felt takes water inside of it from the web. This is only possible if felt has low enough flow resistance for water to flow to compressed felt at the nip. Good dewatering, as discussed earlier, improves dry matter after press section which improves paper machine runnability and lowers drying section’s energy consumption. (Häggblom-Ahnger & Komulainen, 2006; KnowPap, 2019; Pikulik, 2013)

Optimizing dewatering is the most important goal for press felt manufacturers (Valmet, 2019 B). This is hardly the only goal to be considered because configuration of the press section, raw materials used, grade produced, machine speed and press loads are all among the multitude of influencing factors to the function of the press felt (Adanur, 1997; Häggblom-Ahnger & Komulainen, 2006; KnowPap, 2019). Thus, every felt must be tailored with precision to match customer needs. As an example, lightly loaded rubber-coated nip suffices light basic fabrics but on the other hand steel grooved rolls require stiff weft with coarse fibers (KnowPap, 2019). Therefore, cooperation between felt manufacturer and customer is crucial when selecting the right felt. Major tools which help the development and correct selection of press felts are analyses of used felts and press felt moisture and permeability measurements from the running machine (Häggblom-Ahnger & Komulainen, 2006; KnowPap, 2019).

To maximize the effectiveness of press felt and its reliable life, felt conditioning is required. Felt conditioning is performed both on and off-line (Adanur, 1997; KnowPap, 2019; Paulapuro, 2008). On-line conditioning, which is continuous during running process, include high and low-pressure spray jets and felt suction boxes. Figure 3 illustrates a regular felt cleaning composition. Sometimes felt may get so compacted that it can't be cleaned with on-line conditioning methods but it needs chemical cleaning during a shutdown. The cleaning program and chemicals used are chosen based on the impurities found in the felt. The most common shutdown cleaning method is an alkaline wash using sodium hydroxide (NaOH). In addition to on and off-line conditioning methods the effectiveness of nip dewatering must not be overlooked. The water flowing through the felt in the nip tends to eliminate impurities from the felt making it a pivotal conditioning method for felts (Adanur, 1997). It is known, that felts have been found impure in cases where felt dewatering is primarily used by eliminating all water by felt suction. (KnowPap, 2019)

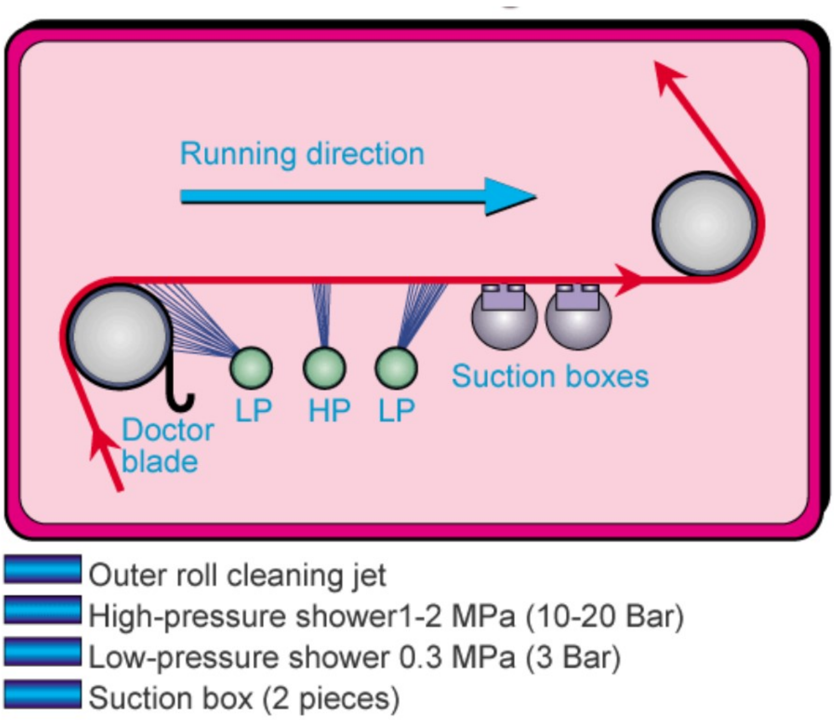

Figure 3. *Felt conditioning methods (KnowPap, 2019)*

As discussed, the main reason for press felts removal from service is usually felt plugging (KnowPap, 2019). In its regular lifetime, felt runs through pressing nips thousands if not millions of cycles. This load compresses felt’s structure and over time, combined with contamination from impurities of the process, compress the felt leading to reduction in dewaterability, compromises in the moisture profile and results in various runnability problems (Adanur, 1997; Häggblom-Ahnger & Komulainen, 2006). As the felt ages, plugging intensifies. This is a result of impurities being compressed into felt and therefore being more difficult to eliminate with felt cleaning methods (Adanur, 1997; KnowPap, 2019). Even though felt plugging is a main reason to change, press felts are usually changed before its actual failure. Unplanned downtime in a papermaking process is expensive and therefore in most cases felt runtimes are divided to before-set running periods for felts to function well from start to end (Holik, 2013; Paulapuro, 2008).

2.1.3 Shoe press belts

The newest member to the family of paper machine clothing is shoe press belt. The shoe press nip is a relatively new innovation in a field of paper making and its success story has been incredible (Valmet, 2019 B). By using the shoe press the dry-content after the press section is higher and web qualities are better in comparison to traditional nip solutions (KnowPap, 2019; Paulapuro, 2008). This is a result of a longer nip with a shoe press which subjects the web to pressing longer and allows the point load towards the web to be at lower levels (Holik, 2013). Shoe presses also allow increase in the speed of the paper machine and better energy efficiency due to higher dry-contents (Holik, 2013; KnowPap, 2019). In typical shoe press configuration (Figure 4), there are two rolls from which another one is the shoe. In addition to rolls, the shoe press nip has from one to two press felts in it (KnowPap, 2019). The shoe functions by having multiple load cylinders inside applying pressure to the shoe. This pressure makes the shoe to settle against the opposing roll and therefore creates a pressing nip. Between the belt and the shoe is a constant flow of oil to preserve lubricating oil film always. (KnowPap, 2019; Paulapuro, 2008)

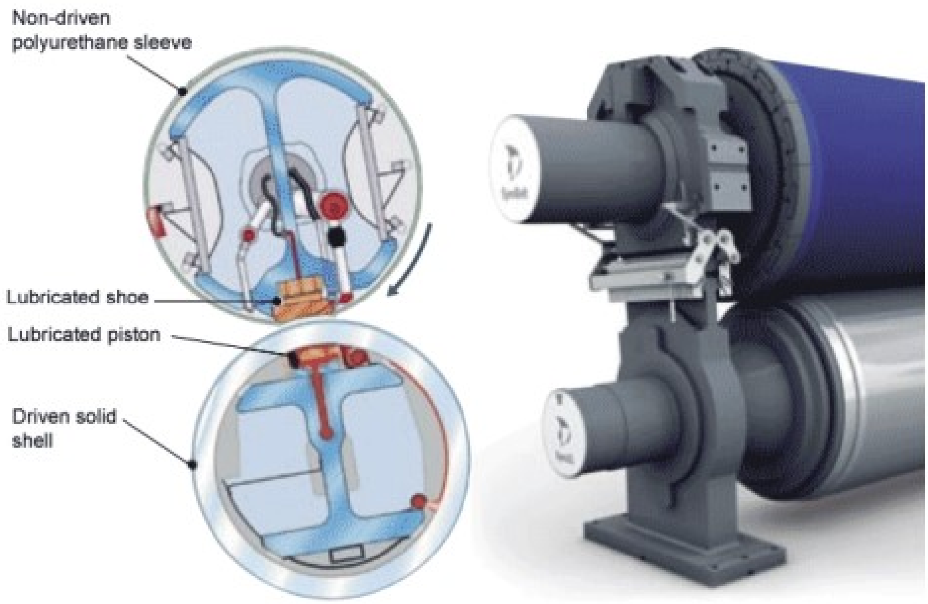

Figure 4. *Shoe press configuration (KnowPap, 2019)*

In its running conditions, shoe press belts are subject to rough conditions. Belt must be durable against pressing, oil and water resistant and resistant to abrasion (KnowPap, 2019; Paulapuro, 2008). One key attribute of shoe press belt is its tenacity which allows belt to endure even swift impacts. This is because shoe presses are in normal running conditions a subject to highest loads varying from 8 to 10 megapascals. In an event of something additional passing through the shoe press nip, belt might be affected by even 10-30 times higher loads which might lead to damages in belt. This potential issue has been picked up by the belt manufacturers by for example adding reinforcements (two or three-layered usually) within the belt. (KnowPap, 2019)

At the time of launch, shoe press belts were all smooth from the surface which led to all water removed in a nip having to fit in corresponding press felt (KnowPap, 2019; Paulapuro, 2008). To achieve higher dry-contents after the press section, belt-designs started to move towards grooved surface designs (KnowPap, 2019). Today there are smooth, grooved, semi-grooved, discontinuous grooved and high-density grooved belts on the market (Valmet, 2019 B). Smooth belts are still used in shoe press nips where most of the dewatering goes with the press felt to suction boxes (Paulapuro, 2008). Grooved belts are designed for fast paper machines where high nip dewatering is in demand (KnowPap, 2019; Paulapuro, 2008). Discontinuous grooving of the belts means that it makes the back flow of water impossible in a nip (Paulapuro, 2008). In recent developments, the water-space in belts has grown remarkably. Today the water-space is typically from 380 to 520 ml/m^2 while the open area being from 30-42 % (KnowPap, 2019; Paulapuro, 2008).

2.1.4 Dryer fabrics

The final fabrics of the papermaking process are called dryer fabrics. Their main objective is to support and carry web through drying section and to enhance the effect of drying (Adanur, 1997; Paulapuro, 2008). The good runnability in drying section equals efficient drying with as low as possible costs (Holik, 2013). In addition to the efficient drying, the dryer fabric must maintain the good qualities of the end-product (Holik, 2013). A good dryer fabric must also stay open and to have sufficient air permeability, good runnability and high drying capacity. (Adanur, 1997; KnowPap, 2019; Paulapuro, 2008)

In general, the speeds of paper machines and stricter quality demands have driven the dryer fabric manufacturers to develop products even further (Valmet, 2019 B). Dryer fabrics must have uniform quality and better quality which results in longer runtimes and lesser energy consumption (Adanur, 1997; Paulapuro, 2008). Furthermore, the drying efficiency has become one of the key metrics to measure runnability of the paper machine (Holik, 2013; Häggblom-Ahnger & Komulainen, 2006). Thus, the dryer fabric manufacturers aim to contribute to better runnability of the drying section and lesser shutdown needs (Valmet, 2019 B).

To maximize the effectiveness of drying fabric they must be surveyed and maintained frequently. During operation, fabrics must be regularly cleaned to avoid fabric soiling which would lead to poorer runnability and paper quality (Adanur, 1997; KnowPap, 2019). Different cleaning methods for drying fabrics are for example cleaning spray jets, cleaning apparatus with high-pressure water and compressed air and brush apparatuses and doctors (Adanur, 1997; KnowPap, 2019; Paulapuro, 2008). In addition to cleaning, the drying fabrics should be frequently surveyed when machine is running and particularly during the shutdowns (Paulapuro, 2008). Dusting, inefficient guiding and fabric wear are all examples of points to survey from the fabrics (KnowPap, 2019).

Neglecting this will result in lesser probability to run full runtimes with good paper qualities and runnability by a fair margin (Adanur, 1997; KnowPap, 2019).

2.2 Spare part inventory management

For paper machine, it is a necessity to have spare parts for all consumable positions at all times. In a rough average, one hour of paper machine downtime costs approximately 50 000 $ (Holik, 2013). Thus, the spare part inventories in paper machine must be managed with great precision. Susan Grinsted and Gwynne Richards (2016) state that spare parts inventory is usually managed with the help of forecasts projected from the historical data and by stocking inventory to cover the expected demand. In that sense, it works precisely like regular inventory but more specifically expected demand covers both spare parts needed for regular maintenance and for unexpected breakdowns (Arts, 2013; Grinsted & Richards, 2016). To achieve healthy spare parts inventory, one should consider options which help to maintain a spare parts inventory. Such as in the case of paper machine, options helping to maintain well-functioning spare parts inventory include using consignment stock agreements, using asset condition monitoring to anticipate failures and increasing the proportion of planned maintenance (Arts, 2013; Wang & Syntetos, 2011). On annual basis, the value of spare parts inventory should be reviewed against the level of service to review current inventory strategy (Ghiani, et al., 2013). High downtime cost per minute because of stock-outs in inventory are an example indicator of lacking spare parts inventory strategy. (Grinsted & Richards, 2016)

Service level is usually seen as an overall level of customer satisfaction. Ghiani et. al. (Ghiani, et al., 2013) state that company’s profits are directly connected to the service level offered to customers. However, the main goal of companies is to be profitable and therefore service level should be optimized in a reference period. Usually maximization of the profits occurs in cases where service level is high but still less than the maximum (Ghiani, et al., 2013; Wang & Syntetos, 2011).

2.2.1 Reorder point system

Reorder point system is suitable method for items subject to independent demand. System also suits well to dependent demand conditions, such as for components or spare parts used in production schedules like in papermaking process. It is a method of continuous review where replenishments can be sent with varying intervals. System also allows changes in the order quantity per the rate of demand. Thus, the reorder point system works well in today’s data driven atmosphere by being able to address changes in demands well. (Grinsted & Richards, 2016; Jain, 1999)

Idea of the reorder point is to trigger order for predetermined amount of a product when the stock level hits to or below a certain level (Jain, 1999). The key of adjusting correct reorder point is to meet expected average demand during the lead time and to have stock as ideally low as possible. Figure 5 details the relationship between safety stock, demand, supply and the reorder point (Grinsted & Richards, 2016). If safety stock is used within a reorder point system, the reorder point must be placed so that safety stock will not be used under average demand. After new item is supplied, the remaining inventory will be checked against the safety stock. If stock level is below or at the point of reorder, new order will be automatically created. (Grinsted & Richards, 2016)

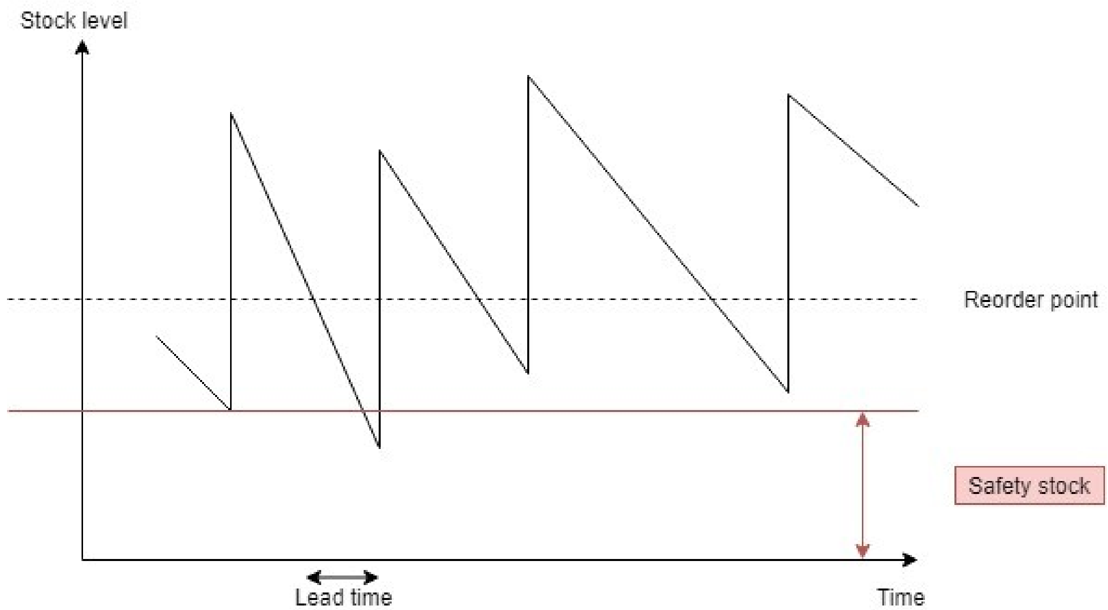

Figure 5. *Reorder point system with alternating demand. Adapted from (Grinsted & Richards, 2016)*

Grinsted & Richards (Grinsted & Richards, 2016) illustrate that setting reorder point system requires five steps: 1) analyzing demand to get average demand per time unit; 2) obtaining lead time; 3) setting parameters for order quantity and safety stock levels; 4) determining reorder point and 5) continuously monitoring average demand and lead time to finetune reorder point accordingly. Finetuning of reorder point systems is today flexible and more accurate towards the real demand with the help of stochastic tools and increased computing power of computers (Arts, 2013; Wang & Syntetos, 2011).

2.2.2 Safety stock

In papermaking process, delays in production are extremely expensive. All possible causes of delay must be mitigated and one important factor is to have sufficient inventory of spare parts (Holik, 2013; Häggblom-Ahnger & Komulainen, 2006). For paper machine clothing suppliers, this means that possibility of stock-out of fabrics would possibly even lead to the loss of contract or customer. Furthermore, conditions at the paper machine can vary remarkably which on the other hand adjusts fabric suppliers to invest heavily in sufficient safety stock (Holik, 2013).

The key in having an adequate safety stock is that in a case of average demand it should not be used (Grinsted & Richards, 2016). This adequate amount in safety stock required correlates from the service level where high level means less chance of stock-outs (Ghiani, et al., 2013). All required information about correct levels can be derived from historical demand or in spare parts case usage. Historical data about the demand should be parametrized for distribution (in simplest case standard deviation) where higher peaks in demand can be identified (Arts, 2013; Wang & Syntetos, 2011). Then the decisions must be made how much irregularities in the demand will be covered and therefore how much safety stock will be kept.

2.3 Reliability engineering

The term reliability focuses on the ability of product or process to perform its intended function (Nachlas, 2005). Reliability is a key attribute of a product for many reasons. For example, reputation, customer satisfaction, warranty costs and competitive advantage are all good reasons why good reliability is in high demand (Birolini, 2007). Mathematically reliability can be explained as the probability that an item (product, process or even a service) will continue to perform its intended function without failure for a specified period under certain conditions (Birolini, 2007; Nachlas, 2005).

It is unlikely that all failures can be eliminated from a design of a product. Failures are therefore in most cases inevitable but with correct actions, manageable. Systematic application of reliability engineering has risen to tackle issues caused by these failures. Reliability engineering’s goal is to identify the most likely failures of a design and then to apply appropriate actions to mitigate their effect on the process. Another goal is to evaluate natural reliability of a product or a process and to highlight areas where reliability could be better. The reliability evaluation process itself varies a lot. Different reliability analyses relate to one another by conducting reliability examination from different points of views to determine possible issues and to make suggestions for corrective measurements and possible improvements. (Birolini, 2007; Nachlas, 2005)

2.3.1 Reliability prediction

Reliability predictions are a vital process to get information about how item's reliability varies over time. Reliability predictions can be made for example by conducting life tests by testing large number of the product at given conditions (Kumamoto & Henley, 1996). Using these methods for predictions takes number of units and their operating hours of survival before failure into account (EPSMA Technical Committee, 2005; Kumamoto & Henley, 1996). In a case of new product launch, there might be insufficient amount of test samples at the beginning. If this is the case, calculated predictions become essential to map out possible reliability related issues (EPSMA Technical Committee, 2005).

There are multiple benefits of using reliability predictions accordingly. Identification of potential design weaknesses, evaluation of life-cycle costs and providing data for future reliability and availability analyses are all products of reliability predictions (EPSMA Technical Committee, 2005). One key benefit of reliability predictions is also logistic support strategy planning which is utilized in this thesis.

Components have many kinds of failure modes and therefore different failure distributions. With these limitations in mind system reliability analysis through analytical models are both restrictive and tedious (Kumamoto & Henley, 1996; Matsuoka, 2013). Simulation models on the other hand offer more straightforward solution to tackle multiple complicated conditions in a single analysis framework (EPSMA Technical Committee, 2005; Kumamoto & Henley, 1996). One commonly used reliability prediction method is called the Monte Carlo Method (Matsuoka, 2013).

2.3.2 Monte Carlo method

Monte Carlo method is a numerical method to solve complex mathematical problems by simulating random variables. It became popular alongside with the rise of computing power offered by the success of computers. Simulating random variables by hand is an arduous task but on the other hand solving the issue with random sampling (usually referred as Monte Carlo method) is quite the opposite. Key advantage of using Monte

Carlo method is it’s simply-structured computational algorithm. In many cases a program is written to conduct one random trial which will be repeated N number of times each trial being independent of the rest. With a higher amount of random trials, the computational power required increases but also so does the accuracy of the simulation. In the end of a simulation, the results of all trials are averaged. (Matsuoka, 2013; Sobol', 1994; Kumamoto & Henley, 1996)

Any process influenced by random factors is a good target for Monte Carlo simulations (Matsuoka, 2013). Since its introduction after World War II, the Monte Carlo method has been widely used by professionals in the fields of energy, manufacturing, engineering and logistics (Sobol', 1994). In general, the Monte Carlo simulation performs risk analysis by mapping out the possible results of a process by using quantile functions of probability distributions (Kumamoto & Henley, 1996). Probability distributions allow much more realistic way of describing uncertainty of variables in a risk analysis (Matsuoka, 2013). In reliability engineering Monte Carlo method functions particularly well by allowing user to simulate possible outcomes and the probability of them being in safe or failure domain (Kadry & Chateauneuf, 2007). Figure 6 illustrates the reliability assessment principles by using Monte Carlo simulation.

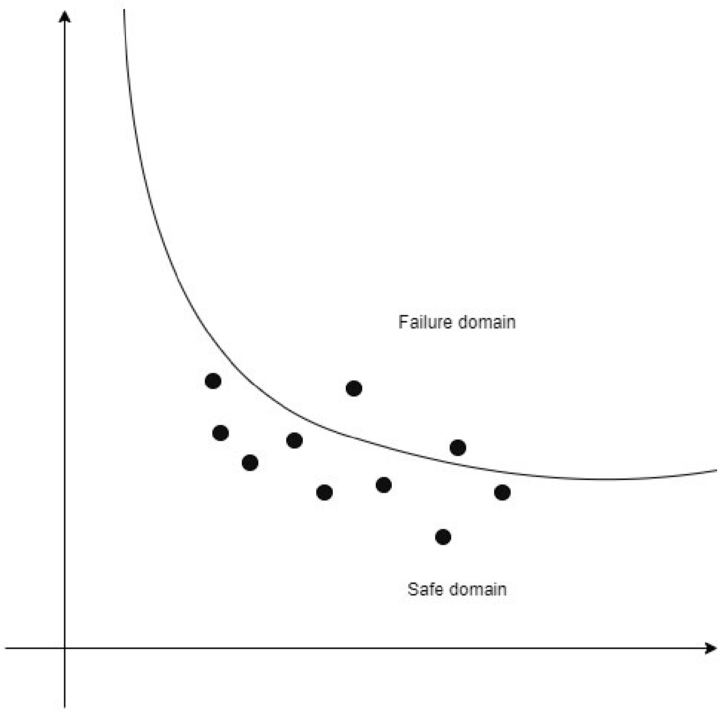

Figure 6. *Illustration of reliability assessment principles by using Monte Carlo simulation. In this figure there is total of ten simulation outcomes and the simulated reliability is 80%. Adapted from (Kadry & Chateauneuf, 2007)*

The Monte Carlo simulations use quantile functions to produce random outcomes for simulation calculations (Kumamoto & Henley, 1996). The usage of probability distributions in Monte Carlo method simulations is illustrated in formula 2.1. In formula 2.1 the capital *X* is the quantile function which is employed to simulation. Small *x* represents one possible outcome of the simulation and its subscript *i* is a rolling index which results in *N* number of possible outcomes. Because the point in The Monte Carlo method is to generate *N* number of possible random outcomes, stochastic variable *u* is needed. In practice, stochastic variable is usually in Monte Carlo simulations a random number between 0 and 1. Formula 2.1 also illustrates parameters *p* of quantile functions.

$$x_i = X(u, p_1, p_2 \dots, p_n) \tag{2.1}$$

The Monte Carlo Method allows much more freedom compared to classic analytical methods by being able to avoid restrictive modeling assumptions that had to be put in place in analytical methods to generate valid solutions (Matsuoka, 2013; Sobol', 1994). The basic procedure in Monte Carlo Method follows a certain pattern: 1) define a domain of possible events, 2) generate events randomly, 3) perform deterministic judgments of system states based on the events and 4) count the occurrence number of a specific system state among total number of observations (Matsuoka, 2013).

For a decision makers Monte Carlo Method allows a glimpse of future. It clarifies possible outcomes of a process and the probabilities why they occur. Important attribute in Monte Carlo simulations is its ability to show even the most extreme occurrences. Thus, Monte Carlo Method is an excellent tool to see all the possible outcomes of one’s decisions and to assess the impact of risk at any given outcome – resulting in superior decision-making. (Matsuoka, 2013; Sobol', 1994)

2.3.3 Probability distributions

Function that describes the likelihood of obtaining the possible values a random variable can assume is called a probability distribution (Cramer, 1946; Frost, 2019). It is useful when there is a specific need to know which outcomes are most likely and how likely the different results occur. Different distributions generate different outcomes for the variables and therefore probability distribution functions can be set to model wide range of different phenomena (Frost, 2019).

Jim Frost (Frost, 2019) continues that probability distributions are indicators about the likelihood of an event to manifest. Probability on the other hand describes the chance of random variable taking a value of x. This is commonly noted as p(x). The sum of all probabilities for all possible values of a phenomenon must equal to 1. And to continue, a specific value or a range of values must be between 0 and 1. Probability 0 means that the occurrence will never happen and 1 that it will always come to pass. (Cramer, 1946; Çınlar, 2011; Frost, 2019)

Probability distributions are generalized to two sub-types for single variables: probability mass functions for discrete variables and probability density functions for continuous variables (Cramer, 1946). For example, coin toss is a discrete distribution because it doesn’t get the values in between – only heads or tails. Some commonly used discrete distributions are for example binomial distributions to model binary data, Poisson distribution to model count data and uniform distribution to model events with same probabilities (Frost, 2019; Çınlar, 2011).

Continuous nature of a variable can be assumed if the variable can get an infinite number of values between any two values (Cramer, 1946). It is most effectively used when probability is needed rather over ranges of values than single points. In that case probability illustrates the likelihood that a value will fall within an interval (Frost, 2019). Just like in the case of discrete distributions, there are several different distributions for continuous variables. Key attribute which define the distributions are called parameters. Most continuous distributions have from one to three parameters and their purpose is to define the shape and size of the distribution (Frost, 2019; Cramer, 1946; Çınlar, 2011). Table 1 presents these parameters which are used in distribution fitting section of the model development. Table 1 also contains the quantile functions needed for the Monte Carlo method. In numerous cases of continuous distributions, exact closed-form representation for their quantile does not exist (Yu & Zelterman, 2017). Thus, numerical approximations are needed. Computer algorithms can make accurate approximations and within the scope of this thesis work, Table 1 represents the used quantile functions in their Mathcad form if the exact representation does not exist.

Table 1. *Distribution fitting parameters Adapted from (Cramer, 1946; Çınlar, 2011; Frost, 2019)*

Distribution	Normal	Weibull	Logistic	Extended beta
Quantile function	$qnorm(u, \mu, \sigma)$	$\alpha \cdot (-\ln(1-u))^{\frac{1}{\beta}}$	$\mu + s \cdot \ln\left(\frac{u}{1-u}\right)$	$a + (b-a) \cdot qbeta(u, \alpha, \beta)$
Random seed	u	u	u	u
Parameter 1	μ *(mean)*	α (*shape)*	μ *(mean)*	a *(min value of sample)*
Parameter 2	σ *(standard deviation)*	β (*scale)*	s (*scale)*	b *(max value of sample)*
Parameter 3	-	-	-	α *(shape)*
Parameter 4	-	-	-	β *(shape)*

The most established continuous distribution is the normal distribution (also called as Gaussian distribution or the "bell curve") (Cramer, 1946). It is widely used within statistics because it fits to many natural phenomena. Some good examples of normally distributed variables are for example heights and IQ scores of the population (Frost, 2019). Normal distribution uses two parameters which are mean and standard deviation of the population. Two flaws in normal distribution are that it does not fit into high Kurtosis (tail in sample distribution) or skewed data because it is a symmetrical distribution (Çınlar, 2011). This is where for example the Weibull and lognormal distributions are particularly useful (Çınlar, 2011). The Weibull distribution is widely used within the realm of reliability engineering (Matsuoka, 2013). Some other widely used continuous distributions are for example logistic function, t-location, beta and gamma distributions (Çınlar, 2011; Frost, 2019). Distributions used in this thesis work's distribution fitting section and their strengths and weaknesses are displayed in Table 2.

Table 2. *Characteristics of distributions used in distribution fitting section. Adapted from (Cramer, 1946; Çınlar, 2011; Frost, 2019)*

Distribution	Strengths	Weaknesses
Normal	Easy to use and configure. Represents normally distributed data well	Does not fit into skewed or high Kurtosis data. Can result in negative numbers which is not optimal situation for reliability engineering
Weibull	Often used to model the time until occurrence of an event where the probability of occurrence changes with time	Configuration algorithm needed for parameters
Logistic	Resembles normal distribution but has heavier tail (Kurtosis)	Configuration algorithm needed for parameters. It does not appear often in risk analysis modeling
Extended beta function	Highly flexible in shape and has been quite popular for attempting to fit to a data set for a bounded variable	Configuration algorithm needed for parameters

The number of different distribution combinations is infinite and one distribution might not fit into two separate cases (Cramer, 1946). To get the most out of a dataset's properties, distribution fitting must be conducted. Distribution fitting is a procedure of selecting statistical distribution which best fits to a randomly distributed dataset (Karian & Dudewicz, 2000). Randomly distributed dataset in means a set of data which contain random factors resulting in a level of risk or uncertainties (Karian & Dudewicz, 2000). Levels of risk and uncertainties are threats to businesses and by using probability distributions correctly is a way of tackling these issues by making informed business decisions (Stark, 2010).

When making important decisions, correct tools are crucial. In a case of probability distributions, this statement is also true. Selecting and applying wrong distribution for dataset will lead to incorrect calculations and therefore most likely to wrong decisions (Karian & Dudewicz, 2000; Stark, 2010). By conducting a distribution fitting correctly develops the potential to deal with uncertainty better and to make the right decisions.

Selection of a correct distribution should not be a guess but a scientific process. First and foremost, one should choose candidate distributions depending on the nature of dataset (Karian & Dudewicz, 2000). For example, Weibull distribution is common in the realm of reliability engineering because it is a non-negative distribution (failure time can’t be negative value) (Matsuoka, 2013). Good tool to compare candidate distributions is to build a histogram of the dataset and determine if it’s symmetric or skewed.

After pre-selection, in conducting the actual distribution fitting for the selected distribution, parameter estimation must be used. There are many scientific and commercial methods to conduct parameter estimation (Karian & Dudewicz, 2000; Stigler, 1981). Two good examples are maximum likelihood and least squares methods (Stigler, 1981). In this thesis, least squares method is used to estimate parameters for distributions. In general, the best fit in the least-squares minimizes the sum of squared residuals (difference between observed value and fitted value provided by the model) (Stigler, 1981). Equation 2.2 illustrates error function used for Weibull distribution in this thesis work.

$$E(\alpha, \beta) = \frac{1}{N}\sum_{i=0}^{N-1}(X(F_i, \alpha, \beta) - AA_i)^2 \tag{2.2}$$

In equation 2.2 the variables are X = quantile function, N = length of the runtime sample, $i = 0 \dots N-1$, $F_i = \frac{i+0,5}{N}$, and $AA_i =$ samples as a vector. The goal of the equation (2.2) is to minimize the error between fitted quantile function and samples which are runtimes of fabrics in this case. Different quantile functions require different parameters and this equation with two parameters is for Weibull distribution. The error function doesn’t make parameter optimizations itself – error minimization algorithm is needed.

Error minimization algorithm optimizes distribution parameters with lowest possible overall error, in other words, the best fit. The first part in the algorithm is to seek the lowest possible least-square error. Second part is to increase and maintain algorithm robustness by searching only from the positive numbers (due to non-negative nature of the fabric runtimes). The last part of the algorithm seeks the best fitting parameters through minimum error function.

2.4 Process data from paper machine

Papermaking process contains hundreds if not thousands of affecting variables (Holik, 2013; Häggblom-Ahnger & Komulainen, 2006; Paulapuro, 2008). To even being able to run the machine, having an automation system is a necessity (KnowPap, 2019). This is where distributed control systems (DCS) have become popular. DCS is an ecosystem of sensors, controllers and associated computers that are distributed throughout the plant (Control station, 2019; Kirubashankar, et al., 2009). Each of these items serve unique purposes and they communicate through plant's local area network which is often referred as control network (Control station, 2019). So, in a way DCS can be viewed as a brain of the plant. With the use of DCS plant's staff can easily keep track of performance of the process even though the number of variables is humongous (Kirubashankar, et al., 2009). And since the DCS has been constantly evolving during past few years, the Industrial Internet developments can be seen an evolution branch of the DCS (Valmet, 2019 B).

The flow of data from DCS to IIoT (industrial internet of things) applications doesn't happen without an effort. Few key interfaces must be installed before the data can flow from the field to visualized results. First step to move the local area network (LAN) data to cloud is to set up a server. Purpose of the server is to gather and to move all the process data to a single database. Without this step the use for cloud-based IIoT system would be virtually impossible. After this step the dataflow can be set as continuous and it will not require any additional actions from customers point of view.

2.4.1 Industrial internet of things

Industrial internet of Things (IIoT) is mainly referred as interconnection of sensors and instruments together with computers' industrial applications (Boyes, 2018; McClelland, 2016). This interface of systems allows enhanced data usage by facilitating productivity and economic benefits (Boyes, 2018). IIoT is an evolution DCS which allows high level of automation to optimize process controls (Boyes, 2018). Internet of Things (IoT) adds value to three major areas: increasing efficiency, improving safety and to create better experience (Boyes, 2018; McClelland, 2016). In this thesis, we will be discussing about IIoT because per McClelland (2016) it has broader meaning and more specific point of view towards industrial applications than IoT.

Today connectivity is cheap and data flow to cloud is relatively easy. This in connection with increasing knowledge in data-analytics and innovations in machine-learning allow possibilities to gain valuable insights about processes (McClelland, 2016). And with these insights' the productivity can be increased and cost can be reduced (McClelland, 2016; Boyes, 2018). Exceptional example of applying IIoT is the use of predictive maintenance.

Four most important technologies which enable IIoT are: Cyber-physical Systems (CPS), cloud computing, big data analytics and artificial intelligence. CPS is the basic technology platform which works as the main enabler to connect machines to net.

Cloud computing services on the other hand allow the flow of data to cloud-based storages. Last two technologies are more about harvesting the insights of the data. First the data is collected, prepared and analyzed and then artificial intelligence (AI) and machine-learning (ML) algorithms make the most out of it by making estimations without explicitly being programmed. (Saturno, et al., 2017; Sridhar, et al., 2012)

Industrial Internet of Things doesn't come without barriers. One major concern is data security because increased interconnectability results in increased potential of cyberattacks (Sridhar, et al., 2012). And when everything is linked together, cybercrime has a possibility to take remote control of a system which may lead to financial losses or even injuries (Sridhar, et al., 2012). Another concern is interoperability which will be more introduced in this thesis. In the world of data and interconnected devices, everything must be precise. With large number of different system and devices this becomes real issue at the point of commissioning of the system (McClelland, 2016).

2.4.2 Cloud systems

Key aspect of the data flow in Valmet's IIoT offering is cloud computing. In a retrospect cloud computing delivers compute power, database, storage and other IT resources as an on-demand service (Amazon, 2019; Microsoft Azure, 2019). The benefit in comparison to traditional local servers is its scalability to changes in IT resource demand (Amazon, 2019). The need for large upfront investments is nonexistent and time consumed towards hardware management is outsourced (Microsoft Azure, 2019). Payment is also usually more flexible – pay-as-use being the most dominant option (Amazon, 2019; Microsoft Azure, 2019).

Cloud computing however is not a rigid process and one type of cloud might suit someone but hardly everyone. There are several different models, types and services which are tailored to meet customer's demands the best. For example, there are three different types of cloud services: public, private and hybrid cloud. While public cloud is owned and operated by a third-party provider, private cloud refers to cloud computing resources which are used exclusively by a single organization. (Amazon, 2019; Microsoft Azure, 2019)

As discussed earlier, data flows from customer DCS system to the cloud through Valmet server. And with Amazon AWS being the supported partner, data is moving to analyzable form with ease and security (Amazon, 2019). From the cloud data is now accessible and processable to give customer insights about their processes.

2.5 Artificial intelligence

Artificial Intelligence (AI) revolves around intelligent behavior of artifacts which in turn involves acts of perception, reasoning, learning and acting in complex environments (Nilsson, 1998). Thus, a goal of the artificial intelligence is to do these things even better than humans do. Even though there have been remarkable breakthroughs in the field of AI, it is generally known that the goal of machine achieving the intelligence of human appears is still distant (Mitchell, 2019).

The fuzz about the AI is loud in today’s media. Self-driving cars are a good example where artificial intelligence is used to conduct previously impossible feats (Mitchell, 2019). The advantages of the AI are nowhere limited to one application – the absolute amount is rising exponentially. Automating repetitive learning, adding intelligence to existing products, analyzing greater amounts of data and achieving incredible accuracy are all benefits which make the use of artificial intelligence mandatory in many branches of industry (Overton, 2018).

The world is changing and will be changed even more in near future from the use of the artificial intelligence but its limits must be acknowledged before it can fully take over. As previously discussed, AI system works like a brain by learning from the data (Nilsson, 1998). There are no shortcuts to overcome this and the learning process means that the accuracy of the AI system will grow over time, not instantly (Nilsson, 1998; Overton, 2018). One another disadvantage today is that all AI systems are designed to conduct specific tasks. For example, self-driving AI system can’t automate production lines and wise versa (Mitchell, 2019).

2.5.1 Machine learning

The heart of human intelligence lies in learning through personal experience and knowledge passed on for generations. The built-in systems of the brain keep learning from the surroundings by detecting and unveiling structures and regularities of various patterns around us (Nilsson, 1998; Theodoridis, 2015). Detecting these possible hidden structures and patterns help us to analyze and understand the nature of the data (Theodoridis, 2015; Bashier, et al., 2016). Thus, with understanding the data we can make predictions about the future.

General goal of the machine learning is to mimic the learning process of the humans by conducting tasks of classification and regression (Nilsson, 1998; Theodoridis, 2015). While artificial intelligence is broader science of copying human intelligence, machine learning is a specific subset that trains machine how to learn (Bashier, et al., 2016). Besides modeling underlying patterns and structures, a significant interest in machine learning is to develop efficient models used for analysis and predictions (Theodoridis, 2015). Predictions have risen to improving importance since we are living in the big data era with massive amounts of data available requiring decision-making to be swift and correct. Making correct predictions and analysis sets demands on algorithms to be efficient and robust in performance (Theodoridis, 2015).

Two of the most adopted machine learning methods are supervised learning and unsupervised learning. In supervised learning, the algorithms are trained by using inputs where their desired outputs are known. Supervised learning is commonly used in applications where historical data projects well towards future. In an unsupervised learning, the data has no historical labels and therefore no desired ‘right answers’ will be told beforehand. Thus, the goal of the learning is to explore the data and find structures and patterns within. Other machine learning methods are semisupervised learning and reinforcement learning. Semisupervised learning combines two beforementioned methods by typically mixing small set of labeled data and large set of unlabeled data. Using semisupervised learning adds accuracy in comparison to unsupervised learning and is cheaper than supervised learning. The reinforcement learning’s algorithms on the other discover which actions yield the greatest rewards by trial and error. The method is widely used in robotics, gaming and navigation where learning the best possible policy is in high demand. (Bashier, et al., 2016; Theodoridis, 2015)

The name machine learning comes from an analogy where machine learns in analogy to how the brain learns and predicts. Many methods and techniques fall under its umbrella: pattern recognition, data mining, machine vision and industrial automation to name a few (Theodoridis, 2015). They all want to address certain issues through two machine-learning problems: classification and regression tasks (Nilsson, 1998; Theodoridis, 2015). In classification task goal is to assign an unknown pattern to one class out of number of classes which are known (Bashier, et al., 2016; Theodoridis, 2015). Good examples in classification tasks are for example picture recognition tasks or making predictions of the authorship of a given text (Bashier, et al., 2016). Another machine learning task is regression task where the goal is basically to answer a curve fitting problem (Theodoridis, 2015).

To get the most value from machine learning, one should pair the best algorithms with the right tools. Key algorithms used in machine learning are for example neural networks, decision trees, random forest, support vector machines, self-organizing maps and principal component analysis (Bashier, et al., 2016; Theodoridis, 2015). The tools for mapping the correct tool for the algorithm and the problem at hand are for example data management and visualization tools and possibility to make comparisons of different machine learning models to quickly identify correct solution. The test for a machine learning model is a validation error on new data, not a theoretical test proving a null hypothesis (Bashier, et al., 2016).

2.5.2 Neural networks

The most complex, nonlinear and parallel computer in our everyday life are still our own brains. Brains compute calculations and situations from completely different point of view compared to conventional computers. The advantage of brains calculational power lies in its capability to organize structural components (neurons in this case) to perform certain computations such as pattern recognition, perception and motor control way faster than any supercomputer can today. As a good example brain routinely completes recognition tasks such as recognizing familiar face in approximately 100 to 200 milliseconds whereas it might take even days for conventional computer to perform the same task. (Haykin, 1999; Nilsson, 1998; Overton, 2018)

It was noticed that conventional calculational methods were too stiff to tackle many real-life issues (Nilsson, 1998). Brains ability to adapt to its surrounding makes it remarkably more versatile than computer algorithms which focus on addressing a certain issue (Mitchell, 2019). To mimic the advantages of the brain, idea of neural networks was brought (Haykin, 1999; Nilsson, 1998). Neural network is basically a machine which task is to model the way in which brain performs a task or a function. Like a brain of an infant, neural network must work towards performing valid computations through a process of learning (Haykin, 1999). In addition to learning process, good performance requires neural networks to employ massive amounts of singular computing units which are usually discussed as neurons (Haykin, 1999; Mitchell, 2019). The strengths of the connections between the neurons are called synaptic weights which store acquired knowledge and to optimize the accuracy of the performed functions (Haykin, 1999).

Superiority in computing power and the ability to generalize and adapt make the use of neural networks preferable in many cases (Bhatia, 2018; Haykin, 1999). Other valuable properties of neural networks are their nonlinearity, possibility to map out inputs and outputs separately, adaptivity and potentially inherent fault tolerance (Bhatia, 2018; Haykin, 1999). Input-output mapping allows user to teach the network through mapping unique input signals of the sample to its corresponding desired responses. The network is then presented with a randomly picked sample and the synaptic weights are modified to minimize the difference between the desired response and the actual response. Adaptivity on other hand makes neural networks to be able to evolve even in real time by adjusting the synaptic weights to match desired response to actual response more precisely (Mitchell, 2019; Haykin, 1999). (Haykin, 1999)

Learning algorithm which trains the neural network is closely linked to the formation of the neurons in a neural network. The architectures can be generalized in three different classes: 1) single-layer feedforward networks; 2) multilayer feedforward networks and 3) recurrent networks. In a layered neural network, the neurons organize in layers. In its simplest form, layered network has input layer which projects onto an output layer but not vice versa – thus bringing the word “feedforward” into the mix. The second architecture distinguishes from the first with the presence of one or more hidden layers. The function of these hidden layers is to intervene between input layer and network output in some useful manner. Figure 7 illustrates an example of multilayer feedforward network. A recurrent network on the other hand has at least one feedback loop in the neural network (Bhatia, 2018). The presence of feedback loops has profound effect on the learning capability of the network and its performance. (Haykin, 1999; Skapura, 1996)

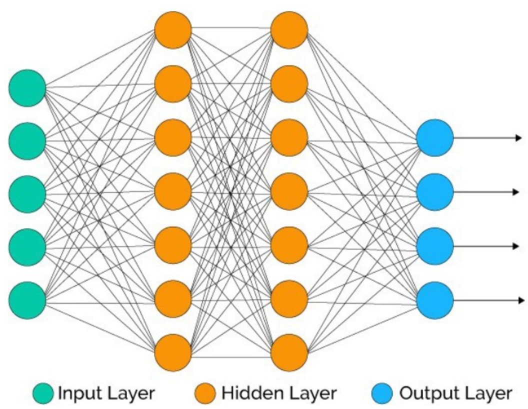

Figure 7. *Multilayer feedforward network (Bhatia, 2018)*

Neural network might be answer to many problems but it isn't always the case. A blog-entry written by Rahul Bhatia (Bhatia, 2018) addresses three dilemmas which link heavily to the use of neural networks: results might be hard to interpret, neural networks require massive amounts of data and they take a lot of time to develop. So, while the performance of neural networks is usually in high demand, one should always look for the best tool towards the current problem. With these cons in the use of neural networks, another machine-learning algorithm might be more suitable towards a specific machine-learning issue. (Bhatia, 2018)

2.6 Synthesis

Literature review consisted of five topics which are interlinked together in this thesis work. Theory topics themselves are quire distinct because applying artificial intelligence to the field of paper machine clothing has not been studied a lot. Therefore, choice of the relevant theory to research is defined by which synthesis of theory benefits the goal of the research the best. Linkages between theory topics are illustrated in Figure 8. Goal is to bring added value with artificial intelligence to PMC supplier's industrial internet platform so it is vital to know basic operating context of fabrics, general information about the industrial internet (and data flows) and introduction towards artificial intelligence. General path of linkage between topics is that fundamentally fabrics operate in paper or board mill which are operated by DCS (Adanur, 1997; Häggblom-Ahnger & Komulainen, 2006; KnowPap, 2019; Paulapuro, 2008). This operational data from DCS is moved through cloud operations to industrial internet platform where artificial intelligence can be utilized further.

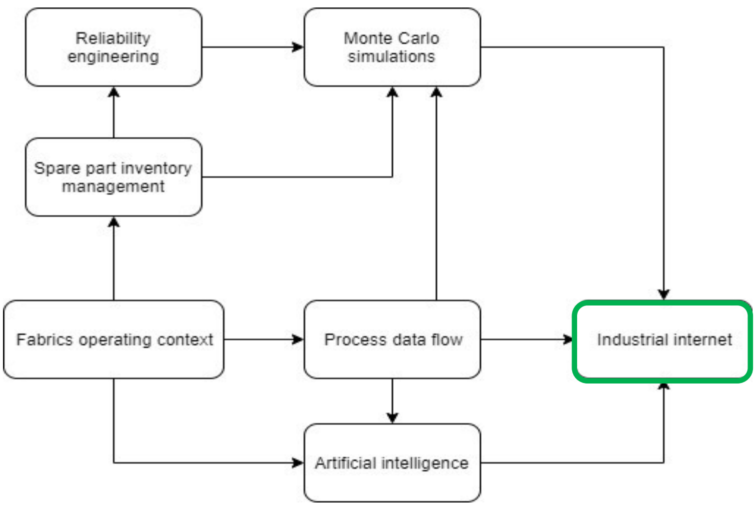

Figure 8. *Theory synthesis. Depicts the theoretical process of creating value-adding industrial internet AI models from the fabrics' operating context*

In planning and application of different AI models for fabrics it is necessity to know the operating context well. Like demonstrated in literature review, each fabric groups have different requirements and goals. Even though, if the AI models are constructed with specific product group, it might be possible to use the same models with different parameters. In other words, similarities can be spotted even if the requirements are usually different. It also helps to know fabrics operating context because only then the right questions for relevant feedback can be asked from the customer.

It is also vital to understand the flows of process data when trying to model it further. Flow starts from papermaking process and moves to DCS. Next phase is data flowing from DCS to cloud where the industrial internet platform is. In industrial internet platform, the data can be harnessed to simulations and AI applications. In short, there are multiple links between fabrics operating context and views from industrial internet platform and it is vital to know how the steps in-between function.

Stock level simulations are introduced as one possible addition to industrial internet platform and therefore it is essential to find out how spare part inventories are generally managed. Fact is that running a fabric warehouse involves a lot of risk (Holik, 2013; Grinsted & Richards, 2016). Fabrics are an essential performance products and points of shortage are not allowed in machines (Holik, 2013). Modeling this risk with the help of reliability engineering and applying that to spare part inventory management will aid in optimizing fabric inventory (Arts, 2013; Kumamoto & Henley, 1996). The simulations in this thesis work are conducted with Monte Carlo method. Simulations have possible step further if fabric lifetime estimations with neural network prove feasible. With that option, remaining runtime could be estimated and added to stock level reliability calculations.

3. RESEARCH METHODS AND PRESENT STATE ANALYSIS

3.1 Research approach

Applying artificial intelligence towards the performance of paper machine clothing is a subject which has not been covered much in science releases. Therefore, this research must have innovative tools at its use. Good method for creating new and applying existing methods in a thesis is to use constructive research approach. Kari Lukka (Lukka, 2001) describes the constructive research approach as a method for conducting case-study. Lukka continues that it is a research approach which has gotten a lot of good feedback and at this moment is widely used particularly in economic and technology sector studies.

Constructive research approach is a method which produces innovative constructions. Every model, plan or even new commercial products are constructs if they are made by man. Thus, construction is an abstract concept which has endless number of possible outcomes. A key attribute in constructions is that they are cannot be found, they must be invented. (Lukka, 2001)

For constructive research process, it is mandatory to conduct weak and strong market tests to find out the applicability of the proposed solution (Kasanen, et al., 1993). Kasanen et al. (1993) continue that weak market test means that the target company is willing to apply to construction to actual decision making. The strong market test on the other hand means that the build construction produces better results than the results are without the construction.

In his material Lukka (Lukka, 2001) continues that for research approach to be truly constructive approach, it must validate certain core features:

- it focuses on real-life problems,
- produces innovative construct which aims to solve original problem,
- contains attempt to apply construct towards practice,
- researcher and practical experts work together as a team,
- is carefully linked towards theory and focuses to reflect empiric findings towards it.

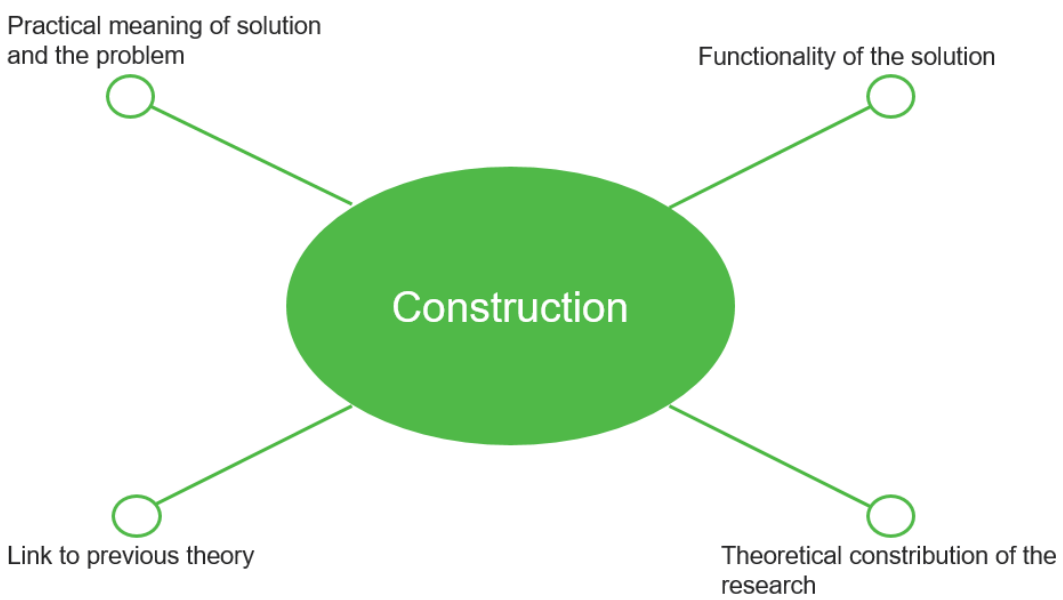

Figure 9. *Elements of constructive research method. Adapted from (Lukka, 2001)*

It is characteristic for a researcher in constructive research method to be highly involved. Therefore, constructive research is an experimental method and influence towards real-life is part of the method itself. Ideal result in constructive research is that the real-life problem is solved with new construction and whole process generates contribution to practice and theory. It must be noted that also negative result might contain significant theoretical meaning. (Lukka, 2001)

Choosing constructive research method for this research allows academic freedom to link existing theory together. This is particularly important because paper machine clothing and artificial intelligence or industrial internet are together non-studied matter. In this thesis work existing theory from these fields are collected to generate fruitful synthesis for scientifically unknown combination. Customer feedback can also be more agilely addressed when researcher has more scientific freedom to modify models during the research process.

3.2 Research process

Since the main goal of the thesis is to generate additional value to PMC unit's industrial internet offering - the nature of the software must be noted. Analysis of the present state of the Valmet PMC Industrial Internet applications is more described in 3.3. From customer and Valmet PMC expert feedback (which is detailed in 4.1) improvement goal was focused towards supply chain side of the program. Figure 10 illustrates the research process.

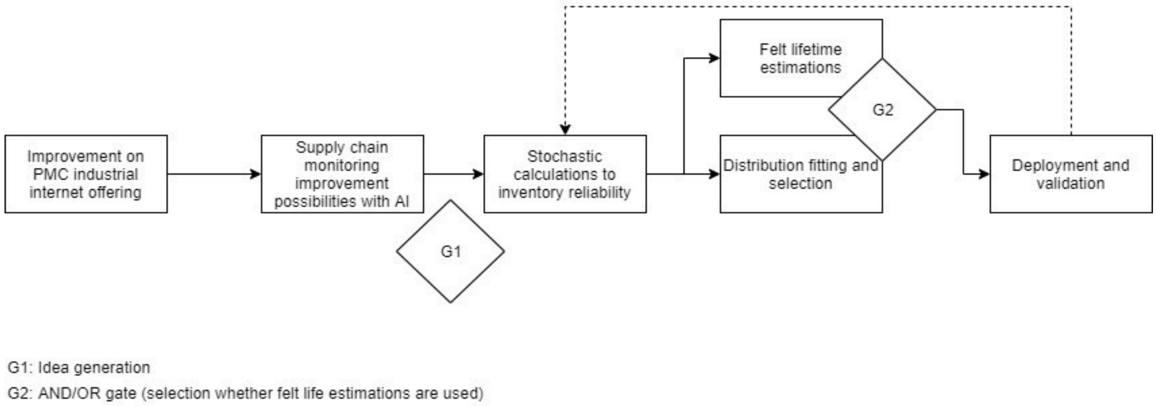

Figure 10. *Research process flowchart*

Research process, as illustrated in Figure 10, consists of one branch and two gates. Gate 1 acts as a phase of idea generation and feedback. Idea generation is conducted by introducing one theoretically backed solution by listening to feedback from both PMC unit's experts to find suitable value adding methods for the program. Gate in this part of the process acts as a validation process whether to continue with selected value adding solution or to make corrections if needed.

Development work in first branch of the research process, supply chain monitoring, continues after gate 1 by building the model needed for stochastic calculations. To make estimations with high accuracy, calculations require probability distribution which corresponds most accurately to failure times of the fabrics. Therefore, after failure times are corrected, distribution fitting is conducted with four preselected probability distributions to find the most fitting distribution. In parallel, current fabric lifetime estimations are examined whether neural network model from process data could give accurate estimations about remaining runtime. Gate two acts as a validation point whether to continue with just stochastic simulations about remaining inventory or to add analytic estimations about remaining runtimes to the mix as well. After gate 2 model is deployed and validated through one case study. Validation process is continuous and should be conducted as an iterative process to optimize the constructed model. Customer feedback is a parallel branch of the research process because it aims to develop the existing solution more.

Generating models for simulations and neural networks requires tools which allow possibility for quick iteration rounds. Thus, the tools used for calculations in thesis work are

Mathcad and Alteryx. Mathcad is a clear and easy to use software for calculation of mathematic and scientific formulas. Advantage compared to other mathematical tools comes from possibility to use and calculate formulas symbolically. Alteryx Designer application on the other hand offers more efficiency to data preparation. Making predictive analyses from prepared data samples is also swift with the application because no additional coding is required for creating models. For both applications, result visualization and validation are emphasized and therefore both Mathcad and Alteryx support iterative process of model creation. (Alteryx, 2019; PTC Mathcad, 2019)

3.3 Present state of the applications

Industrial internet applications for target organization’s PMC unit are called Valmet PMC Monitor and PMC Analytics. It is a web-based service for tracking and monitoring paper machine clothing in real time. Valmet PMC Monitor’s main objective is to be a hub for customer which contains all crucial paper machine clothing information from their fabrics in one place and to be an efficient tool them. Another application, PMC Analytics, gives tools for customers to monitor condition of the whole papermaking process by making tracking of possible deviations in a process much easier. Having these tools to easily analyze process data will also assist PMC experts to develop products by giving better overall view of the customer’s process.

Supply chain monitoring tool, PMC Monitor, contains all customer-specific PMC information in one view. Runtime statistics and warehouse levels are all displayed within the first view of the application. From overview dashboard, customer can dig deeper to monitor their current fabric pipeline for each fabric position to track warehouse levels and delivery times of ordered fabrics. Customer can click forward from pipeline dashboard to view single fabric cards which contain all relevant information of current and ran fabrics. One example dashboard is illustrated in Figure 11.

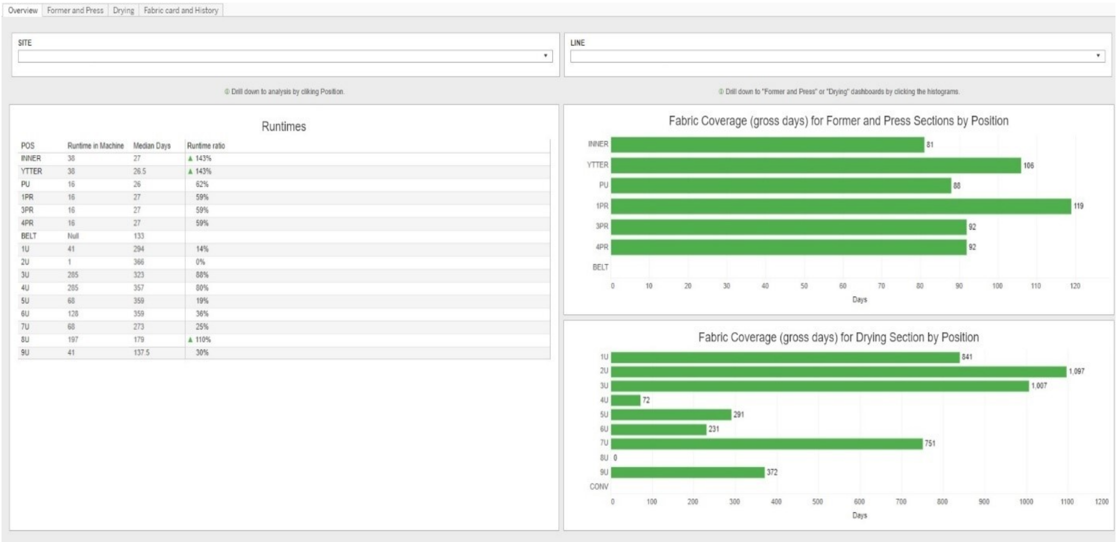

Figure 11. *PMC Monitor - Supply chain management dashboard. Allows user to easily monitor fabrics that are currently in machine and also to check up on inventory situation*

Another application is called PMC Analytics. It is a tool to monitor fabrics performance by benchmarking fabrics against fabrics from the same machine and position. Benchmarking is conducted through selected fabric KPI's from process data and with advanced calculations about relative nip dewatering and relative energy usage. Production rate and dewatering are good examples of values which are compared by averaging these production values to fabric lifetimes and comparing them against each other. Advanced calculations for dewatering and energy usage are basically applying relative element to correspond to different process scenarios in paper machines. For example, dewatering and energy usage are by default higher when machine is running heavier grades (Holik, 2013). Dashboard in PMC Analytics is illustrated in Figure 12. In addition to benchmarking averages in column graphs, dashboard contains graphs to follow-up and compare fabrics dewatering and energy usage. Dashboard is for one fabric position at a time and by changing the position, from for example pick-up felt to 1st press felt, the values change accordingly.

Figure 12. *PMC Analytics - Performance monitoring dashboard. Benchmarking tool for user to compare fabric's performance*

Application is currently under beta phase for one pilot customer. Goal is however to expand PMC Monitor and PMC Analytics rapidly to several customer. At the time, the development of applications has stalled a bit because of issues within the interfaces of different data sources. One stalling element was also re-engineering of advanced calculation packages due to calculations being too explicit for rapid expansion to several customers. After the re-engineering application's scalability increased enormously so after the data flow issues have been solved, the applications can be issued to multiple customers in a matter of hours.

Both applications are designed for customer's use by giving them easy to use and quick way to monitor fabrics. Because customer is the number one stakeholder towards application, developmental phases have been conducted in collaboration with pilot customer. Pilot customer's feedback has driven the application towards their needs and hopefully towards the needs of other customers as well. At this point, only developmental phases have been conducted with the customer but the real work begins when the platform has been given for customer's daily use. Other key stakeholders towards application are PMC unit's fabric experts. Previously there has been limited or no view towards customers' production data and this platform would give huge step toward more data-driven decision making in sales support and product development.

Data flows to industrial internet platform have proven to be quite frail. And with developmental phase being conducted to only one pilot customer, the question mark remains that how the applications function when there are multiple additional data sources in play. These issues are solvable with time but key challenge for future is that how will the application be welcomed after release and how the general interest towards the use of PMC Monitor and Analytics develop. Another key challenge is to keep taking a good care of customer's data. Transparency in data flows and strict role-based access control (RBAC) in application are essential to continuation of both applications. Production data from paper machines is highly classified and even one occurrence of data leak might lead to whole project being shut down.

Next phases for PMC Monitor are already being sketched and implementations are planned for near future. First development, manual input option for fabrics, is already nearing its implementation. With current application, all fabric data is flowing through Valmet's CRM (customer relationship management) system so customer doesn't have an option to add or modify existing fabric information in a system. In future, customer will have this option through input display view which allows more "diary-like" use of the PMC Monitor. Another developmental direction is to integrate measurements and laboratory data to application. This would move application even further to be a complete hub for all crucial fabric information because on-site fabric measurements and laboratory reports are essential in fabric's development. One possible developmental addition towards PMC Monitor and Analytics is to add AI into the mix. This addition and its feasibility is discussed further in this thesis work.

4. MODEL DEVELOPMENT

4.1 Pilot customer feedback

First and foremost, the key stakeholder for PMC Monitor and PMC Analytics is customer. As illustrated before, developmental phases have been conducted through customer feedback. In this thesis work, one crucial part of the work has been to get this feedback from the pilot customer and plan how to use it. At the start of the project customer hadn't been introduced to applications so work began with thorough introductions. After introductions, the feedback was gathered with conceptual work only and therefore the platform wasn't yet available to be given to customer's day-to-day operation. Thus, these two Q&A visits to customer's mill were mainly about displaying the possibilities of the platform while more feedback and training needs to be conducted after official launch of the program. General questions asked and feedback from customer and Valmet PMC experts about applications are illustrated in Table 3.

Table 3. *PMC Monitor and Analytics questions and feedback*

Question	**Pilot customer answers**	**Valmet PMC experts answers**
What benefits do you expect to have from this service?	Ease of use and having all fabric related data in one place. Easier look of process data trending. Prospect of time saving	Better view to customer process data, optimization of fabrics would be easier due to easier distinction of good process run periods. New value-adding method for sales
What are the key metrics you track about PMC performance?	Nip dewatering in press felts, breaks and KPI-comparison	Laboratory values, fabric age, comments from customer
What do you think about simulating the fabric supply chain reliability?	Additional increase in reliability to operation of fabric warehouse	Major upgrade to existing methods. Having a certain trigger time for placing an order at a right time would be a major benefit
Is lifetime estimation of current fabric relevant?	Potential is high, now seen as adequately beneficial	Potential is high, now seen as adequately beneficial

Before even thinking about adjusting PMC Monitor or PMC Analytics, we need to know what customer wants to know about fabrics and their performance. Therefore, from fabrics point of view, first question was to ask pilot customer what the key aspects are they want to know about fabrics operational capability. First answer was that fabrics are closely attached to overall performance of paper machine. Thus, tracking the development of few overall process data KPI averages through fabric lifetimes seemed important. Second, more precise answer about press felts governed the fact that in pilot customer's case nip dewatering is a key attribute for press felts. Third key figure in the fabrics operational capability were breaks and other time loss events and even more if they can be pinpointed towards individual fabrics. Customer acknowledged that papermaking process is a function of hundreds of variables but pointed out that these variables should be possible to be compared against each other. For example, spotting correlations between fabric KPI's and various process parameters were seen important. With correlations customer continued that it would be important to have possibility to monitor correlations between fabric KPI's, process data parameters and paper quality properties to be able to finetune the papermaking process.

Having an application like PMC Monitor and PMC Analytics to be part of day-to-day operation means that it needs to bring additional value. In Q&A sessions with customer possible points of added value were inquired. Main points where applications could prove to be a real asset to day-to-day operation were related to containing all fabric related data in one place, being easy to use and possibility to enhance own operation through improved view of data. Now customer gets their fabric related data from numerous sources usually to email and therefore it can be hard to find information about specific details. Thus, one repository with all key fabric information would free time because the information would be more easily acquirable. Customer also pointed that they don't currently have tools which would make production data trends easily accessible. Existing trend tools were seen rather slow and time-consuming and one thing that they don't have is time. Thus, swift and easy to use data comparison and visualization tool would allow personnel to dive into root-causes of process deviations more effectively. Also, the possibility to compare process data from fabric change timeframe point of views instead of real time data would allow process optimization by seeing how process parameters change as a function of fabric age. In addition to possibility to enhance whole process, customer saw that addition of platform would allow more cooperation with them and fabric supplier. For example, optimization of fabrics would be easier due to easier distinction of good process run periods.

In visits to pilot customer only beta versions of PMC Monitor and PMC Analytics were introduced. Therefore, real feedback is yet to be achieved because PowerPoint slides and semi-functional application give just a window towards attributes of the application and not much about user experience. However, the pilot customer was able to shed excellent feedback and showed bias towards the use of PMC Monitor. At overall customer was delighted with the program and said that it could bring additional value to day-to-day operation. Application was seen easy to use and customer pointed that it must stay like that. However, customer emphasized heavily their concern that data security must continue to be held in high regard because their production data is highly classified.

As discussed earlier, in a timeframe of this thesis the platform wasn’t given to customer. Therefore, the aspects in need of refinement were limited because the application couldn’t be tested in day-to-day operation. Thankfully, in visits to pilot customer, some points in need of fix and developmental hopes were identified. Aspects of possible refinement discussed in pilot customer visits governed bugfixes, layout options and possibilities, content of fabric information in the application and possibility to add correlation between process parameters. From layout point of view customer found it hard to track fabrics based on Valmet sales ID number. This was excellent feedback and immediate action was taken to make monitoring of fabrics based of their supplier and installation date. Even though customer appreciated the PMC Monitor being a centralized hub for fabric related information they found the platform lacking few important aspects. Especially laboratory report data should be applied to individual fabric cards. Adding laboratory data, runtime records and performance KPI-values would allow more streamlined view of fabrics and to enhance R&D in Valmet PMC product.

Because the key emphasis in this research was to figure out how applying artificial intelligence to industrial internet platform would improve the offering feedback was also gathered from pilot customer and from target organization’s fabric experts. The reason for gathering additional feedback from Valmet personnel was mainly the point that pilot customer’s fabric warehouse is managed by Valmet and therefore customer did not see supply chain simulations as the most crucial thing to have. There was however some interest from additional increase in reliability to operation of warehouse. The feedback from target organization illustrated that supply chain simulations could be a major upgrade to existing methods. Today all order cycles are defined by rather simple average demand estimations. These situations lead unfortunately often to situations where stock levels suffer from surpluses or even shortages. This generates extra workloads for sales and production planning and therefore the feedback was that the simulated order cycles from customer consumption would allow more risk mitigation and optimization. Fabric experts continued that having a certain trigger time for placing an order at a right time would be a major benefit. Another AI possibility concerning neural network based fabric age estimation was seen adequately beneficial by both customer and target organization's personnel. Main comment was that increase in everything new is welcomed because for example industrial internet is very new phenomenon in the field of paper machine clothing. Both parties continued however that even though the idea is great need is greater to launch basic applications first before adding deeper intelligence to the mix.

4.2 Fabrics stock level simulation

Fabrics are a vital part of a papermaking process and there must be fabrics at every position when paper is being made. The fabrics are prone to unexpected changes due to being crucial performance parts. For example, in cases of poor process performance fabrics are among the first spare parts to be changed to improve the situation. This can be the case even if the fault is not related to fabric. Usually it just is the cheapest option to replace for process performance improvement potential. (Adanur, 1997; Holik, 2013; Paulapuro, 2008)

Fabric changes are usually tied to strict maintenance schedules. Therefore, fabric lifetimes can be shorter than their potential could be. This works also as a preventive method in risk management and to maintain performance as well. However, in a case of stock level optimization, this randomness doesn't reflect to fabrics "actual lifetime" but it gives more general idea of the whole process cycle which ultimately benefits pipeline planning the best. But it has to be kept in mind that the optimization must not be conducted too strictly because it is a necessity to have additional fabrics in storage due to high downtime costs (Holik, 2013).

General idea of the stock level simulations in this thesis work is to observe uncertainty in various steps of the process. These steps can include for example runtimes in machine, delivery and manufacturing times. Simulations become more accurate with each step which has been included to the simulation. Higher accuracy on the other hand results in better view of the situation and thus supports the decision making better. Fabric stock level simulations start from legacy data collection of past runtimes of the fabrics. Without this information, it isn't possible to conduct stock level simulations with these methods. Every machine and every fabric position are different so the same simulation does not apply into two separate positions.

Goal of the fabric stock level simulations is to find optimal delivery cycles and optimal levels of fabric stock. First step in simulations is to find the best probability distribution fit for runtime distribution. This is more described in the next subchapter but the goal is to A) list failure times and illustrate them against failure distribution B) find the most fitting distribution for failure distributions by comparing different probability distributions C) optimizing probability distribution parameters with least square method (lowest least square error means the most suitable distribution). The fitted distribution will be key in simulations and with its quantile function, runtimes can be simulated with Monte Carlo method. Adding adequate amount of simulation rounds and including stochastic calculations for delivery and manufacturing times increases the accuracy of the simulation.

With simulated runtimes, the inventory reduction can be simulated. Inventory reduction can be simulated to cover any needed period but for these simulations, it is advisable to check the development of reliability between different delivery cycles. To get the best added value to the pipeline planning, simulations should be used to cover X amount of deliveries to find out, whether the risk is ascending or descending. Thus, key variables in stock level simulations are reorder point and interval between deliveries. Adjusting the variables change the risk associated to that situation and might result in fabric inventory surpluses or shortages. By having high reorder point the makes it harder to run out of stock fabrics. Key is to find the best compromise which doesn’t overstock the inventory but also takes risk in to account. Also, safety stock levels can be adjusted through reorder point adjustments.

As discussed, the fabric runtimes are prone to randomness. Having this in mind, simulation should be a key tool to use when adjusting correct delivery cycles to customer. With uncertainty being displayed as a number, correct actions can be taken. In stock level simulations, the nature and the importance of fabrics must be noted – a point of absolute shortage must be set to minimum. Many contracts also dictate that inventory level must be kept over certain amount and therefore being below that could potentially mean penalties. Also, having an uncertain and too strict stock amount could result in a loss of sales.

4.2.1 Distribution fitting

The first step towards the simulation of fabric stock levels is to conduct distribution fitting towards the runtimes associated with the fabric warehouse. Thus, the goal is to find the most fitting probability distribution to match runtime patterns. Runtime patterns can vary enormously between different machines and positions. Therefore, it is advisable to find universal fitting solution which is easy to implement for multiple targets and is precise enough. Good fit will provide preciseness to all calculations, especially in case of Monte Carlo simulations. The fitting of distribution will be inspected with least square error method. Before evaluation, the steps in distribution fitting go as: 1) listing runtimes in ascending order 2) pre-determining four different distributions 3) conducting distribution fitting to arranged set of runtimes with least square error method 4) comparing the distribution fits. Evaluation will be based on the LSE (least square error) of the fits and on other qualities such as the scalability and the combability towards Alteryx software.

Listing runtimes of past fabrics (each machine and position individually) in ascending order and creating histogram of that data creates a good window to see the patterns behind runtimes. As discussed, we can’t unambiguously talk about failure patterns because in many cases felt changes are not related to the condition of a fabric. This characteristic is examined more thoroughly in fabric lifetime subchapter 4.3. Figure 13 is a collection of 3 different actual press felt runtime histograms. It illustrates the vast differences between the runtime patterns. This creates a dilemma towards generating a universal runtime distribution – excess preciseness creates a good fit for one case but on the other hand might be worse solution for others. Therefore, generalized fitting solutions must be examined thoroughly as well.

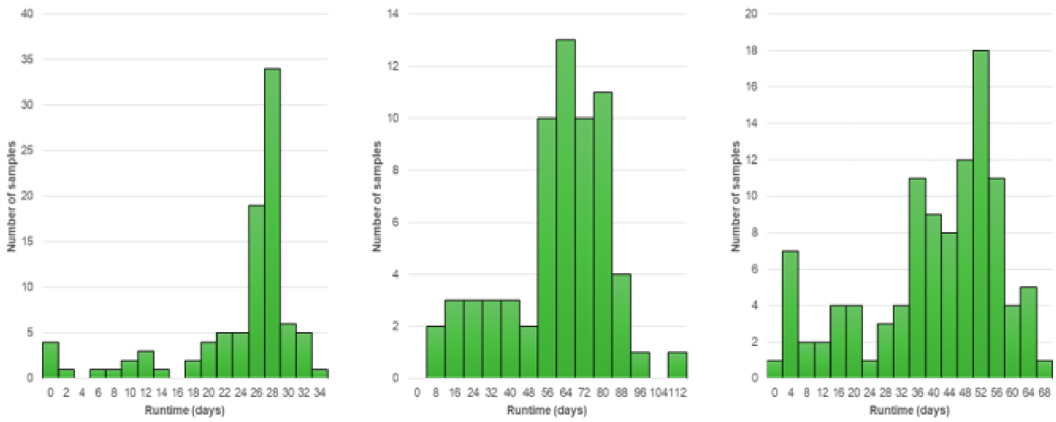

Figure 13. *Three runtime histograms of a same position press felts. Demonstrates the differences between runtime patterns of separate paper machines*

Next phase is to conduct distribution fitting. Distribution fitting means matching probability distribution to fault or in this case runtime pattern as precisely as possible. This thesis work presents four probability distributions for comparison: normal distribution, Weibull, Logistic function and extended beta function. Presented probability distributions possess different capabilities which were more thoroughly discussed in 2.3.3. To use the Monte Carlo method, the quantile functions are required. The quantile functions themselves don't give precise distribution fits – the key is to optimize the parameters of the quantile functions.

In short, distribution fitting procedure requires three things: 1) least square error function (as presented in formula 2.2) 2) initial guesses for the distribution parameters and 3) error minimization algorithm. The error function calculates the distance between fitted quantile function and the actual runtime values. Many parameters, such as mean and standard deviation, can be calculated directly from the original data. The initial guesses are required for parameters which can't be directly calculated. For example, the shape and scale of the distribution need initial guesses. For initial parameter guesses, the better the guess the better the error minimization algorithm functions. Error minimization algorithm gives optimized parameter values and thus fitting has been conducted. Applying these values to quantile function generates a graph which resembles the runtime pattern in ascending order.

This thesis work presents least square error between runtimes and fitted distributions the key benchmarking option in distribution comparison. Lower LSE between the fit and actual runtime pattern yields better results for upcoming calculations such as stock level simulations. Table 4 represents the least square errors for three runtime patterns (Figure 13) with four different probability distribution fits.

Table 4. *Least square errors of distribution fitting. The bolded value means the lowest LSE in that runtime pattern*

Distribution	Normal	Weibull	Logistic	Extended beta
Runtimes 1 LSE	16,18	14,05	14,77	**7,51**
Runtimes 2 LSE	**27,06**	33,28	27,67	29,55
Runtimes 3 LSE	30,65	24,36	28,94	**11,89**
TOTAL	73,89	71,69	71,38	**48,95**

Results of Table 4 illustrate the fact that different runtime patterns can't be uniformly fitted. Thus, least-square errors of different probability distributions vary enormously. From least square error point of view, extended beta distribution is the best because in two out of three cases it has the lowest error. In second runtime case, where extended beta isn't on top, its value is close to be the lowest (29,55 versus 27,06). Cumulated least-square error from three runtime cases also shows that extended beta distribution produces the best fit at least for these three cases. Figure 14 displays these distribution fits by plotting different fitted quantile functions against the actual runtime patterns.

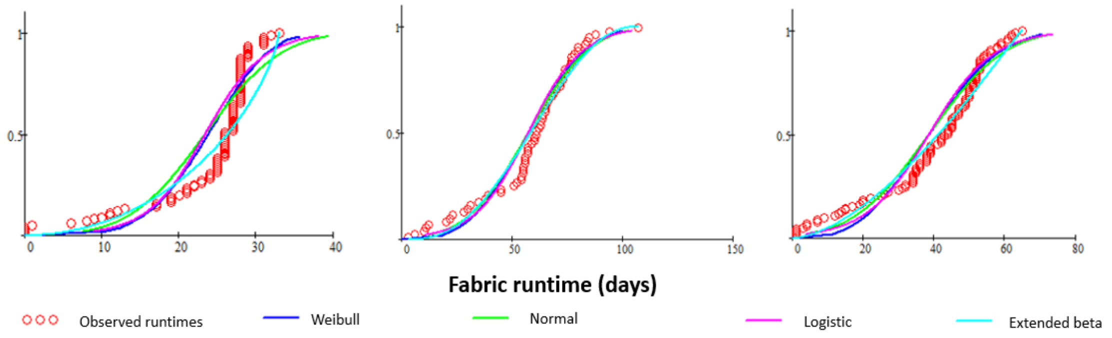

Figure 14. *Comparison of different distributions by fitting them to fabric runtimes*

From fitting point of view the result is obvious, extended beta function performs on a level above the rest. However, other more quantitative qualities, must be looked at. For comparisons, especially the scalability to other patterns and the robustness of fitting are vital attributes. Because the analysis will be continuous in the cloud, interface limitations and possibilities must be discussed as well. The further simulations will be conducted with Alteryx and not on Mathcad as in this chapter which results in a set of limitations. As it stands, only normal distribution is agile enough for Alteryx simulation tool from pre-selection of four distributions. Further analysis is needed to create code for additional options to include for example extended beta function in it.

4.2.2 Simulation calculations

Calculations continue by choosing the most adequate fitted distribution from previous section which in this case is normal. Next the quantile functions are used in accordance with optimized parameters to simulate possible runtimes for that runtime pattern like in formula 2.1. Amount of simulation rounds can be defined however wanted – more simulation rounds mean more preciseness but also require more computing power.

To make the stock level simulator functional, a fabric runtime simulator must be implemented. The fabric runtime simulator uses the same principles as distribution fitting section 4.1.1. The goal is to simulate runtimes for further steps of simulation. Runtime simulator generates simulated runtime patterns for one fabric position at a time. Figure

15 illustrates the main process flow of the fabric runtime simulator in Alteryx. In runtime simulator, the only input is to list all past runtimes of the position in days in .txt format. Process flow cleans the data and then simulates runtimes adjacent to inputted runtime patterns distribution fitting. The tool to conduct simulations is called simulation sampling and it uses the Monte Carlo method with normal distribution. The process workflow in Figure 15 contains 30 simulation tools for consumption calculations. Having 30 simulation tools allows more simulation steps to investigate consumption cycles for up to 30 fabrics. By default, simulation all tools have 1000 simulation rounds which then adds up to 30 000 simulated runtimes in total. Last phase in runtime simulator is to collect results to .csv which file allows more robustness in next phase – the inventory reliability calculator.

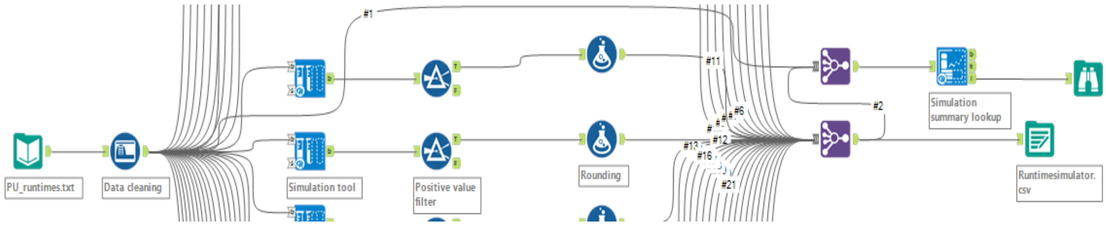

Figure 15. *Runtime simulator process flow. The fabric runtimes are used as an input to conduct Monte Carlo simulations*

With simulated runtimes, we can also simulate inventory reduction during a predefined period. This period can be set manually or reflect to true value – such as delivery time. Inventory reduction during simulated runtime is defined in formula 4.1.

$$Inventory\ reduction = \frac{Time\ period}{Simulated\ runtime} \tag{4.1}$$

In this thesis work, one inventory reliability calculator model will be presented. This means that user can manually check the reliability of their fabric inventory with different order cycle parameters. Parameters for this calculator are 1) minimum allowed level of stock (reorder point) 2) fabrics currently in stock 3) reorder quantity and 4) time between deliveries. This tool aims to give user optimal order cycles to match their fabric consumption pattern.

The inventory reliability calculator is constructed with Alteryx -software and its process flow is illustrated in Figure 16. The calculator starts from the left by adding simulated runtimes and calculator parameters to the mix. The next phase is to conduct consumption simulation during N amounts of deliveries. In current model, there are option to track reliability change within 1, 2, 3, 4, 5, 10 and 15 delivery cycles. After consumption simulations, the next phase is to calculate stock levels of each delivery cycle option. With the simulated stock levels, last phase is to conduct reliability calculation within each option.

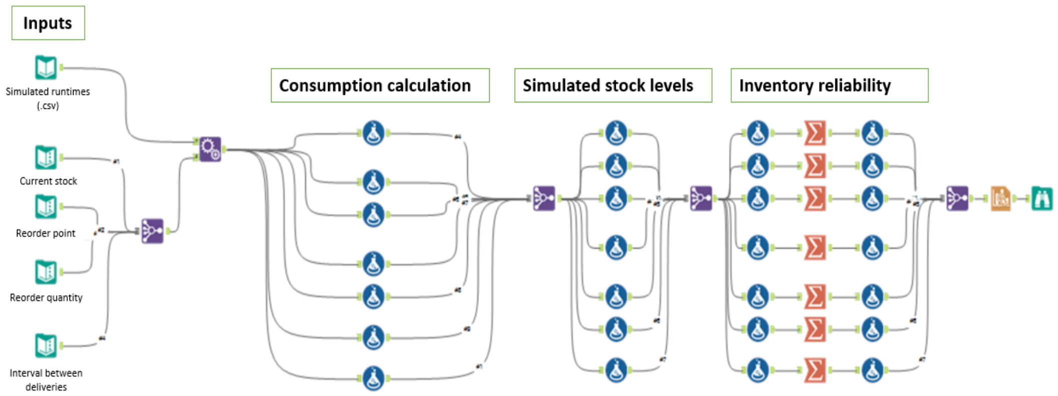

Figure 16. *Inventory reliability calculator. The left part represents the inputs of the process flow. The adjacent parts process the data to show how the inventory reliability changes with different input parameters*

Formula 4.1 covers only one consumption cycle and to add it for multiple cycles light IF-logic is needed. Logic for the calculation is described in Figure 17 and it tells the logic between consumption during x amount of delivery cycles. It defines that how many fabrics are ran during defined consumption cycle X. For example, if time between deliveries is 30 and we want to check how many fabrics are consumed during two cycles. If simulated runtimes are 24, 21 and 26 the calculator will give result of two in fabric consumption because the first and second if-sentences trigger but not the third. This is because simulated runtimes add to 71 and timeframe to 60 days.

```
Consumption = IF ([Simulated runtime 1] < ([Time between deliveries] * X)) THEN
1 ELSE 0 ENDIF) +
      IF ([Simulated runtime 1] + [Simulated runtime 2]) < ([Time between
      deliveries] * X) THEN 1 ELSE 0 ENDIF) + … +
            IF ([Simulated runtime 1] + [ Simulated runtime 2] + … + [Simulated
            runtime N]) < ([Time between deliveries] * X) THEN 1 ELSE 0 ENDIF)
```

Figure 17. *Consumption algorithm in Alteryx*

Next phase is to simulate stock levels *v* after *N* amount of deliveries. This calculation is illustrated in formula 4.2. The index *i* outputs a vector containing desired amount (1000 by default) of simulated stock levels.

$$v_i = Current\ stock - (Consumption\ N\ cycles)_i + Reorder\ quantity * N \tag{4.2}$$

Next step after stock levels have been simulated is to calculate the reliability of the inventory. This calculation is depicted in formula 4.3. In the calculation simulated stock levels are compared against defined reorder point. This gives a % at what possibility stock level is below defined minimum. *N* in formula 4.3 stands for amount of simulation rounds used.

$$Inventory\ reliability = \frac{1}{N}\left[\sum_i (v_i \leq Reorder\ point)\right] \tag{4.3}$$

Having 5 different options for delivery cycles allow users to check whether the current fabric pipeline is sufficient. The first delivery option checks whether the reliability is currently at adequate levels and options for 10 and 15 deliveries pinpoint whether the reliability will be ascending or descending. An example development of reliability between two different delivery cycle options is depicted in Figure 18. On Figure 18 the left interval between deliveries is 20 days and on the right 25 days.

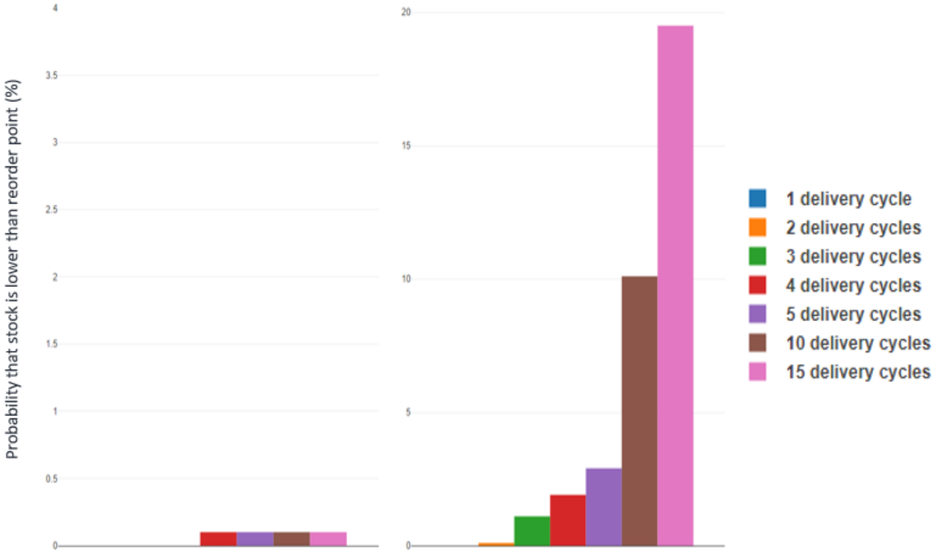

Figure 18. *Reliability of inventory with two different delivery cycles*

Point of having this kind of calculator is to allow users manage fabric inventory risk more efficiently. One option would be to have one optimized cycle as a solution but this gives more freedom for user to define levels accordingly towards risk.

4.3 Fabric lifetime estimations

Tracking and monitoring fabric's condition is a key in successful control of papermaking process. Traditional methods such as felt measurements and shutdown inspections play a pivotal role in optimization of fabrics (Adanur, 1997). These methods require physical presence of paper machine clothing expert on-site and currently the options for offering help off-site are somewhat limited. Papermaking process is a continuous process and it is conducted all over the world. While travelling to sites takes loads of time, the data flows are today almost instantaneous. Thus, this thesis work aims to give framework for additional fabric condition monitoring method through estimating remaining fabric lifetimes. In many cases fabrics are prone to be changed at fixed intervals which means that they are usually changed before their potential has been used to full (Holik, 2013; Paulapuro, 2008). However, fabrics are sometimes prone to damages and therefore this model aims to spot deviations in the process before the unexpected fabric change occurs.

The goal of the fabric lifetime estimations is to estimate fabrics remaining useful life with neural network conducted from process data parameters. While the amount of process data parameters is usually 15 000-20 000 in paper machines, this research bases its models from data collection which contains approximately 70 parameters. These parameters affect straightly (or are affected from) fabrics. The process data includes daily averages from that list of parameters. In addition to that it contains the fabric data of remaining lifetime of the fabrics linked to that data. The data contains approximately three years of data from the mill. For optimization purposes some data filtering has been put in place. Because the data parameters are linked to a running process, filtering must only select values from ongoing process. Therefore, key filter is to have lower limit for machine speed. Another adequate filter in this case is also the web break signal which tells whether the process is ongoing or not.

Remaining useful life (RUL) of the fabric is the output of the neural network and process data parameters are inputs. The goal is to find patterns between inputs and output to find whether the remaining fabric lifetime can be estimated. Backpropagation multilayer network is the general configuration of the neural network. With backpropagation, the network learns continuously from the correct input-output values. The learning processes update the network at the times of fabric changes because only then the correct remaining days of that fabric are known.

Alteryx software supports only neural networks with single hidden layer due to robustness but the number of nodes in the hidden layer can be configured. The first hidden layer combines all inputs linearly and an activation function is applied to the weighted linear combination of the parameters. In the second and subsequent hidden layers, output from the nodes prior to the hidden layer are also linearly combined. The results of the last hidden layer are combined in a final output layer that is consistent with the target type.

Accuracy of the model can be increased by increasing the number of nodes in the hidden layer (Haykin, 1999). With inadequate number of hidden layers, the model underfits. Underfitting means that neural networks prediction isn’t close to actual values and therefore model performs poorly. However, adding nodes to hidden layers can lead to model being overfit. Overfitting gives good results with current dataset but predictions to new input-output combinations can deviate extraordinarily. Goal is to find the golden mean with the number of nodes in the hidden layer. Good way to monitor model's performance is to calculate residuals between observed and predicted values (Skapura, 1996). Formula 4.4 illustrates the calculation of residual.

$$Residual = Observed\ value - Predicted\ value \tag{4.4}$$

Analytical platforms use residuals to display neural networks performance. Alteryx has three plots which illustrate the model's accuracy in various points (Figure 19). In this example residuals line up near residual value 0 so models' accuracy is adequate.

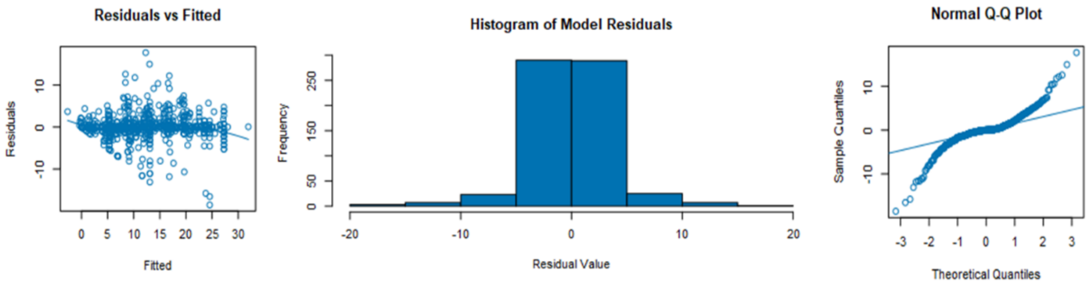

Figure 19. *Neural network performance monitoring plots in Alteryx*

The effect that single input parameter has towards output can be nonlinear in neural networks. Thus, there doesn't have to be linear correlation between inputs and output. Instead, the single parameter effects can be illustrated with specific effect plots. Figure 20 is an example of two effect plots. The point of effect plot is to illustrate the effect on the target associated with changes in the predictor field examined in each plot.

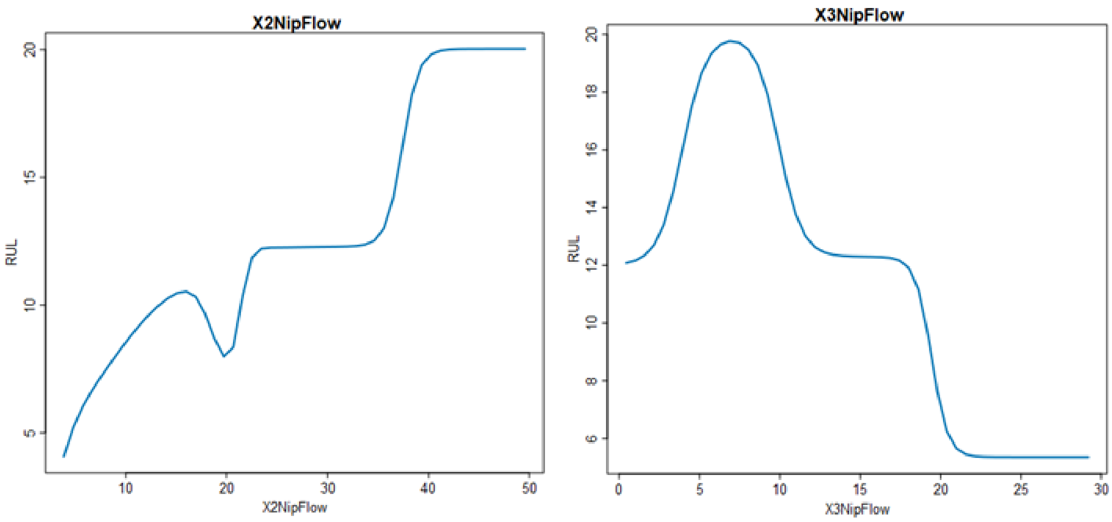

Figure 20. *Neural network effect plots examples*

In this thesis work two neural network models will be compared. The models will be constructed for press felts and the key divider between them is the number of parameters used in the model. The first model will have all possible input options currently in the data collection and the second model aims to select key variables listed in theory section. As (Häggblom-Ahnger & Komulainen, 2006) defined, the most important attribute for press felt is to remove water efficiently. Häggblom-Ahnger and Komulainen continued that materials used, grade produced, machine speed and press loads are all among the multitude of influencing factors to the function of the press felt. Also, the steam consumption and related drive usages were mentioned as important factors towards press felt performance. Thus, second model will include parameters from press section dewatering, grade specific values, machine speed and energy usages.

5. APPLICATION OF MODELS TO PROCESS

Aim of this chapter is to deploy the models portrayed in chapters 4.2 and 4.3 for one machine and for one position. Conducting a case study in a research following constructive research methods is vital because it illustrates the linkage to the real-life problem. The case study material consists of approximately three years of process data (in daily averages) and fabric information about all current and past fabrics of that machine. All calculations are position-specific but easily scalable to other positions as well. Thus, it is worth studying the models from one position's perspective to check whether the models prove feasible or not.

5.1 Inventory reliability calculator

First phase is to conduct distribution fitting towards the runtime pattern of that position. Second phase is to use this distribution in stock level simulations and to generate functioning stock level reliability calculator. Last phase is to evaluate fabric lifetime estimation models and to deploy them with available process data. Models are generated with Alteryx software and they are designed to be universally scalable to all positions and to be self-learning.

The distribution fitting in this case study was conducted in chapter 4.2.1. The case study governs the first runtime pattern in comparisons. Runtime histogram for the case study runtimes is illustrated in the Figure 21.

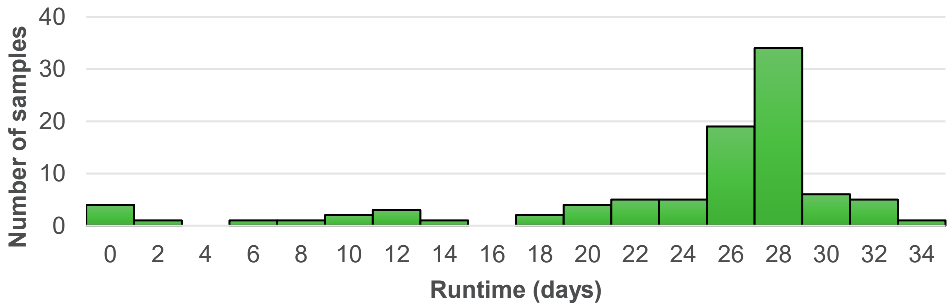

Figure 21. *Case study runtime histogram*

After listing the runtimes in ascending order, distribution fitting of case study data could be conducted. Table 4 contained the comparison of different probability distributions in distribution fitting of fabric runtimes. Furthermore, the first runtime pattern being also the case study pattern, it was evident, that the extended beta function conducted the best fit. Figure 22 illustrates the runtimes compared to the fitted normal distribution quantile function.

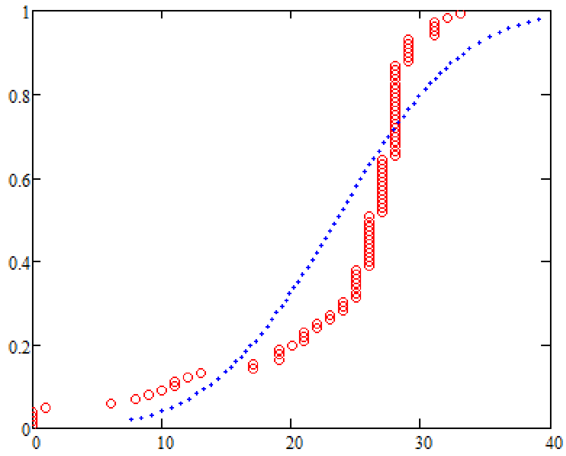

Figure 22. *Case study runtimes compared to fitted distribution*

Unfortunately, by default Alteryx supports only a handful of different distributions for its simulation tool. This negates the good result given by extended beta function and drives the process to use normal distribution instead. As discussed in 2.3.3, normal distribution doesn't respond well to higher tails or skewness. Thus, particularly in this case study, data is skewed to the right which creates relatively high LSE to normal distribution fitting. Now process must continue with higher fit LSE but in future this must be looked more closely to find a way around to use more distributions in automatic fitting.

Next step for the application of model is to add the runtimes to fabric runtime simulator (as illustrated in Figure 15). Inputting the text file about runtimes of past fabrics of case study's position generates 30000 simulated runtimes by using normal distribution as a fitting option. As discussed, this generates error to further calculations because using the normal distribution isn't the most optimal distribution but mandatory in this case. Simulator creates comma separated value file (.csv) which will be one input for inventory reliability calculator.

The first input for inventory reliability calculator (Figure 16) has been defined with csv file generated by runtime simulator (Figure 15). Other four inputs are all customizable by user but it is advised to use current level of stock which in these calculations includes the current fabric in machine. Reorder point can be set as low or as high as wanted and number of combined orders can be adjusted as needed. Setting different reorder points is a strategy choice which affects to shortage possibilities. The most important input in inventory reliability calculator is interval in days between orders. This input affects calculator the most because it defines the consumption interval for calculations. With low intervals, fabrics would arrive faster to warehouse which would result in better overall reliability between different amount of order cycles. For this case study, few different input combinations and corresponding inventory reliabilities are displayed in Table 5.

Table 5. *Inventory reliability calculator with case study data*

Input combination	**% stock level is lower than reorder point (delivery cycles)**						
	1st cycle	2nd cycle	3rd cycle	4th cycle	5th cycle	10th cycle	15th cycle
Current stock: 5 Reorder point: 4 Reorder quantity: 1 Delivery interval: 20	0	0	0	0,1	0,1	0,1	0,1
Current stock: 5 Reorder point: 4 Reorder quantity: 1 Delivery interval: 25	0	0,1	1,1	1,9	2,9	10,1	19,5
Current stock: 4 Reorder point: 3 Reorder quantity: 1 Delivery interval: 22	0	0	0,3	0,5	0,9	0,6	0,8
Current stock: 4 Reorder point: 3 Reorder quantity: 1 Delivery interval: 26	0	0,3	1,5	2,9	4,7	19,7	35,3

Table 5 illustrates that the second and the fourth input combinations result in increasing risk. The first and the third give the most reliable fabric inventory and probability to have fewer fabrics than the desired reorder point is very low. In the first case, even with high reorder point the probability of being under four fabrics is minimal. Thus, it seems that 20-day interval is too frequent and would result in inventory surplus. Adjusting the delivery interval to 22 days in third combination indicates more sufficient level of risk. With the use of inventory reliability calculator, it is evident that even the slightest change in delivery intervals can result in rapidly increasing risk. Current calculator gives ballpark-figures about the reliability and in future accuracy enhancement must be looked more closely. Two possible enhancements are giving more options for distribution fitting (such as possibility to use more demanding distributions) and to possibly add estimation of remaining fabric lifetime which has been discovered with either against the median or from data with neural network.

5.2 Remaining useful fabric lifetime model

As discussed in 4.3, the goal of the fabric lifetime estimations is to estimate fabrics remaining useful life with neural network conducted from process data parameters. In total, remaining useful fabric lifetime estimations include approximately 60 process parameter daily averages from three years of time. After filtration of data, this adds up to 800 rows of input-output combinations for neural network which might unfortunately prove to be too few and lead towards under or overfitting of the model. The construction and performance evaluation of neural network models will be conducted in Alteryx. The Alteryx process flow for remaining useful fabric lifetime estimator is illustrated in Figure 23.

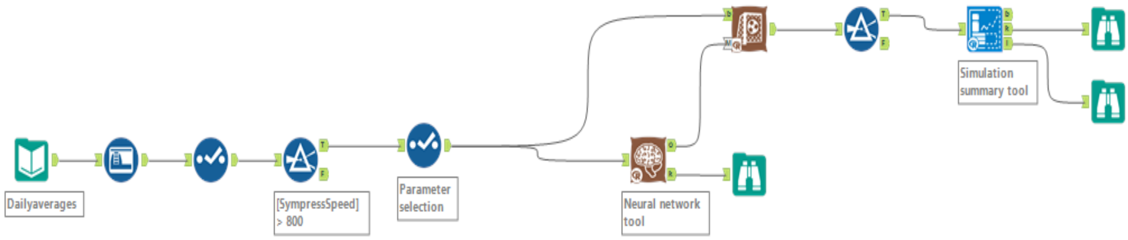

Figure 23. *Alteryx process flow for the neural network to make RUL predictions with the available process data*

In Figure 23 data is filtered and then is up for parameter selection. This phase allows to compare the two frameworks presented for models earlier: full selection of all signals and relevant selection containing the most important factors for press felts. After selection point process flow continues to neural network tool which allows the user to select the number of hidden layers in the model. Adjusting the number of nodes modifies the performance of the estimator: high number of nodes in the hidden layers results in better guesses but also might lead to overfitting. In neural network tool, user can also select the maximum number of weights allowed in the model and maximum number of iterations for model estimation. In this case study, neural network has a maximum of 1000 weights and 10 000 iteration rounds for optimization. The last phases after neural network tool are to score the simulation and illustrate the result of the model with scatter plot.

The first model consists of only predetermined parameters which affect (or are affected from) the press felt. Selected signals consist of values from fabric age, press section dewatering, uhlebox vacuums, press section drive usages and loads, main steam flow and pressure, machine speed and dry weight of the end-product. In total, it amounts in 37 input signals and one output signal (remaining fabric lifetime in days). The second model takes all available signals into account.

The effect that single input has towards the final output can be observed through effect plots. For relevant signal selection, few key effect plots are listed in the Figure 24. These are selected for demonstration because the value changes within the parameter effects most of the RUL scale. Some parameters had only limited effect affecting only a certain part of the RUL estimation. The effect plots show that neural network can find patterns beyond linear correlation.

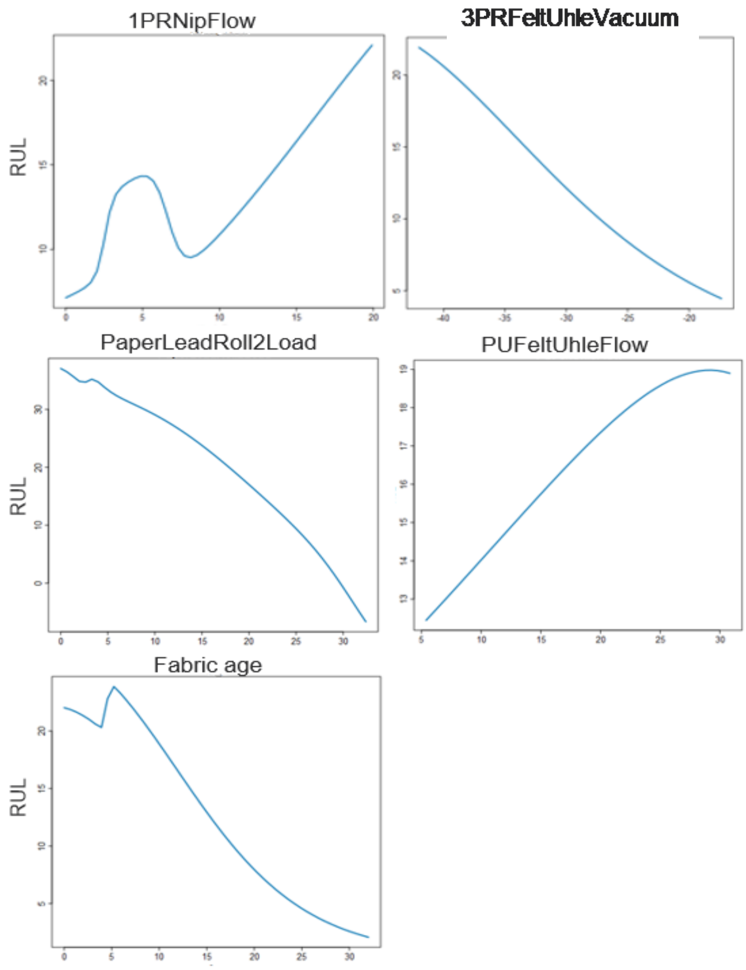

Figure 24. *Five key effect plots of relevant selection model. Selected effect plots represent signals which have effect towards output (RUL) scale*

Scatterplots of predictions made by these two models against the real RUL values are presented in Figure 25 where predicted values are on the y-axis and real values on the x-axis. In addition to model comparison, Figure 25 illustrates the function of the neural network with two different number of node options.

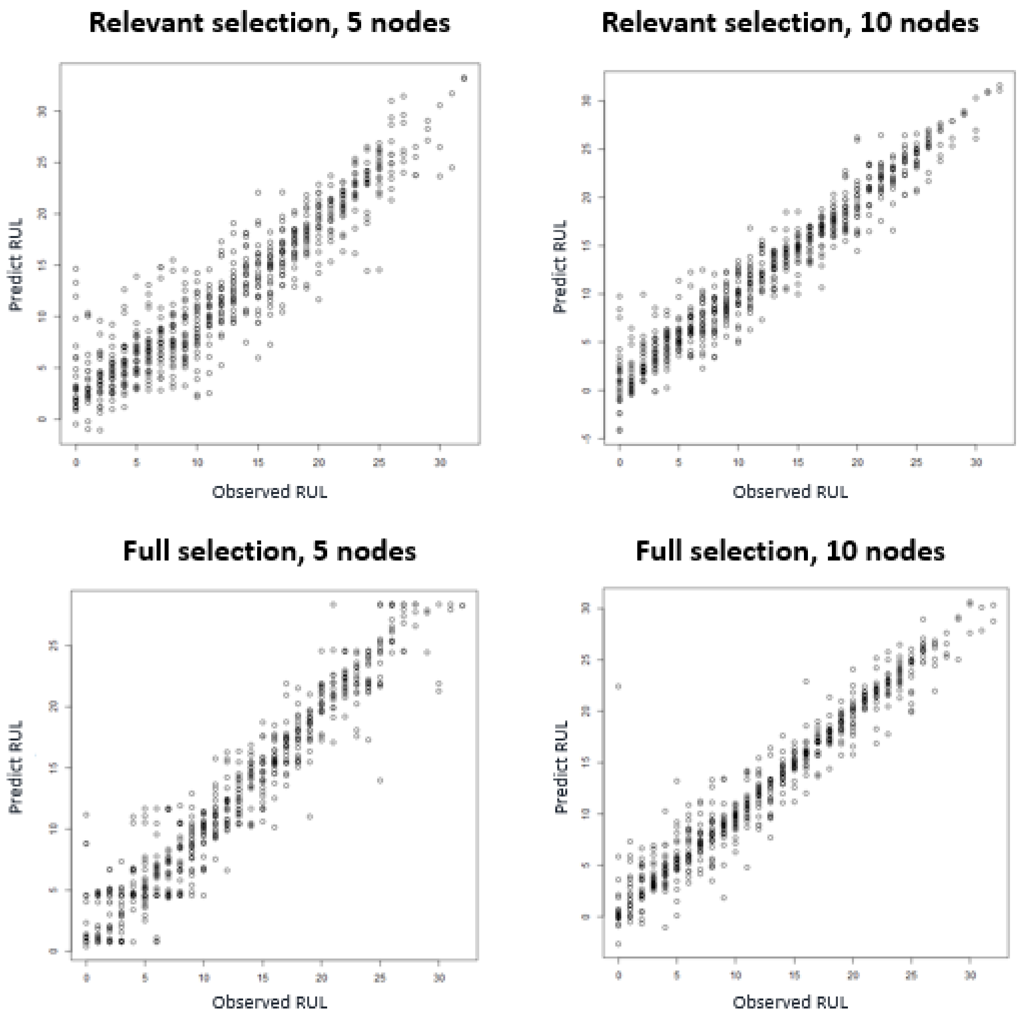

Figure 25. *Comparison of RUL estimation models with scatter plots. Demonstrates that different networks provide good correlation between observed and predicted values*

Figure 25 illustrates that all neural network models provide good predictions considered against the real RUL values of the fabrics. As an example, the neural network model formed by the relevant selection and five nodes in the hidden layer, is a 37-5-1 network with 196 weights. It's correlation coefficient against the true remaining useful lifetimes of the fabrics is 0,927 which is relatively high. All correlation coefficients and net structures are listed in the Table 6.

Table 6. *Correlation coefficient of prediction and RUL and the corresponding net structures*

Model and number of nodes in the hidden layer	Net structure	Correlation coefficient against RUL
Relevant selection, 5 nodes	37-5-1, 196 weights	0,927
Relevant selection, 10 nodes	37-10-1, 391 weights	0,967
Full selection, 5 nodes	56-5-1, 291 weights	0,958
Full selection, 10 nodes	56-10-1, 581 weights	0,968

All correlations illustrated in the Table 6 are high but having a high correlation might not be optimal for this situation. This might be a result of overfitting which would have a negative effect on future predictions. The results between models are however almost exact which means that the presented model with selected key variables also generates good predictions. Thus, selecting the relevant model and 5 nodes could be one cure against overfitting due to having less options for neural network to conduct overfitting with.

Even with the fewest amount of different process parameters the web conducts good predictions of remaining fabric lifetime. The 37-5-1 networks predictions follow fabric changes adequately and steadily which means that the residual hardly spikes at these points. Furthermore, the special cases of lower runtime are predicted with decent precision. Comparison of actual observed remaining fabric lifetimes and predictions and the associated residual with 37-5-1 neural network is portrayed in Figure 26. The neural network model can predict runtimes for shorter periods as well.

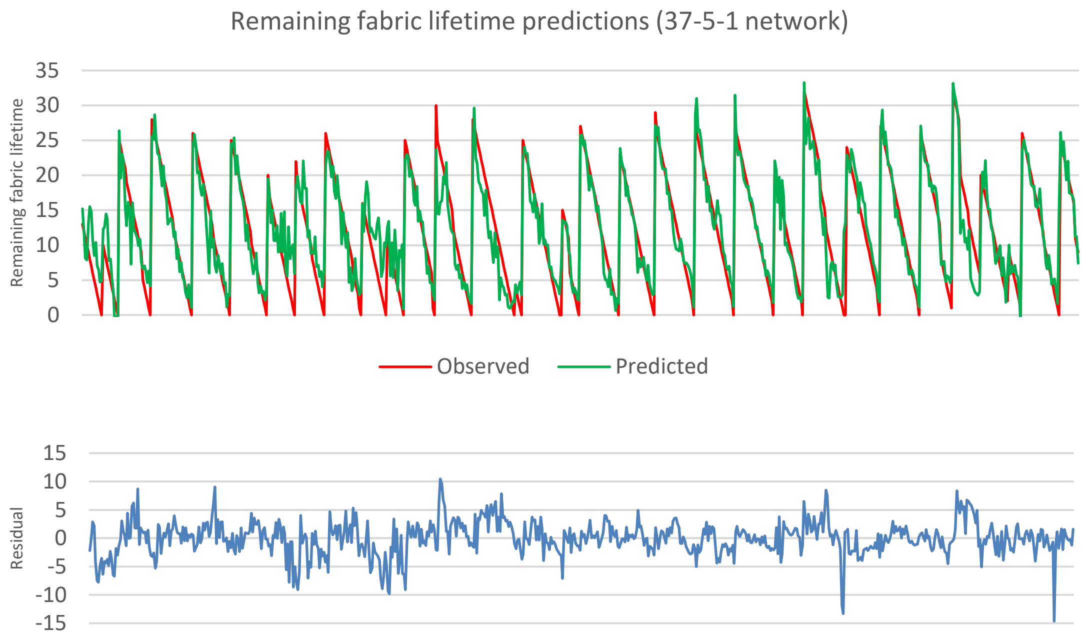

Figure 26. *Model predictions with 37-5-1 network and how large the residual (difference between observed and predicted value) is at each point of prediction*

As discussed, the major issue that questions the reliability of the neural network estimations is that the amount of data for model. In this case study, the overall amount of data is relatively low and thus might lead to overfitting easily. Smith et al. (2003) also pointed out that adding significantly more data would be essential in building effective predictive models with neural networks. In addition to neural network needing a high amount of data, the black-box nature seem to deviate neural network from being the optimal method for the question at hand. For example, decision tree method would allow the user to see variable influences to output and to function with more limited dataset thus making it more optimal for fabric lifetime estimations.

6. DISCUSSION

Hence the scarceness of the previous research within the field, this research had to select suitable research approach to match the innovative needs. Selecting constructive research approach proved to be successful choice towards model creation. It allowed researcher to start problem solving from real-life perspective and to intertwine distinct theories together adequately. In addition, the research approach allowed the use of customer feedback well because constructive research process allows more intervention from researcher (Lukka, 2001). For constructive research process, it is mandatory to conduct weak and strong market tests to find out the applicability of the proposed solution (Kasanen, et al., 1993). However, due to time limitations, only the weak market test was conducted. This means that large-scale case study wasn't conducted, and the research had to settle for one limited application of the construction. For wider feedback towards the usability and applicability of the proposed solution, more data and time would be required.

For constructive research process, it is mandatory to discuss the potential scope of the solution and to analyze the theoretical contribution (Kasanen, et al., 1993). This research had the motivation to improve PMC supplier's industrial internet offering with artificial intelligence thus the initial scope was condensed. However, the two presented models could be utilized to other fields of industry where reliability is in high demand. Particularly, in fields where it is always vital to have performance spare parts at the stock, these models could be used. For theoretical contribution, this research aimed to create a new construction through combining existing methods to a field where they have yet to be discussed in previous publications. Kari Lukka (2001) describes overcoming this kind of theoretical gulf one potential theoretical contribution provided through constructive research process.

As discussed, the previous research within the combinatory field of fabrics and artificial intelligence is at this point nonexistent. Thus, it was crucial to set valid scientific goals through informative research questions. The first question "*What customer needs to know about the fabrics operational capability?"* was answered in this thesis work through comments gathered from the pilot customer. There was no specific framework for questions, but the fundamentals of fabrics operational capability were successfully gathered. Pilot customer pointed the dewatering and web breaks as performance indicators for fabrics operational capability. Criticism must be pointed for the research process for not laying more emphasis on customer feedback. In a way, this is because the initial industrial internet applications were not operational within the timeframe of this research thus the lack of feedback from day-to-day usage. Answers to the first research question were also sought in theory section of this research. Literature review pointed out key attributes for all fabric types about the fabric's operational capability. Thus, conducting a literature review on fabrics operational context was useful in creation of both models and to get valid feedback from the pilot customer.

The second research question "*What are the key parameters which affect fabrics industrial internet AI applications?"* was aimed to gather information about the possible development directions for industrial internet offering. In practice, the information was gathered through a literature review of the theory surrounding operating context of the fabrics and present-state analysis of the PMC unit's industrial internet applications. Also, the customer feedback from prototyping phase was crucial to answer the question. Theoretical framework provided answers to capabilities of industrial internet within the operating context of paper mills. It was evident that a lot of data is flowing through systems during ongoing process. Thus, it became clear that data must be processed well within the industrial internet application to provide best added value. Feedback from the customer backed this claim due to application's ease of use being one of the most important factors towards day-to-day use. Linking theory and customer feedback also provided operational parameters which should be looked within the artificial intelligence models. For example, the remaining useful fabric lifetime model with filtered selection of signals was created with the help of theoretical background and customer feedback.

The third and the final research question *"What kind of AI models would benefit the company and the customer the most?"* set forth to investigate the most value adding artificial intelligence models towards fabrics industrial internet platform. Due to the timeframe and the scope of this thesis, this phase was conducted by introducing two model frameworks and examining their feasibility. Major source for the selection of the models was the target company which provided initial comments whether to continue with proposed model or not. Prototyping phase also shed some information whether the customer would have additional value from the proposed solutions, but because of the issues within the original industrial internet platform, the feedback was limited. Thus, the real comparison of different models wasn't as thorough as the correct answer to this research question would indicate.

This research didn't provide clear scientific framework for getting feedback from the customer. That didn't prove to be totally wrong direction but having a clear framework would have possibly resulted in better answers. In the beginning goal was to start prototyping together and get feedback from the use of the application. Feedback was gathered during three visits to pilot customer site. First visits were about the introduction of industrial internet applications which was a crucial part of research assignment. However, major issue during the project were the issues with the industrial internet platform. Prototyping process was inadequate because we were not able to provide functioning applications to pilot customer for day-to-day operation. All feedback was gathered from PowerPoint slideshows. Issues with the initial application also projected difficulties to AI model developments. Understandably customer couldn't give valid feedback about future developments without seeing a solid base. All in all, customer participated well to Q&A sessions and if the applications would have been ready during (or before) this project, the prototyping results would be a lot better. Pilot customer gave good feedback about the required parameters to monitor fabrics performance and about the needed attributes for the industrial internet offering. During the timeframe of this research the base industrial internet platform was tweaked and finalized per feedback but the problems with the base platform also postponed the possible implementation of AI models presented in this thesis work to foreseeable future.

The first artificial intelligence model presented in this research governed inventory simulations with Monte Carlo method. In previous research Monte Carlo simulations for inventory level simulations have been aimed more to scenarios where shortages wouldn't potentially hinder the whole transaction. For example, (Leepaitoon & Bunterngchit, 2019; Phupha, 2014) focus to calculate economic order quantities and reorder points to a retail store where amounts are high and there is more need to balance shortages and surpluses. Thus, many Monte Carlo simulation case studies focus to reduce inventory and the motivation differs from this research.

By comparing fabric runtime histograms, it was noted that different machines, positions and fabrics provide wide range of different patterns. This thesis work only examined press felts and by changing to different product, the runtime patterns could be even more scattered. Thus, in this case it proved to be difficult to find one universal distribution for distribution fitting. Pre-selection of four different distributions (normal, Weibull, Logistic and extended beta) proved to be successful for comparison. Extended beta function performed particularly well towards the three felt runtime patterns presented in the histogram. This result indicates that fabric changes are tied to predetermined runtime periods and thus are not normally distributed.

Unfortunately, the tool for creating the inventory reliability calculator, Alteryx, didn't support other than few general distributions. Thus, the normal distribution was selected for inventory reliability calculations. Selecting normal distribution is a streamlining choice, but in this case, it generates relatively high error. That must be noted in predictions conducted with the calculator and looked at in the future. Compared to the runtime simulator conducted with Alteryx, the inventory reliability calculator itself proved to function robustly. Changing parameters was easy and user could easily find out how the reliability of the fabric inventory alternates. Adding a possibility for user to manually set bottom limit for their inventory and then comparing the reliability towards that allowed more freedom to manage the warehouse with different strategies. Compared to current methods, which rely on just inputting fabric orders to system with against the median, adding the inventory reliability calculator would bring more data-driven actions to tackle risk concerning the management of fabric warehouse.

The second model presented in this research was to estimate remaining useful lifetime. For this thesis work neural network was the chosen machine learning method to estimate remaining fabric lifetime. As Simon Haykin (1999) mentioned, neural networks use all available data and learn from it. In case of paper and board mills they have hundreds of relevant process parameters which could be considered when finding trying to find correlations between process parameters and remaining fabric lifetimes. In previous research concerning machine or software reliability estimations, few case studies had been conducted with neural networks. One of the first studies in the field (Karunanithi, et al., 1992) demonstrated that neural networks can handle more complex estimations compared to analytic models. Karunanithi et al. (1992) also listed two advantages for using neural network in reliability predictions: black-box approach where user does not need to know much about the underlying failure process and easy adaptability to models of varying complexity. Newer studies for neural network reliability predictions have also been successful. For example, Kuo & Lin (2010) studied that neural networks can be used to estimate reliability of washing machines and Smith et al. (2003) to forecast condition-based maintenance on the door systems.

Remaining fabric lifetime estimations with neural network provided interesting results. Both models provided high accuracy in estimations, but high accuracy might not result in good estimations in live conditions. The major issue that questions the reliability of the neural network estimations is that the amount of data is relatively low and thus might lead to overfitting easily. Smith et al. (2003) also concluded that adding significantly more data would be needed to build effective predictive models with neural networks. This study proved that it is possible to forecast remaining fabric lifetime with machine learning method. For future references, it would be beneficial to conduct a case study with different machine learning methods (such as decision tree or support vector machine) and with different data set. The black-box nature and a requirement of high amount of data deviate neural network from being the optimal method for the question at hand. For example, decision tree method would allow the user to see variable influences to output and to function with more limited dataset.

The two presented models have good compatibility towards each other. This is because the remaining lifetime estimation would provide an input for inventory reliability calculator. Unfortunately, the collective results could not be efficiently examined due to issues with the data flows. The first model would fit into current Valmet PMC industrial internet offering with ease. PMC Monitor application already collects all data about the runtimes of the fabrics. Thus, with just a few calculation packages inventory reliability simulator would be operational. From customer and Valmet PMC point of view adding the first model to industrial internet would allow exponential increase in data-driven decisions. However, it must be noted that the issues with the distribution fitting of the runtime pattern is something not to overlook. The second model provided an interesting glimpse towards machine learning world and good both versions of the model had good prediction accuracies. However, the concern with accuracy of the prediction and overfitting of the model are too deep issues at this point. Another point from customer point of view is that fabric changes are related to predetermined schedules. Thus, there is no real need to know the absolute remaining fabric lifetimes at this point. Clear linkage was found between process parameters and remaining fabric lifetime so in future other parameter (such as dewatering) could be observed with machine learning method to predict fabric condition.

7. CONCLUSION

The motivation of this research was to improve Valmet's PMC unit's industrial internet offering. The conducted improvement actions were to enhance the existing offering through customer feedback and to provide additional value with artificial intelligence. The approach towards the subject was to find out the existing theory behind the operational context of the fabrics, discover possible developmental actions through prototyping and by creating value-adding AI models to support the offering.

Developmental work began with prototyping the initial applications with pilot customer. During the timeframe of this research, the applications were not functional and therefore the full potential of the feedback couldn't be harnessed. All things considered, pilot customer was able to give excellent feedback with limited knowledge about the platform. The discussions with the pilot customer resulted in many improvement points about the industrial internet applications and laid base to the development of artificial intelligence models.

Inventory reliability calculator was illustrated as the first value-adding AI method for the industrial internet platform. The need for simulating the fabric supply chain through fabric runtimes came from the target company. Current practice in target company is to look at the median of the runtimes and fill the manufacturing pipeline accordingly. Thus, the risk of shortages or surpluses had not been modeled. Study began with comparison of three different press felt runtimes which illustrated that fabric runtime patterns are anything but uniform. Thus, it was essential to compare different probability distributions which would be then used in Monte Carlo simulations. For the three runtime patterns illustrated, extended beta distribution proved to be best fitting option. However, due to the limitations brought by the Alteryx software, which would be used for later simulation phases, normal distribution had to be selected. Even though the Alteryx software had limitations within the simulation of runtimes, it proved to be an effective tool for inventory reliability calculator. The presented model was easily adjustable to user selected parameters and was functioned robustly when changing the runtime pattern. Therefore, this research suggests that this model would be applied to the PMC unit's industrial internet offering and developed further in distribution fitting phase.

The second model, estimating remaining useful fabric lifetime, was brought to enhance the first model by estimating the current fabric lifetime for reliability calculations. Neural networks were selected as an initial machine learning method due to their ability to take advantage of high amount of data. However, during the case study it was noted that the overall amount of data was relatively low for neural networks. Thus, the presented model yielded towards overfitting. The model was presented with two different versions: relevant selection of parameters backed by theory and feedback and selection of all available parameters. The difference between the two version was not major thus it would be beneficial to conduct more tests with more data available. For future references, the research doesn't suggest applying this model to industrial internet applications. However, the promising results of conducting estimations with relevant parameter selection could be looked further with different machine learning methods.

The research process itself proved to be successful under the existing circumstances because the initial applications were non-functional for the most part of the thesis timeframe. Thus, collecting more thorough customer feedback with more refined interview methods would possibly not have resulted in better feedback because the applications weren't in daily usage. The method for initial selection of the proposed AI models was subjectively based on hopes of the target company. Therefore, the real comparison of all possible models was limited in the scope of this research.

During this research process it came evidently clear that the initial industrial internet applications, PMC Monitor and PMC Analytics, would have good applicability at least in pilot customer's daily routines. Having an easy to use application to track and monitor all fabric related information would be a real asset. Thus, after the problems of the platform have been solved and applications successfully launched, the developmental work should truly commence. This research suggests that more thorough study for customer feedback must be conducted after the applications have been in daily use for solid amount of time. Also, more thorough literature review on different machine learning methods should be conducted when the real value-adding targets of the industrial internet offering have been identified.

REFERENCES

Adanur, S., 1997. *Paper Machine Clothing.* Lancaster: Publishing Company, Inc.

Alteryx, 2019. *Alteryx Designer.* (Online)
Available at: https://www.alteryx.com/products/alteryx-platform/alteryx-designer
(Accessed 11.10.2019).

Amazon, 2019. *What is Cloud Computing?.* (Online)
Available at: https://aws.amazon.com/what-is-cloud-computing/
(Accessed 29.05.2019).

Andritz, 2017. *ANDRITZ presents "Metris – Industrial IoT Solutions".* (Online)
Available at: https://www.andritz.com/group-en/news-media/news/2017-05-31-andritz-presents-metris-group
(Accessed 27.11.2019).

Arts, J. J., 2013. *Spare parts planning and control for maintenance operations,* Eindhoven: Technische Universiteit Eindhoven.

Bashier, E. M., Khan, M. B. & Mohammed, M., 2016. *Machine learning.* Boca Raton: CRC Press.

Bean, R. & Davenport, T. H., 2019. *Companies Are Failing in Their Efforts to Become Data-Driven.* (Online)
Available at: https://hbr.org/2019/02/companies-are-failing-in-their-efforts-to-become-data-driven
(Accessed 05.11.2019).

Bhatia, R., 2018. *When not to use Neural Networks.* (Online)
Available at: https://medium.com/datadriveninvestor/when-not-to-use-neural-networks-89fb50622429
(Accessed 02.08.2019).

Birolini, A., 2007. Reliability Engineering. In: 1 ed. Berlin: Springer, pp. 1-24.

Boyes, H., 2018. *The industrial internet of things (IIoT): An analysis framework.* 101 ed. s.l.:Computers in Industry.

Çınlar, E., 2011. *Probability and Stochastics.* 1 ed. New York: Springer.

Control station, 2019. *What is a Distributed Control System?.* (Online)
Available at: https://controlstation.com/what-is-a-distributed-control-system/
(Accessed 28.05.2019).

Cramer, H., 1946. *Mathematical Methods of Statistics.* 9 ed. Princeton, NJ: Princeton University Press.

EPSMA Technical Committee, 2005. *Reliability - Guidelines to Understanding Reliability Prediction,* s.l.: s.n.

Frost, J., 2019. *Statistics By Jim - Understanding Probability Distributions.* (Online)
Available at: https://statisticsbyjim.com/basics/probability-distributions/ (Accessed 10.06.2019).

Ghiani, G., Laporte, G. & Musmanno, R., 2013. *Introduction to Logistics Systems Management.* 2nd ed. s.l.:John Wiley & Sons.

Grinsted, S. & Richards, G., 2016. *The Logistics and Supply Chain Toolkit : Over 100 Tools and Guides for Supply Chain, Transport, Warehousing and Inventory Management.* 2nd ed. London: Kogan Page.

Haykin, S., 1999. *Neural Networks - A Comprehensive Foundation.* 2nd ed. Hamilton: Pearson Education.

Holik, H., 2013. *Handbook of paper and board.* 2 ed. Weinheim: s.n.

Häggblom-Ahnger, U. & Komulainen, P., 2006. *Paperin ja kartongin valmistus.* 5 ed. Jyväskylä: Gummerus Kirjapaino Oy.

Jain, P. K., 1999. *Theory and Problems in Financial Management.* 2nd ed. New Delhi: Tata McGraw-Hill.

Kadry, S. & Chateauneuf, A., 2007. Probabilistic Transformation Method in Reliability Analysis. *Turkish Journal of Engineering and Environmental Sciences,* 31(3), pp. 135-148.

Karian, Z. A. & Dudewicz, E. J., 2000. *Fitting Statistical Distributions: The Generalized Lambda Distribution and Generalized Bootstrap Method.* 1st ed. Granville: CRC Press.

Karunanithi, N., Whitley, D. & Malaiya, Y., 1992. Using neural networks in reliability prediction. *IEEE Software,* 9(4), pp. 53-59.

Kasanen, E., Lukka, K. & Siitonen, A., 1993. The constructive approach in management accounting research. *Journal of Management Accounting Research,* Volume 5.

Kirubashankar, R., Krishnamurthy, K. & Indra, J., 2009. Remote monitoring system for distributed control of industrial plant process. *Journal of Scientific & Industrial Research,* Volume 68, pp. 858-860.

KnowPap, 2019. *Paperitekniikan ja tehtaan automaation oppimisjärjestelmä,* s.l.: Prowledge Oy.

Kumamoto, H. & Henley, E. J., 1996. *Probabilistic Risk Assessment and Management for Engineers and Scientists.* 2nd ed. New York: Institute of Electrical and Electronics Engineers.

Kuo, Y. & Lin, K.-P., 2010. Using neural network and decision tree for machine reliability prediction. *The International Journal of Advanced Manufacturing Technology,* 50(9-12), p. 1243–1251.

Leepaitoon, S. & Bunterngchit, C., 2019. The Application of Monte Carlo Simulation for Inventory Management: a Case Study of a Retail Store.

International Journal of the Computer, the Internet and Management, 27(2), pp. 76-83.

Li, B., Hou, B., Yu, W. & al., e., 2017. Applications of artificial intelligence in intelligent manufacturing: a review. *Frontiers Inf Technol Electronic Eng,* 18(1), pp. 86-96.

Lukka, K., 2001. *Konstruktiivinen tutkimusote.* (Online)
Available at: https://metodix.fi/2014/05/19/lukka-konstruktiivinen-tutkimusote/
(Accessed 13.08.2019).

Marr, B., 2018. How Much Data Do We Create Every Day? The Mind-Blowing Stats Everyone Should Read. *Forbes.*

Matsuoka, T., 2013. A Monte Carlo simulation method for system reliability analysis. *Nuclear Safety and Simulation,* Volume 4, pp. 44-52.

McClelland, C., 2016. *The Industrial Internet of Things - What's the Difference Between IoT and IIoT?.* (Online)
Available at: https://www.leverege.com/blogpost/difference-between-iot-and-iiot
(Accessed 28.05.2019).

Microsoft Azure, 2019. *What is cloud computing.* (Online)
Available at: https://azure.microsoft.com/en-us/overview/what-is-cloud-computing/
(Accessed 29.05.2019).

Mitchell, M., 2019. *Artificial Intelligence: A Guide for Thinking Humans.* Sante Fe: Penguin UK.

Nachlas, J. A., 2005. *Reliability engineering: Probabilistic Models and Maintenance Methods.* 1st ed. Boca Raton: Taylor & Francis Group.

Nilsson, N. J., 1998. *Artificial Intelligence - A New Synthesis.* 1 ed. San Fransisco: Morgan Kaufmann Publishers.

Overton, J., 2018. *Artificial Intelligence.* 1st ed. Sebastopol: O'Reilly Media.

Paulapuro, H., 2008. *Papermaking science and technology : Book 8, Papermaking : part 1: Stock preparation and wet end.* 2 ed. Helsinki: Finnish Paper Engineers' Association : Paperi ja puu.

Phupha, V., 2014. An Application of Monte Carlo Simulation for Optimal Order Quantity: A Case Study of Raw Materials Procurement in Processed Food Industry. *Kasetsart Engineering Journal,* 88(41-56), p. 27.

Pikulik, I., 2013. Key variables in press dewatering. Volume 1, pp. 902-917.

PTC Mathcad, 2019. *Mathcad.* (Online)
Available at: https://www.ptc.com/en/products/mathcad
(Accessed 11 10 2019).

Räty, R., 2016. *In-depth customer understanding with service design.* (Online)
Available at: https://www.aaltopro.fi/en/aalto-leaders-insight/2016/in-depth-customer-understanding-with-service-design
(Accessed 5.11.2019).

Saturno, M., Pertel, V. M. & Deschamps, F., 2017. *Proposal of an automation solutions architecture for Industry 4.0.* Poznan, s.n.

Skapura, D. M., 1996. *Building Neural Networks.* Houston: Addison-Wesley Professional.

Smith, A. E., Coit, D. W. & & Liang, Y. C., 2003. A neural network approach to condition based maintenance: case study of airport ground transportation vehicles. *IMA Journal of Management Mathematics on Maintenance, Replacement and Reliability.*

Sobol', I. M., 1994. *A Primer for the Monte Carlo Method.* 1 ed. Boca Raton: CRC Press.

Sridhar, S., Hahn, A. & Govindarasu, M., 2012. Cyber–Physical System Security for the Electric Power Grid. *Proceedings of the IEE,* 100(1), pp. 210-224.

Stark, A., 2010. *A Study of Business Decisions under Uncertainty: The Probability of the Improbable.* 1st ed. Boca Raton: Dissertation.com.

Stigler, S. M., 1981. Gauss and the Invention of Least Squares. *The Annals of Statistics,* 9(3), pp. 465-474.

Theodoridis, S., 2015. Machine Learning - A Bayesian And Optimization Perspective. 1st ed. Amsterdam: Academic Press.

Tihinen, M. et al., 2016. The Industrial Internet in Finland: on route to success?, Espoo: VTT.

Valmet, 2019 A. Industrial Internet. (Online)
Available at: https://www.valmet.com/about-us/industrial-internet/
(Accessed 18.04.2019).

Valmet, 2019 B. Valmet DNA DCS. (Online)
Available at: https://www.valmet.com/automation-solutions/valmet-dna-dcs/
(Accessed 28.05.2019).

Valmet, 2019 C. Valmet in brief. (Online)
Available at: https://www.valmet.com/about-us/valmet-in-brief/
(Accessed 18.04.2019).

Voith, 2019. *Papermaking 4.0 by Voith.* (Online)
Available at: https://voith.com/corp-en/industry-solutions/papermaking/nextlevel/article_66318.html
(Accessed 27.11.2019).

Wang, W. & Syntetos, A. A., 2011. Spare parts demand: Linking forecasting to equipment maintenance. Transportation Research Part E: Logistics and Transportation Review, 47(6), pp. 1194-1209.

Yu, C., & Zelterman, D. (2017). A general approximation to quantiles. *Communications in statistics: theory and methods*, *46*(19), 9834–9841. doi:10.1080/03610926.2016.1222433