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DATA ANALYTICS CONCEPT FOR SAWLINE CHIPPER CANTER

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TIIVISTELMÄ

LUT-Yliopisto
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Data-analytiikkakonsepti sahalinjan pelkkahakkurille

Diplomityö

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Tässä diplomityössä käsitellään sahalinjan pelkkahakkurin data-analytiikkakonseptia. Data-analytiikka on osa esineiden internetiä, jonka tarkoituksena on tuotantoprosessin tuottavuuden ja kannattavuuden parantaminen perustuen prosessista kerättyyn tietoon. Tiedonkeruun jälkeen tieto analysoidaan käyttäen valittua analysointityökalua. Tätä analysoinnin tulosta voidaan käyttää muun muassa prosessin optimoinnissa.

Data-analytiikkakonseptin kehityksessä käytettiin kolmea tutkimusmetodia, kirjallisuustutkimusta, systemaattista suunnitteluprosessia sekä esimerkkitestiä. Kirjallisuustutkimuksella selvitettiin työn tausta, systemaattisella suunnitteluprosessilla luotiin kaksi data-analytiikkakonseptia, joita tämän jälkeen testattiin ja tutkittiin esimerkkitestien avulla.

Systemaattisella suunnitteluprosessilla luoduista kahdesta konseptista toinen käyttää vain yksinkertaista tilastollista analyysia ja toisessa on myös useita päätöspuita sisältävä simulointimahdollisuus. Näiden konseptien päätehtävä on valvoa terien sekä energian kulumista seuraamalla servojen momenttien, moottorien virtojen sekä kiihtyvyysantureiden arvoja.

Nämä konseptit myös testattiin esimerkkiarvoilla, jotka kerättiin todellisessa tuotantoprosessissa olevasta pelkkahakkurista. Tässä testissä ei kuitenkaan saatu kerättyä terien kulumiseen liittyvää tietoa, joten konseptien käytettävyyttä ei voitu todeta aukottomasti. Tämän takia vaaditaan jatkotutkimusta, jonka tekemiseen esitettiin myös ohjeita.

ABSTRACT

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Data Analytics Concept for Sawline Chipper Canter

Master's thesis

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Keywords: Data Analytics, Data Collection, Data Analyzing, Internet of Things, Sawmill, Sawline

In this thesis, development process of data analytics concept for sawline chipper canter is discussed. Data analytics is application of Internet of Things, which is used in increasing the productivity and profitability of production processes based on data gathered from the process. This data is then analyzed with chosen analyzing method and analysis result is used in for example optimizing the production process.

The development process of data analytics concept was carried out with triangulation of literature review, systematic design process and example test. Literature review was used in clarifying the background of the topic, systematic design in developing two data analytics concepts and example test in studying and testing the developed concepts.

Within the systematic design process two different data analytics concepts were developed, one with basic statistical analysis and the other with simulation possibilities with random forest-simulation tool. The main function of these data analytics concepts is to monitor blade wear and energy consumption by monitoring servo torque, motor current, and accelerometer values.

These concepts were then tested with example values gathered from real-life chipper canter process. However, in this test blade wear data was not available and the functionality of the concepts could not yet be completely determined, and future research is required. Thus, future work guidelines were also presented.

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Niko Onnila
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LIST OF ABBREVIATIONS

CC	SPSS Control Computer
IoT	Internet of things
IT	Information Technology
PLC	Program Logic Center
RF	Random Forest
SVM	Support Vector Machine

1 INTRODUCTION

IoT (Internet of Things) and data collection possibilities have changed, and are changing, the way industries and companies manage and monitor their production processes. New technological innovations such as artificial intelligence have made possible for example fully automatic production lines or production monitoring with no human hands needed. These IoT innovations and development steps have also increased the amount of data available for companies to work with and analyze. (Maw 2019; Transcendent 2018.) Even though the data collection systems have developed and the amount of data available from production processes is greatly increased, there are still challenges to collect the data and thoroughly take advantage of the data collected. In this research, these challenges are discussed and data analytics (data collection and data analyzing) concept for sawline chipper canter process is developed.

This master's thesis discusses the needs and development process for data analytics concept for Heinolan Sahakoneet. Heinolan Sahakoneet produces mechanical forest industry machinery and technology and they are based in Heinola, Finland. Heinolan Sahakoneet have supplied their machinery and technologies all over the world and their product range include sawline solutions, edging solutions, lumber handling, drying kilns, and different chipper solutions. Heinolan Sahakoneet have also a wide service network (Heinola Service) which addresses all the Heinolan Sahakoneet customers' needs considering supplied machinery and technologies. (Heinolan Sahakoneet 2019a.) Motivation for this research comes from Heinolan Sahakoneet's desire to implement data analytics and IoT possibilities into their sawline solutions.

1.1 IoT and data analytics

Industry is ongoing the fourth big revolution in its existence. This new era of industry becoming more IT (information technology) and digitalism orientated is named the Industry 4.0. In Industry 4.0 machines are monitored and controlled by computers and they are partly or fully autonomous and control themselves without human operation. These autonomous functions can include for example machine learning processes and data analytic possibilities. These new revolutionary development steps are made possible by IoT and all its applications. As network connections, sensors, operator stations, and other electronics are attached to machinery, they are capable of collecting amounts of data that have not been possible in the past. Also, with network connections equipped, machinery can share this data and communicate with each other to develop the production process, sometimes even autonomously. Industry 4.0 and IoT applications aim to ease the manufacturing process and minimize the need of human hands on the production process while making it more productive. (Oztemel & Gursev 2018, pp. 10-35.)

Considering Industry 4.0 and IoT the need for data collection to ensure all the information needed is crucial as the monitoring, remote-controlling, and autonomous functions require it. As attached to IoT, data analytics is used to develop manufacturing processes to be productive and efficient. For example, when a company collects data from their manufacturing processes and analyzes it, they may find some unlike things which influence their processes. Customer satisfaction may also be improved with the help from collected and analyzed data. (Maw 2019.) In the following subchapters IoT and its capabilities and advantages in manufacturing are discussed as well as data analytics (data collection and data analyzing) used in manufacturing environment. This information stated in the following subchapters is also used in the developing process of the new data analytics concept for Heinolan Sahakoneet.

1.1.1 IoT in manufacturing

IoT’s main goal in manufacturing is to increase machinery’s productivity and energy efficiency with cyber elements. As IoT combines physical and cyber worlds seamlessly together, it requires few basic elements to work properly. These are network connection (preferably wireless), smart sensors, data analytics, and cloud computing. These elements enable easy and constant data collection, sharing, and analyzing, which are the backbone of functional IoT configuration. These IoT configurations can be, and usually are complicated and thus, they are divided into different layers. These layers can be named for example data acquisition layer, network layer, service layer, and application layer. This categorization helps in understanding the main principles of the configuration. An example of 4-layer IoT configuration is shown in the figure 1, where the four different layers are exactly those previously mentioned. (Badarinath & Prabhu 2017, pp. 111-115.)

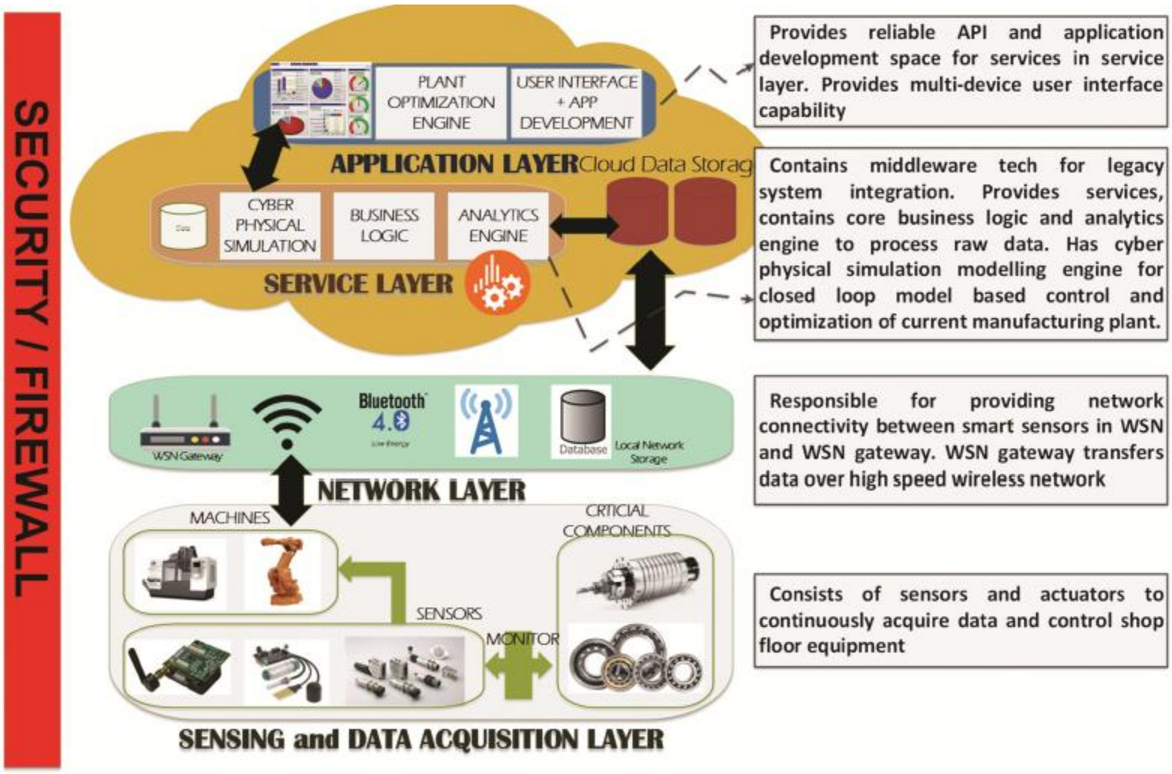

Figure 1. An illustrative example of 4-layer IoT configuration. (Badarinath & Prabhu 2017, p. 1144.)

When these so-called cyber elements are attached to machinery in a way or another, there should always be clear understanding about the function this cyber element or component is capable of doing as any unnecessary components should not be applied. Also, these functions should be beneficial for the production process in a way or another. The actions these cyber components should be able to do are design interpretation, design analysis, process planning, assembly planning, scheduling, simulation, data interfacing and integration, and user interaction modules. The cyber component could perform one of these actions or multiple ones. Also, it is notable that these cyber components may perform these tasks either at the workshop or anywhere else communicating with the machinery via network. (Lu & Cecil 2016, pp. 1143-1145.)

Like said, IoT's main focus is on connecting machinery to controlling units and other machines via network, so they would also allow remote monitoring and controlling those machines. Such remote controlling is already used in industrial environments, but also in households for example in smart lightbulbs which can be controlled by new smartphones. (Girish, Prakash & Balaji Ganesh 2016, pp. 527-532; Javed 2016, p. 111, 138.) Like smartphones, IoT is mostly considered to be new technology and thus its implementation into older factories may be concerning. However, studies have shown that these remote controlling and monitoring systems can be utilized in older workshops as well if some new technology is installed to take full advantage of IoT's capabilities. (Chen, Zhang & Liu 2016, pp. 257-259.)

1.1.2 Data collection and storing

As IoT requires data analytics to be fully functional, in the first place the data have to be collected and stored. There are multiple ways to collect data, but in this case the focus is on those methods that fully maximize the potential of IoT. Mostly the data used in IoT applications are collected by sensors or other digital devices, as this data is already in digital form and may be transferred easily via network. However, as the data is collected one should always be certain it is in the right format as there are plenty different. Thus, data formats used in collecting and analyzing data should be standardized within the company or companies using the data. After data is collected, it is stored somewhere for future use. When IoT is considered, the storage used is mostly cloud storage system as it has virtually unlimited storage space and may be accessed from almost anywhere via network. (Zhong, Newman, Huang & Lan 2016, pp. 581-583.)

1.1.3 Data analyzing and applications

After data is collected and stored it still must be analyzed and/or visualized. Data analyzing is the phase in which all the collected data is taken advantage of. Data analyzing can be categorized in three different topics, descriptive analysis, predictive analysis, and prescriptive analysis. This categorization can be made by categorizing the analysis based on the questions it answers. Descriptive analysis tells what has happened, predictive analysis what will happen, and prescriptive analysis is used to guide decisions based on the data collected and analyzed, so it tells what should be done. (Sami Sivri & Oztaysi 2018, p. 156.) In this research mostly predictive and prescriptive analyses are examined.

Predictive and prescriptive analyses strive to build models based on collected data, which can be utilized to forecast the future by calculating the best possible outcome wanted with inputting different variables. Predictive and prescriptive analyses have many techniques to analyze the data and build these models. According to Sami Sivri & Oztaysi (2018, pp. 163-166) these techniques are:

- Linear regression
- Logistic regression
- Support vector machines
- Neural networks
- K-nearest neighbor
- Decision trees
- Naïve Bayes

When forecasting with these models however, also forecast accuracy and errors should be considered and there are techniques for different accuracy models as well (Sami Sivri & Oztaysi 2018, pp. 166-167). An illustrative workflow diagram of a predictive data analyzing process is shown in the figure 2. This example of workflow is from supervised machine learning process, which have become more popular within the data analytics field in recent years. In the diagram the different phases of building a new predictive regression data model are separated, and data flow is illustrated with arrows. From the figure it can be seen that the workflow is not only linear, and some steps have to be executed multiple times for successful outcome. For example, in the instance of the figure refinement after post-processing may take the process even three steps back to the pre-processing phase, if the outcome is not successful. (Raschka 2014.)

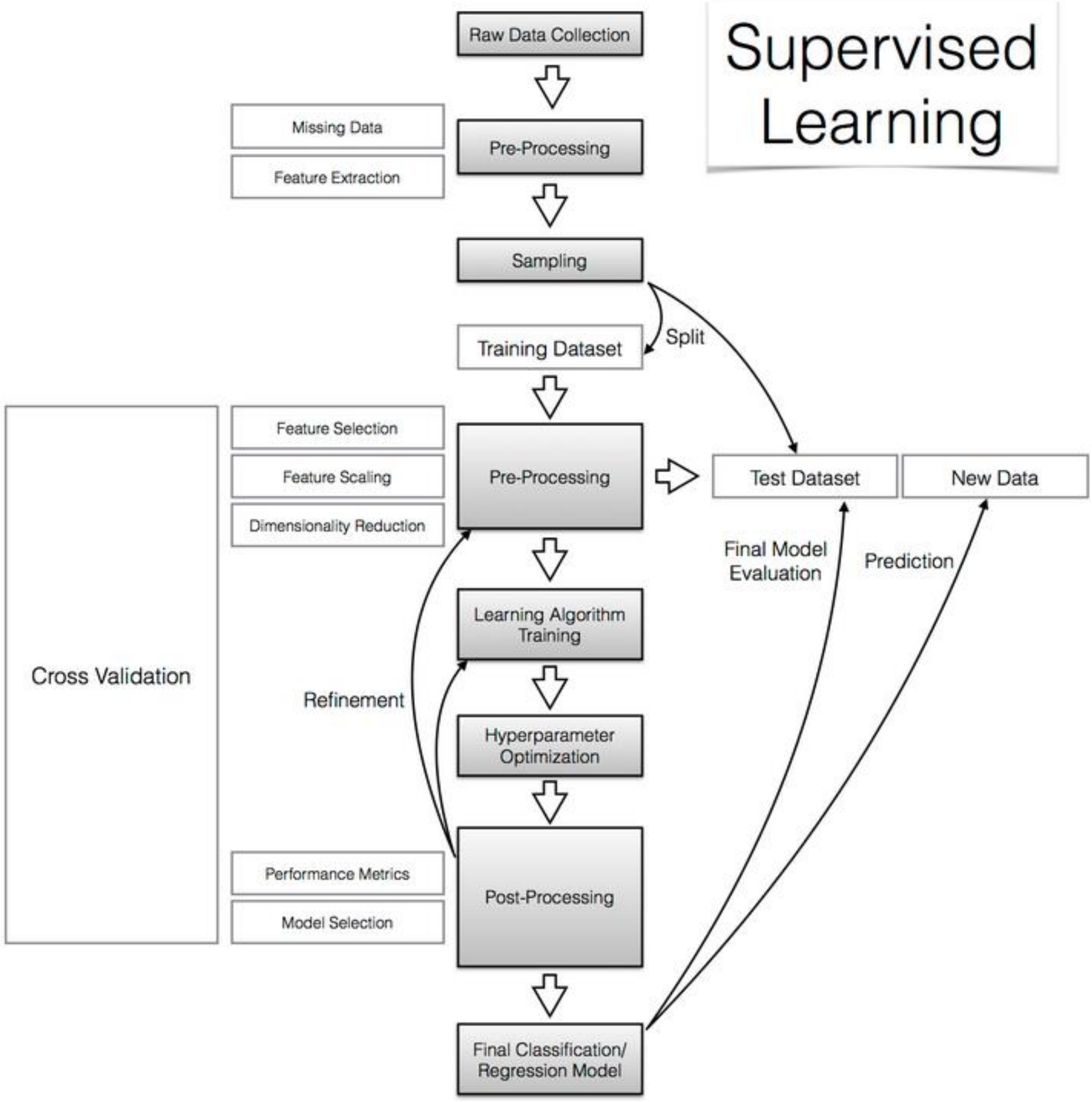

Figure 2. Creation process of a predictive data analysis regression model (Raschka 2014).

Also, the visualization of the analyzed data is important as it eases the interpretation of the analyzed data and models built. Nowadays many software can simultaneously analyze and visualize the data inputted. Visualization software available are for example Qlik Sense, Power BI, and Grafana (Brichni & Guedria 2018, p. 214.) For example, Power BI can create a dashboard of real-time manufacturing functions to illustrate the workflow based on the data collected from different processes. Example of the dashboard is shown in the figure 3. (Microsoft 2019.)

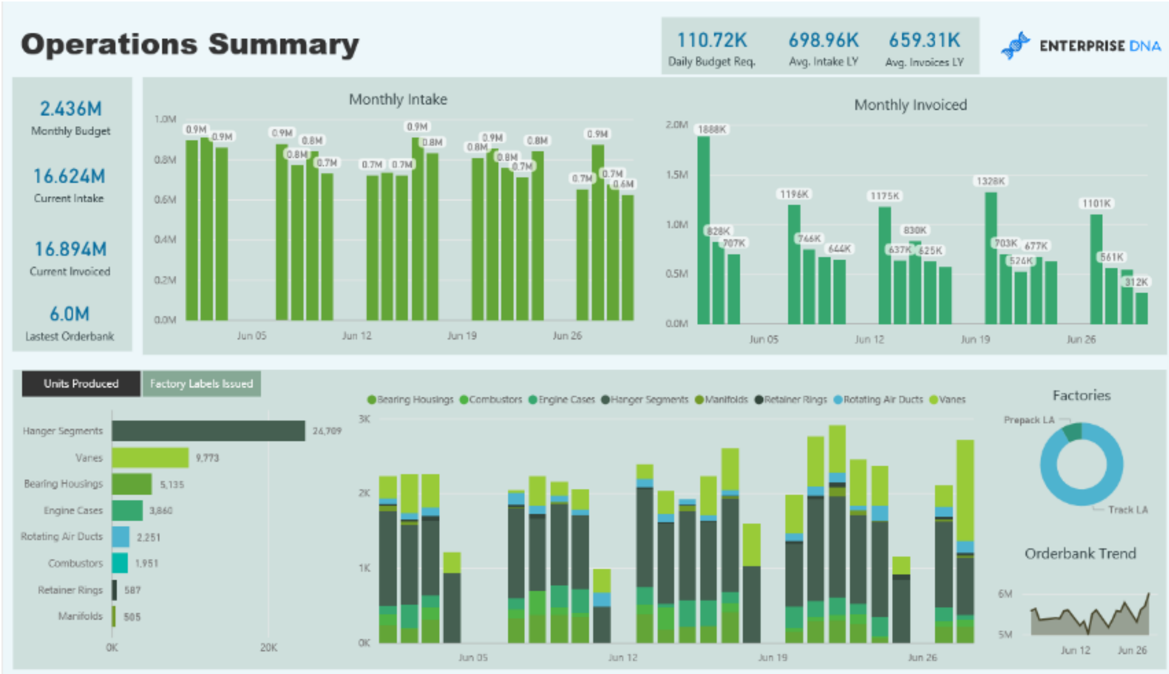

Figure 3. Illustration of manufacturing dashboard made with Power BI software (Microsoft 2019).

Applications of data analytics used in manufacturing are numerous. IoT based analytics system can be used for example in optimizing production and workflow automatically, thus decreasing manpower. Real time data analyzing may also decrease maintenance costs and downtimes as constant monitoring will optimize maintenance strategies and detect maintenance needs before breakage. Also work safety can be improved by constant monitoring of the working environment and detecting hazardous environments. (Badarinath & Prabhu 2017, pp. 115-117.)

1.1.4 Challenges with data analytics

Even with all the possibilities utilizing IoT and data analytics gives, there are some challenges. These can be divided into technical, industrial, and organizational challenges. Technical challenges include multiple functionalities, design and deployment, scalability and decentralization, and big data. These challenges are mainly caused by the technical difficulties to analyze either the correct data or the data correctly. Industrial challenges include interoperability and standardization. As stated in previous chapters, standardization is crucial when data is collected and analyzed. Interoperability is linked to standardization as it addresses the challenges of physical and digital information required to communicate with each other. Organizational challenges include expertise, resources, and culture as they are all linked to personnel working with the data. (Brichni & Guedria 2018, pp. 214-218.)

Other important thing to keep in mind with the data collection and storing is the security aspects of used data. As data collection and storing is becoming more common and the amount of data collected is constantly increasing, security challenges and vulnerabilities are also increasing. If security aspects are not considered, the company's vulnerable data may end up in the wrong hands. (Tedeschi, Emmanouilidis, Farnsworth, Mehnen & Roy 2017, pp. 391-393.)

1.1.5 IoT and environment

Nowadays environmental aspects are thoroughly considered, and IoT can have a huge impact on these environmental aspects regarding manufacturing. Energy efficiency is among the highest priorities in manufacturing sector as it consumes roughly third of the whole global energy consumption. When energy efficiency is optimized the first step is to be aware of how much energy is consumed. IoT provides the tools for real-time monitoring of the energy consumption tied to the changes in the production process. IoT also helps in analyzing this data and providing models of the energy consumption, which can then be utilized by adjusting the production process to reduce energy consumption. Another example of the effect of IoT on increasing environmental friendliness is the possibility to improve the production process's productivity and decrease lead times. As lead times are decreased, also idle times of machines are shortened, thus their energy consumption is decreased. (Miragliotta & Shrouf 2013, pp. 96-100.) A real-life example of this increased environmental friendliness is from BMW's production facility in the USA, where applying IoT to constantly monitor energy consumption decreased energy consumption over 100 000 kWh in a year as energy consumption habits could be altered (Badarinath & Prabhu 2017, p. 116).

1.2 Sawline processes

Sawline is the main element of sawmill production in which logs are sawed to lumber. Sawlines may consist of many different processes, but mostly the basic elements of sawline are chipper canter, profiling unit, and the actual sawing process. Also, conveyors and log rotators are used, but in this thesis the focus is on the three main components. Sawline and these three main processes can be seen in the figure 4. From left to right behind the person standing are chipper canter, profiling unit, and circular saw. Sawline’s process combination and layout may however vary greatly depending on the end-product needs. The sawing process may vary from bandmill to circular saw, depending on the needs of the production. These different production variations may for example be caused by different raw material base, different end-product types, or the layout of the existing sawmill. (Heinolan Sahakoneet 2019b.) In this thesis however, only circular saw process is discussed as it is the usual choice in Heinolan Sahakoneet sawlines. (Hannula 2019.) In the following chapters the three main components of sawline are introduced more profoundly.

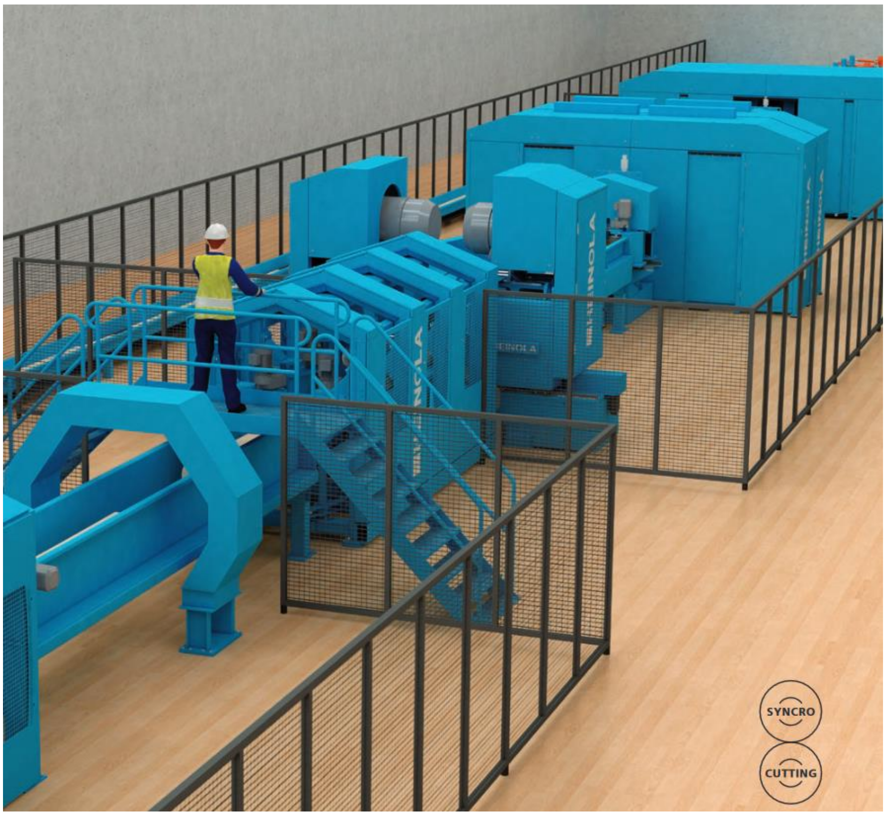

Figure 4. Heinolan Sahakoneet sawline with a circular saw (Heinolan Sahakoneet 2019c).

1.2.1 Chipper Canter

In sawline chipper canter is located before the sawing process to pre-treat the log before feeding it to the actual sawing process. In chipping process, the sides of either a log or a cant (depending on the location of the chipper canter) are cut off with reducer heads to improve the surface of the sawed products and ensure correct measurements. Chipper canter has a great effect on the chips produced so the condition of the reducer heads should be taken care of. Many sawlines have a chipper canter as it has a great effect on the final product’s surface quality. Heinolan Sahakoneet chipper canters have either 5, 6, or 8 blade heads in 2 different zones, which ensure the good surface quality. Illustration of Heinolan Sahakoneet chipper canter is shown in the figure 5. (Hannula 2019; Heinolan Sahakoneet 2019d.)

Figure 5. Heinolan Sahakoneet chipper canter (Heinolan Sahakoneet 2019d).

1.2.2 Profiling unit

Another pre-treatment process used before the log is sawed is profiling. Profiling unit is used to saw corners to the log, from which the side boards are sawed in a way the yield is optimized and as high percentage as possible of the log is used. Thus, in profiling phase the number of side boards wanted is determined. Heinola profiling units have 2, 3, or 6 chipping blades and a horizontal blade on each side to ensure good side board and chip quality as they are affected greatly by profiling process. (Hannula 2019.) In the figure 6 is an example of a log cutting pattern in which the side boards and cants, and their placement and dimensions are shown. In this figure, inside the red circle are the corners sawed with a profiling unit to determine the side board dimensions and placement.

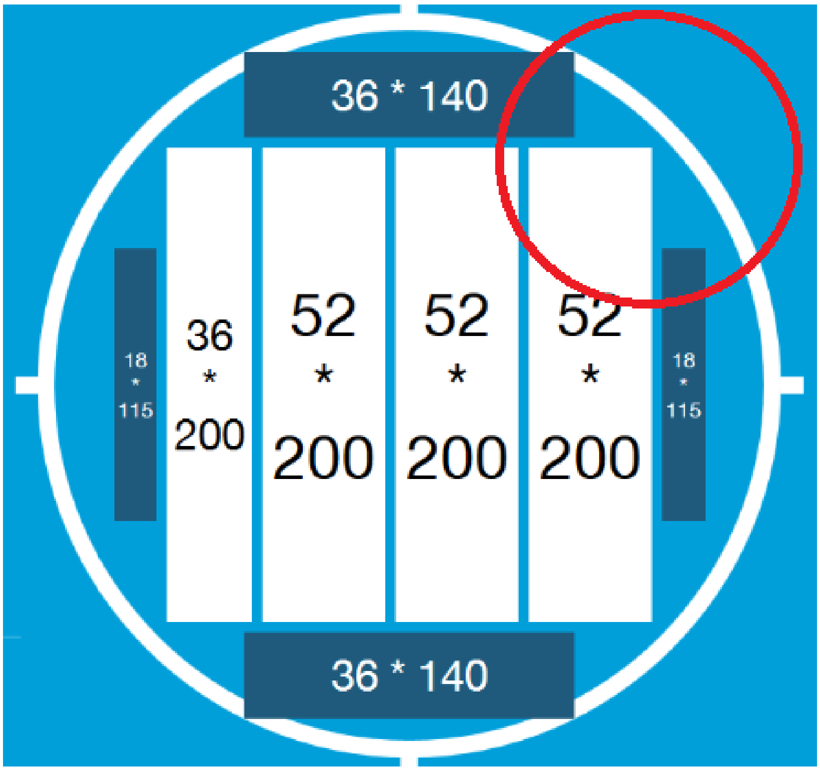

Figure 6. Example log cutting pattern and one of the four corners sawed with profiling unit is circled in red.

1.2.3 Circular saw

The actual sawing process of the sawline is done with a circular saw. This circular saw can be used as a log circular saw or a cant circular saw. Log saw is the primary saw and cant saw the secondary which is used after first side boards and cant(s) are sawed. Log circular saw has 4 and cant circular saw 6 blades divided by two on the opposite sides of the log. These blades can be moved horizontally and vertically depending on the log dimensions to ensure that required end product measurements are met. Heinola circular saws have also patented Syncro Cutting system in which the blades rotate in synchronized motion and the upper blade runs inside the arc of the lower blade. The alignment of the blades can be seen in the figure 7. This system increases the yield of the sawline especially as the alignment of the blades ensure minimal sawing area and enable curved sawing of the logs and cants. (Hannula 2019; Heinola Sahakoneet 2019e.)

Figure 7. Cross section of Heinolan Sahakoneet circular log saw (Heinolan Sahakoneet 2019e).

1.2.4 Key parameters in sawline production

Sawline has many different parameters, which affect the production process. The key parameters are related to production processes and material properties. Production process-parameters include parameters linked to machinery, such as line speed, cutting speed, cutting forces, blade geometry and downtimes. These parameters are mostly used in programming the machinery or in production planning. Material properties-parameters include all the information needed from raw-material and end-products. For example, raw-material dimensions and temperature are important parameters in optimizing the production process and the production parameters. Also, some parameters can be categorized in both of these parameter categories. One very important parameter in sawline production is chip length, which is a part of both, production and material parameters. Chip length may even be the determining parameter which all the other parameters are linked to. Sawline has also parameters linked to energy efficiency and consumption, such as current, as they measure power consumption of the production process. (Hannula 2019; Heinolan Sahakoneet 2019c.)

1.2.5 Tool wear in sawline production

The tool wear in sawmill and sawline production occurs mostly on the saw and chipper blades as these are the tools in contact with timber. In the case of Heinola sawlines, the blades in saws and chipper canters are circular and thus have their own characteristics regarding wear. Tool wear may be caused by either the chemical reactions between the blade and timber or by the mechanical factors which are caused by stresses or friction between the blade and timber. Most of these aspects are determined by the timber wood species and blade materials, but there are still other variables, such as timber temperature which may cause great deviation in blade wear. For example, in arctic circumstances frozen timber causes more wear than defrosted. In sawmill production blade wear varies from the commonly known tool wear so, that the blades are not used until breakage, rather they are sharpened multiple times during their lifetime. So, blade wear will seldom include any damage to the blade, rather than just abrasive wear dulling the blade with occasional tool edge chipping. Also, the blade will maintain its edge radius well during the effective lifetime of the blade. Most common consequences of blade wear in sawmill production are decreased quality, whether it being wrong sized end-products or uneven surfaces, and increased power consumption caused by greater cutting forces needed with dull blades compared to sharp ones. Also, blade changes cause downtimes, which can be costly for the production when performed unplanned. (Cristóvão, Lhate, Grönlund, Ekevad & Sitoe 2011, p. 160; Ekevad, Cristóvão & Marklund 2012, pp. 150-153.)

2 OBJECTIVE AND METHODS

In this chapter the research methods are discussed. First the objective of the research is clarified, and research problem is proposed. To solve this research problem, research questions are composed. After these, the scope of the research is clarified. To conclude, the research methods are presented. In this subchapter also the reliability, validity and sensitivity of this research are discussed.

2.1 Objective of the research and research problem

The objective of this master's thesis is to develop a basis for data analytics concept for Heinolan Sahakoneet. This concept should ensure that all the relevant and needed information is gathered and analyzed from the production process to increase Heinolan Sahakoneet machinery's productivity, usability and energy efficiency. Thus, the research problem is "How collected data from a sawline process can be utilized to optimize the chipping process?" Following research questions can be formed to solve the research problem:

- What are the ways to collect data?
- What data is collected?
- Which available and collected data is relevant?
- What are the ways to analyze the data?
- How the analyzed data can be utilized?
- For who is the collected and analyzed data beneficial?
- How can the process' productivity and energy efficiency be increased with data analytics?

2.2 Scope of the research

Scope of this research is delimited to comprise only one sawline process (chipper canter). This delimitation is done to ensure thorough research without expanding the research too much. However, the developed data analytics concept is developed in a way it could be linked with other sawline processes as well to create a data analytics concept to monitor the whole sawline due the principles of the sawline processes being alike. Also, the actual data collection and storing methods are only briefly discussed as those are already developed or being developed by a partner company and this thesis will centralize on the ways to analyze and utilize the collected data. The test phase is also abridged to cover only few of the possible measured values as the others are only available to gather in the near future. These used values are also only used to determine the concepts being applicable for the machine learning process and actual real-life tests, as the example values cannot determine the actual dull blades and their forming.

2.3 Research methods

This research was carried out by using three different research methods. These methods were chosen to ensure enough data was collected to answer all the research questions and to find a solution for the research problem. The three methods used were literature review, systematic design process, and example test. These methods are discussed more profoundly in the following subchapters. Also, some interviews were used to deepen the information. Both qualitative and quantitative methods were used in this research. Qualitative method was used to answer majority of the research questions based on the literature review and interviews, and quantitative method to evaluate the different concepts developed in the systematic design phase by comparing the statistical example test results. The three used methods are illustrated in the figure 8. In the figure are also shown the major steps used with every method which are categorized in qualitative and quantitative steps.

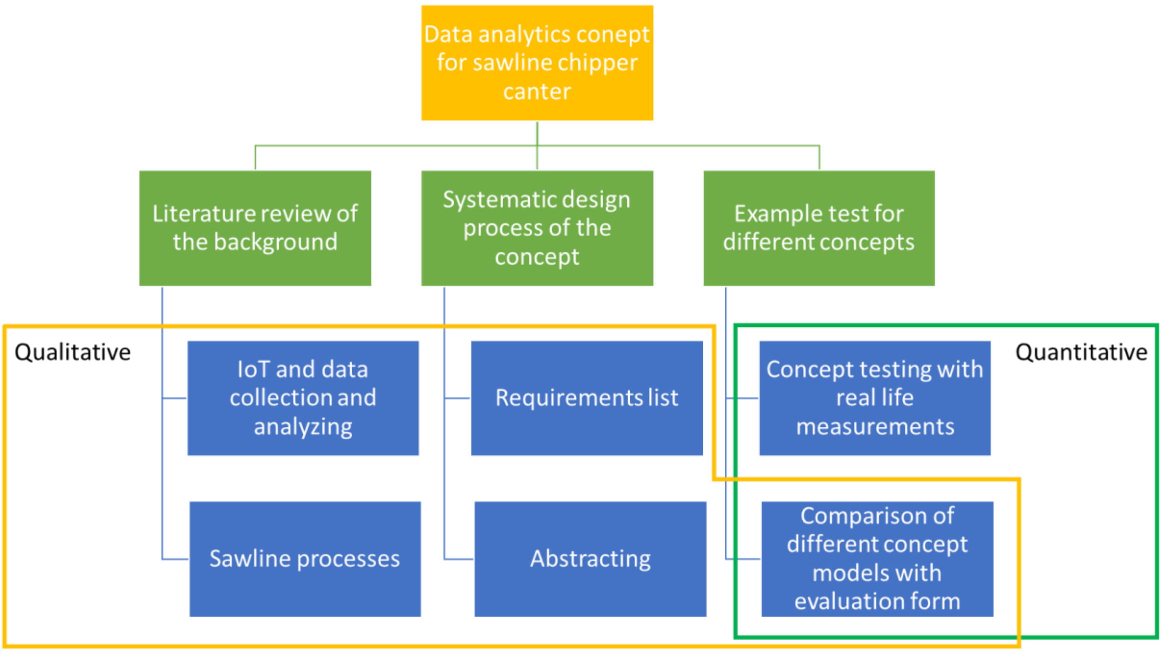

Figure 8. Three research methods used, their major steps and categorization of these steps to qualitative and quantitative methods.

To ensure the reliability of this research, test results and test environment were compared not only to each other, but also to the literature review findings. Thus, all the possible information available was used to ensure that the results are correctly collected. Validity of the research was ensured by testing the concepts developed within the systematic design process with example values gathered from an actual chipper canter process. Also, the concepts developed were further evaluated by forms filled based on the test results to ensure they fulfill their requirements and are applicable for real-life environment. To ensure the sensitivity of this research, an estimation was done that enough information was collected when all the research questions could be thoroughly answered.

Triangulation was also used in comparing the results to further ensure that the conclusions are made by taking all different viewpoints into account. Triangulation was used by comparing the literature review results to those from systematic design process, systematic design process results to example test results, and literature review results to example test results. With these comparisons the conclusions are more reliable as all the information is utilized. An illustrative figure of this triangulation is shown in the figure 9.

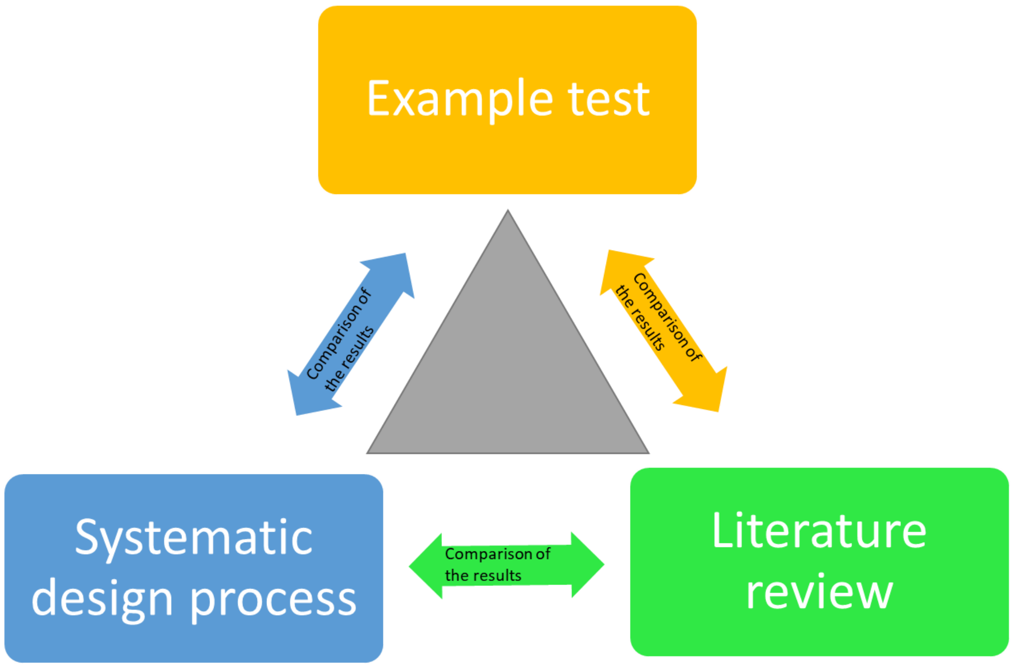

Figure 9. Triangulation used in comparison of the results.

2.3.1 Literature review

Guiding literature review was used to clarify and find background information on the research topic. In this literature review, mainly Scopus, Springer Link, ScienceDirect, and online databases of LUT University library were used to search for references. Publication dates of the references used were kept as recent as possible to ensure outdated information is not used. Thus, references published before 2011 were excluded from the literature review and the amount of references published before 2014 were kept minimum. These exclusions ensure that mostly new scientific information is used as this research topic has become more popular among researchers in recent years and new information is constantly produced. Keywords used to find references were “data analytics”, “data collection”, “data analyzing”, “internet of things”, “industrial internet of things”, “IoT in manufacturing”, “IoT in forest industry”, “data collection system”, “data analyzing system”, “remote control”, “remote monitoring”, “sawline”, “sawline processes”, ”chipper canter”, “sawmill”, “sawmill processes”, “sawmill production”, “mechanical forest industry”, “blade wear”, and “tool wear”. In addition to scientific articles and books found from online databases, some web pages were also used for product and company information. Literature review findings are introduced in the “Introduction” chapter. Results of the literature review were also used in developing phase of the data analytic concepts for information purposes.

2.3.2 Systematic design process

In development phase of the data analytics concept systematic design process and problem solving was utilized according to Pahl, Beitz, Feldhusen & Grote (2007, p. 127). The development process could be seen as a problem-solving process in which the steps finding solution are “confrontation”, “information”, “definition”, “creation”, “evaluation”, and “decision”. In the actual design phase, the focus is on “definition” and “creation”, and their main steps follow this subsequent pattern which was utilized. First, requirements list had to be made to know the needs and wishes for the developed data analytics concept. After requirements were set, the main problem regarding the development process had to be implemented with an abstracting process. To solve this problem, two new data analytics concepts were developed. The systematic design process of new data analytics concepts is thoroughly described in chapters 3.1-3.6.

2.3.3 Example test and evaluation

In example test, the data analytics concepts developed in the systematic design process were tested with example values gathered from Heinolan Sahakoneet chipper canter. The chipper canter from which values were gathered was a sugi (Japanese cedar) sawmill equipped with Heinolan Sahakoneet sawline. The sawmill uses changing cutting patterns and have no log sorting system, which make it different from most of the sawlines as the log variation is greater. Example values of two different variables, servo torques and machine currents, were gathered via cloud service to proof test the different data analytics concepts. With these tests, it was ensured that these developed concepts would work in future real-life tests with all the possible values measured and they could be used with machine learning process as well. In this example test phase, the amount of values gathered were still too low to determine the actual blade dulling process, so in this phase only the principles of the developed data analytics concepts were tested. The example test procedures are more thoroughly described in chapter 3.7, and the test results are presented in chapter 4. After the tests, the data analytics concepts were also evaluated by evaluation form. This filled form and the evaluation and comparison of the different concepts are also presented in chapter 4.

3 SYSTEMATIC DESIGN OF DATA ANALYTICS CONCEPT

In this chapter, the systematic design process of data analytics concept for sawline chipper canter is described. First, basic information of the systematic design process is told. After the process flow is well known, the requirements list is drafted, and the main problem is implemented with the abstracting process. To solve the main problem, two different concept models are developed. These concept models are then tested in example test to determine their usability and comparison between them is made based on the results.

3.1 Systematic design

In this development phase of a new data analytics concept for sawline chipper canter, systematic design process and problem solving are used. A workflow diagram of the problem solving process is shown in the figure 10 which shows the basic steps ensuring successful problem solving. This model and its steps are also utilized in this development process. From the steps shown "confrontation" and "information" are already done as project planning and literature review have been carried out to discover the base data. In this chapter "definition" and "creation" are discussed and the final steps, "evaluation" and "decision", are discussed in chapters 4 and 5. (Pahl et al. 2007, pp. 125-128.)

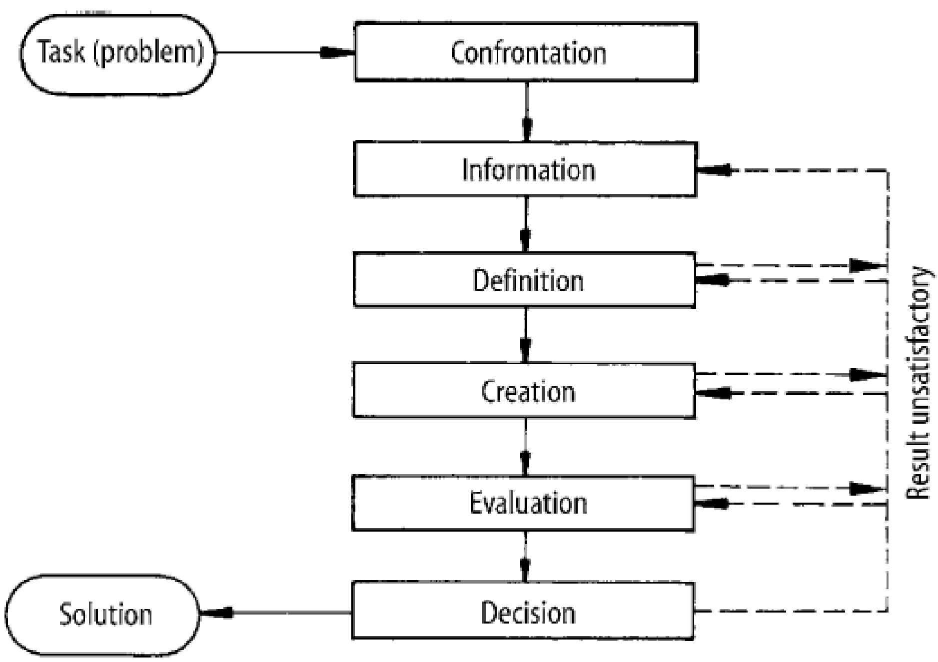

Figure 10. Workflow diagram of the problem solving process (Pahl et al. 2007, p. 127).

“Definition” phase consists of setting the requirements for the developed product or process and implementing the main problem with the abstracting process based on the requirements. A requirements list is one of the key components of product or process development. The requirements list is usually a form with free layout, and it contains information regarding the demands and wishes for the developed product or process. Demands are aspects that must be somehow included in the final design and wishes are aspects, that are not essential, but including them produce value for the final design and thus, they should be thoroughly considered during the design process. Demands and wishes are usually set by customer(s) and they should be listed as precisely as possible, so they are easy to evaluate and determine if they are met or not. Requirements may however update or change during the design process, thus the first list formed may not be the final. (Pahl et al. 2007, pp. 146-158.)

After the requirements list is formed and demands and wishes determined, the abstracting process should be performed. The aim of the abstracting process is to find the main problem based on the requirements list and determine crucial subfunctions, thus making it clear, what needs to be solved for the final design being successful. The abstracting process is also utilized to ensure the design process, and product or process models are not restrained in any matter, thus leaving space for all kinds of solutions. To ensure all restrictions are excluded, the abstracting process consists of five different steps, which are according to Pahl et al. (2007, p. 165):

1. Eliminate personal preferences.
2. Omit requirements that have no direct bearing on the function and the essential constraints.
3. Transform quantitative into qualitative data and reduce them to essential statements.
4. As far as it is purposeful, generalise the results of the previous step.
5. Formulate the problem in solution-neutral terms.

After the fifth step, the main problem and the crucial factors of the development process should be clear. The second part of the abstracting process is determining the main function and subfunctions of the product or process. These are the functions that must be found from the final design to make it properly functional and these are determined based on the main problem. When the main problem and crucial subfunctions are well known, different product or process models can be developed without any influence from restricting factors, still taking all crucial sub-functions into account. The phase after abstracting is called the "creation" phase, in which the aim is to provide as many different solutions to the problem as possible. (Pahl et al. 2007, pp. 161-174.)

3.2 Requirements list

Requirements list for data analytics concept for sawline chipper canter was gathered in co-operation with personnel from both, the designing department and the maintenance department of Heinolan Sahakoneet. With this collaboration it was ensured that all aspects and viewpoints of data analytics would be taken into account in the development process. During the interviewing process, the requirements were also categorized into demands (D) and wishes (W). The complete and final requirements list is shown in the table 1. The Requirements list was slightly modified during the development process as new demands and wishes arose from the personnel.

Table 1. Requirements list for data analytics concept for sawline chipper canter.

Requirements list for data analytics concept for sawline chipper canter	Date 30.6.2019
Requirements	Demand = D Wish = W
Data:	
Collects data from the process	D
Stores the data for future analysis	D
Analyzes the collected and stored data	D
Connects monitoring outcomes to the process circumstances (log species/log dimensions/feed velocity/et cetera)	D
Process monitoring:	
Monitors main motor power take-off	D
Monitors servo torques	D
Monitors vibrations	W
Monitors bearing temperatures	W
Monitors log temperature and humidity	W
Counts cylinder strokes and chain rotation distance	W

Table 1 continues. Requirements list for data analytics concept for sawline chipper canter.

Requirements list for data analytics concept for sawline chipper canter	Date 30.6.2019
Requirements	Demand = D Wish = W
Analysis outcomes:	
Monitors blade wear	D
Monitors energy consumption	D
Detects mechanical failures	W
Detects and predicts patterns in mechanical wear and energy consumption related to process circumstances	W
Compatibility:	
Is compatible with Heinolan Sahakoneet automation and process controlling program	W
Can be used with other sawline processes as well	W

3.3 Abstracting

Based on the requirements list, the main problem regarding the design of new data analytics concepts is implemented. This implementation is done with the five steps of abstraction process presented in chapter 3.1. In this research however, the requirements list is already in qualitative form, so step 3 is excluded from the abstracting process. Also, eliminating personal preferences does not affect many requirements, so step 1 is merged with step 2. The abstracting process for the data analytics concept and its result are shown in the table 2.

Table 2. Abstracting process and its results for data analytics concept for sawline chipper canter.

Step(s)	Abstracting results
1 and 2	• Data is collected, stored, and analyzed • Monitored factors are power take-offs, vibration amplitudes, strokes, and distances • Should monitor blade wear and energy consumption based on the data collected

Table 2 continues. Abstracting process and its results for data analytics concept for sawline chipper canter.

Step(s)	Abstracting results
4	• Data is collected, stored, and analyzed • Monitor process parameters • Detect machines mechanical wear and energy consumption
5	• Collect and store data from process and analyze it for information on the process

As the result of the five steps, the main problem can be described as: "Collect and store data from process and analyze it for information on the process". This problem is used as the impulse in the developing process of the data analytic concept. After the developing process, data analytics concept(s) should be able to solve this problem.

3.4 Basis of the data analytics concept

When developing new data analytics concept for sawline chipper canter, the first step is to determine how and from where is the data collected from the process. Heinolan Sahakoneet have already developed automation program for their machinery, which controls all the process parameters, such as line speed and servo configuration (saw blade alignment). These parameters are determined so, that the yield from the process is as high as possible from every log based on the scan made from the log. From this program operators can also track the process and logs as precisely as their current position on the line every second. Built in this program are also data acquiring possibilities which are not yet utilized, and these possibilities are now put into service in this new data analytics concept. Figure of the automation diagram is shown in the figure 11. In this figure the main components of the data collection and handling, CC (SPSS control computer) and PLC (Program Logic Center), are circled in red. In addition, with the built-in data collection, also co-companies' data collection systems and software are used to collect all the relevant and needed data. These systems are also used in transferring the data via network so, that the data could be accessed remotely as well as locally.

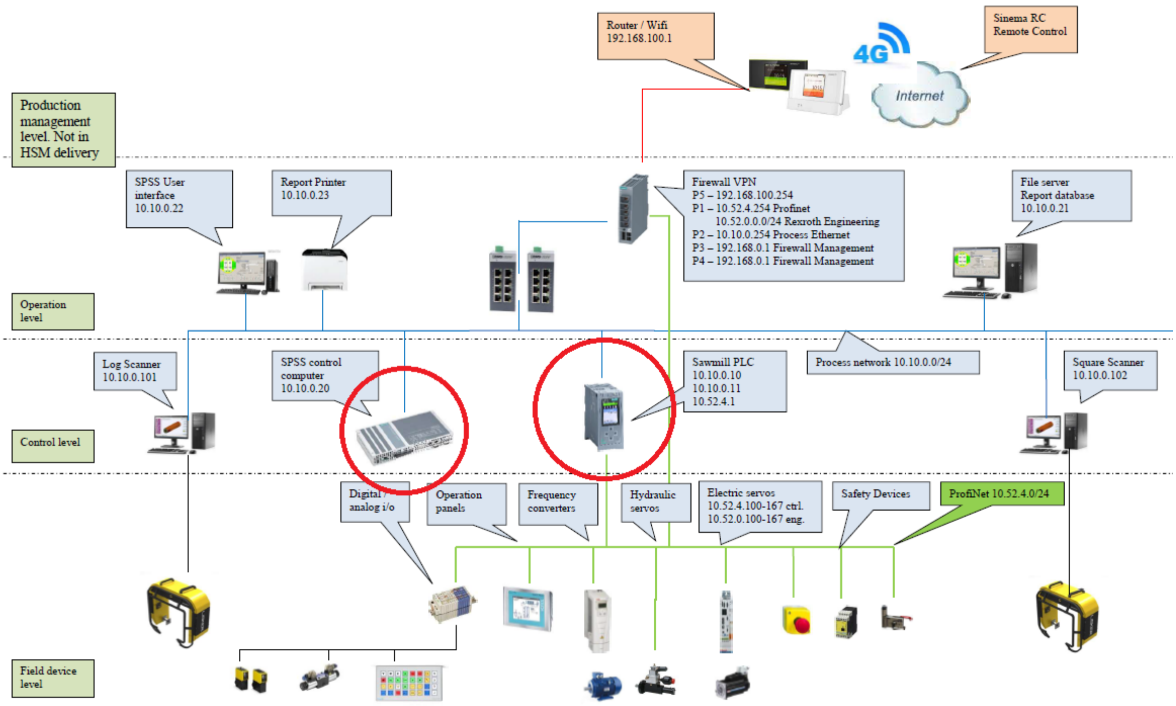

Figure 11. Heinolan Sahakoneet automation program diagram in which the CC (on the left) and PLC (on the right) are circled in red.

So, the data is collected from the process with built-in data acquiring systems and sensors (in this case accelerometers) provided by partner company and stored to cloud service log by log, from where all the relevant data could be retrieved for further data analysis. The data collected and stored includes all the variables on the following list. The collecting component (CC, PLC, or accelerometer) is also shown.

- Log ID (CC and PLC)
- Sawline speed [m/min] (PLC)
- Chipping head rotation speed [rpm] (PLC)
- Chipper canters left and right side currents [A] (PLC)
- Chipper canters left and right side servo torques [Nm] (PLC)
- Chipper canters left and right side vibrations [Hz] (accelerometer)
- Top end diameter [mm] (CC)
- Cutting areas from left and right side [mm^2] (calculated by CC)
- Time stamp (CC)

The currents, servo torques, vibration, and cutting areas are all stored separately from both sides, for more specific information. Also, the batch information, batch exchange and blade exchange times could be collected for possible analysis purposes in their own database and linked to this, the logs can be attached to their specific batches. The possibility to record all the blade changes should also be included to the program, so the correlations between sharp and dull blades and their cutting times could be studied.

As wood is heterogenous material, the logs sawn may vary greatly in size and other material properties. Also, the temperature and humidity of the logs have effect on the sawing parameters needed for successful sawing result. Thus, when collecting data from the sawing process, it is important to know exactly which log has produced the collected values. As the program in sawline can determine which log is sawn at which time, the collected values are connected to this information on the logs. This also allows easy inspection of the data collected as one can choose specific log from the database and see all the values related to that specific log. Also related to wood and logs being heterogenous, the values stored are an average of the multiple measured values from the whole length of the log. This ensures that the data is reasonable and comparable as individual numbers may vary greatly even within one log. Also, the data varies even more when there is no log inside the machine compared to log being chipped, thus the measurement intervals should be set so, that the measurements are done with log inside to prevent any false alarms. Exception to this is the accelerometer values, as they may produce useful information of the machines condition even without ongoing chipping process.

In analyzing part of the data analytics concept the main focus is on developing analyzing tools to monitor, detect, and predict blade wear and energy consumption. These functions are chosen to be the most important based on the requirements list. Blade wear and blade condition are crucially related to productivity, cost-efficiency, and usability of sawline chipper canter as condition of the blades determines the chip quality and partly downtimes. As of now, the blade changes are done in pre-determined cycles which may not reflect to the actual condition of the blade and the amount of wear, or when the blade wear has already caused quality deviation. If the blades were changed only when needed, downtimes from unnecessary blade changes and quality deviations caused by blade wear would decrease, as the blades are changed only when there is wear, but still before this wear affects the timber and chip quality. This is a type of condition based maintenance, in which maintenance procedures are done only when necessary and it is becoming more popular among industries to optimize maintenance costs (Pintelon & Parodi-Herz 2018, pp. 30-32). When energy-efficiency is considered, the optimal process circumstances can be determined as the energy consumption could be monitored and predicted when energy consumption is analyzed. This would decrease energy consumption and increase environmental friendliness as the chipping process would not be forced with dull blades and unnecessary high power that could be avoided by using blades in sufficient condition.

There are multiple tools to analyze and predict blade and tool wear, but the simplest analysis tool is basic statistical analysis in which data is collected and then analyzed by comparing collected values. In this type of analysis, usually previously determined limits are set and as the measured values exceed this limit, alarm is triggered. For prediction of tool wear, algorithms found most suitable and popular for this kind of data and applications are SVM (Support Vector Machine) and RF (Random Forest) decision tree (Schwenzer, Miura & Bergs 2019, p. 2). From these two RF is utilized as it is more versatile to be successfully modified for functioning simulation tool. So, statistical analysis is used for basic analysis to detect blade wear and energy consumption and RF to simulate and predict future trends in blade wear and energy consumption. With these methods two different analyzing concepts are developed, the first with only basic statistical analysis for detection and the second with predictive probabilities with RF method as well. At first, the data analyzed to use in blade wear and energy consumption monitoring are chipper canters motor currents, servo torques, and vibrations, as these values give overall view of the process and are accessible via the built-in data acquisition methods and added accelerometers. Most crucial values are the servo torque and vibration as these will most likely increase when the blade wear begins to influence the chipping process. This happens due to the log forcing dull blades to open, which causes significant increase in the servo torque and overall vibration. The motor current will most likely also increase when dull blades are used as cutting forces increase and more power is required to execute the chipping process. The other values and information are gathered to determine process parameters and circumstances to be used in detecting correlations. The data simulation tool used, RF is briefly explained in the following chapter, so the second data analytics concept would be more understandable.

3.5 RF-analysis

In RF-analysis, classification and approximation are made with computer answering series of true/false-questions, so this method is a combination of multiple decision trees. The outputs of all the decision trees are then combined to construct final classification or approximation from the initial problem. The computer however needs data input before proper usability, as it needs to learn and build some sort of backup database to correctly answer the questions and finding the approximate values. After the initial learning process is carried out and the questions are composed, test data can be input to the computer. The computer will also continue the learning process throughout its lifespan, so in theory the output approximations should become more accurate over time as more data is available. Example of RF approximation process is shown in the figure 12. In this figure the different decision trees are well shown with the final decision being combination from the predictions of these different trees. (Wu, Jennings, Terpenny, Gao & Kumara 2017, pp. 4-5.)

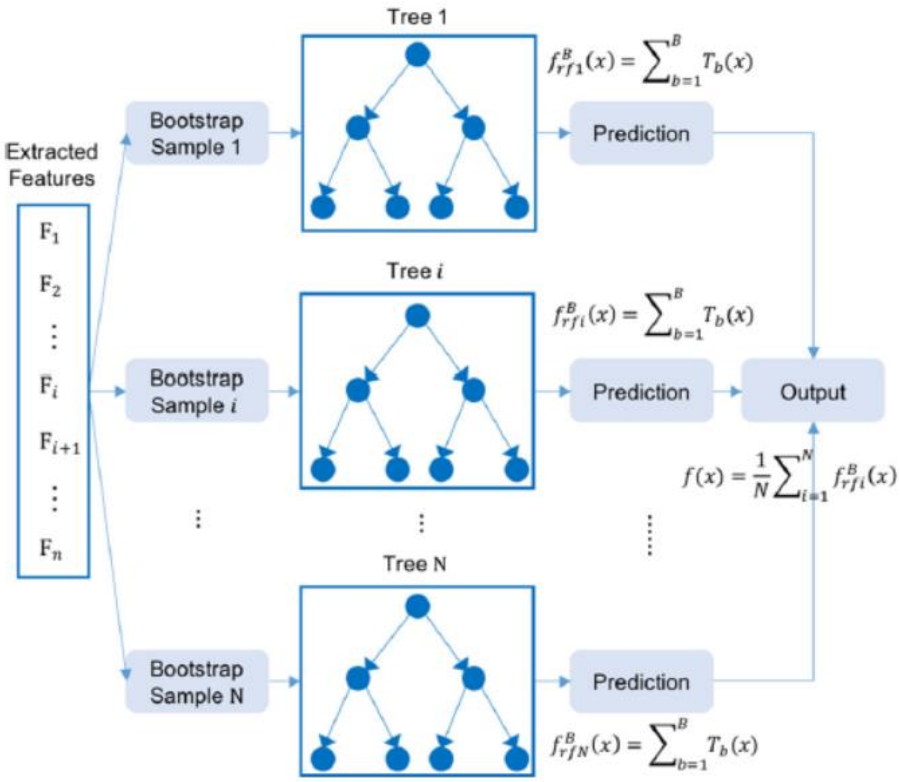

Figure 12. RF-analysis example (Wu et al. 2017, p. 5).

RF-analysis could be used to approximate the blade wear of chipper canter blades and energy consumption as it can be programmed to answer almost any questions imaginable. This is especially useful when more information is available, and the approximation could be modified to be more reliable. As the learning process proceeds, in theory the amount of information and its accuracy on the process would constantly increase and it could more precisely predict blade wear and energy consumption even though logs are not identical being heterogenous material. However, the drawback with RF-analysis is the requirement for the questions to be correct, which might take some time as in the beginning the knowledge may be limited. Thus, the amount of data required before RF-analysis can be used in real-life applications is great.

3.6 Different data analytics concepts

The two data analytics concepts for sawline chipper canter share many functions, such as data acquiring methods and data storing methods described earlier. The differences are in the simulation possibilities and methods. In the following subchapters, the two different data analysis and simulation concepts are described and after that an overview of all the functions is portrayed.

3.6.1 Concept 1

In concept 1 no simulation possibilities are used. Concept 1 can be called alarm limit concept, as the only analysis tool is basic statistical analysis in which an alarm limit is set to determine excessive blade wear and energy consumption. The limits are determined by studying the chipper canter process, blade wear rate, blade change interval, and chip quality. Simultaneously the correlation between these variables and servo torque, motor current, and accelerometer values are studied over long period of time, with for example different cutting patterns, different process parameters, and different log humidity and temperature to ensure at least most of the different process circumstances are covered. When all these correlations and behavior of different variables are well known, the limits can be set. This set-procedure is basically done by determining when the blades are dull and memorizing what the measured values have been at that point. After several values are stored an average can be calculated and determined that this is the limit which tells the blades are usable or non-usable. However, this determined limit should not be fixed to the first position and continuous learning process should be maintained. Also, the limit could be set to different level based on the production process, such as limits being different with different log species. In the figure 13 an illustration of possible diagram of servo torques is shown with an alarm limit set as the orange line, which indicates blade wear being too high and blade change should be executed.

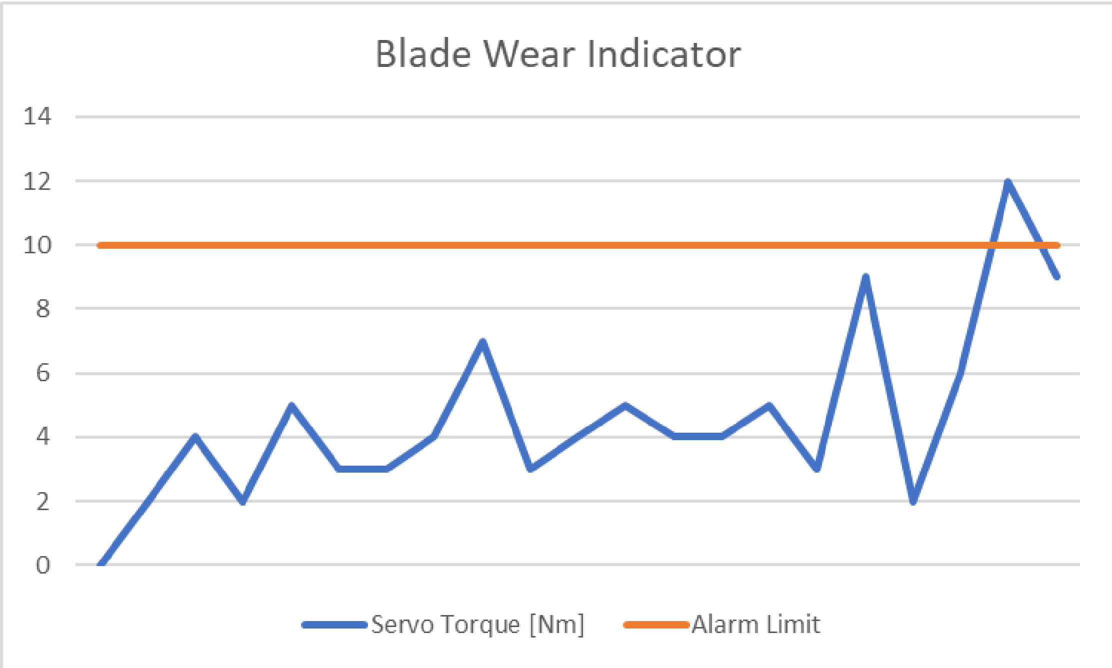

Figure 13. Illustration of alarm limit diagram. Blue line represent possible servo torque values and orange line is the alarm limit, which should not be exceeded.

In this statistical analysis concept, the analysis could produce deterrent information on the blade wear by pre-setting a warning limit at a level in which the blade is not yet dull, but it is becoming dull. As the warning limit is exceeded, operator of the machine knows the blades should be changed in, for example, one hour for optimal blade usage. After this one hour, the values would exceed the alarm limit, which describes the blades being dull and optimal change time has already been surpassed. If the learning process is correctly executed, this warning-alarm method could compensate the lack of simulation possibilities in this concept 1 and produce anticipatory information. However, time span of this information would not be long and would not adjust based on the current production circumstances. The warning limit could be calculated when the alarm limit is known based on the data from blades and servo torques, motor currents, or vibrations. If the correlation between these variables is linear, the warning limit could be for example 80 percent of the alarm limit value. When this correlation is not linear, multipliers are required to compensate the nonlinearity.

3.6.2 Concept 2

Concept 2 uses combination of the alarm limit method and RF simulation tool. Thus, this concept can be referred as RF-analysis concept. The structure of this concept is to use the alarm limit as the basic analysis tool and RF-analysis will back up this information and predict future blade wear and energy consumption. However, RF-analysis is also used in detecting the current blade wear as it can be used simultaneously with the alarm limit method in a way these two could accompany each other and produce more reliable information.

The RF-analysis is based on a similar analysis concept developed by Wu et al. (2017) considering tool wear estimation. In the example model multiple regression trees are constructed with True/False-questions. After these questions are answered and the decision tree completed, output is a prediction value of tool wear or energy consumption. This output is constructed based on machine learning process with the collected data set and information on blade wear. The final prediction is based on the average of multiple prediction values calculated with these decision trees at one wanted point. For example, predicting at which time the chipper canter blades should be changed follows a pattern in which current data is used in the RF-analysis tool to calculate a prediction. After that the prediction is compared to previous predictions calculated with the same process parameters and blade wear. Finally, the average of these predictions (current and previous values) is used to determine the expected blade change time. Also, some of the outputs can guide to change the blades immediately.

In this phase of developing the RF-analysis concept only three decision trees are constructed, as knowledge and data available are limited for more profound questions. The three trees are divided by the measured variable. The first tree focuses on servo torque, the second on motor current, and the third on vibrations. The questions are constructed in True or False-manner to simplify the RF-analysis. The lack of information also limits the questions and their value as validity is challenging to achieve. However, questions constructed are based on current information and should set an example of a RF-analysis tool, which could be utilized in chipper canter blade wear and energy consumption prediction. The boundaries on the questions are not based on real-life data, rather being only examples of possible values used in the final concept. The three RF-analysis decision trees are shown in the figures 14-16. In these trees, t represents the predicted effective blades lifetime left. In this example, the predictive values are only examples as are all the boundaries, as more information on the blade wear is still required to calculate the actual predictions.

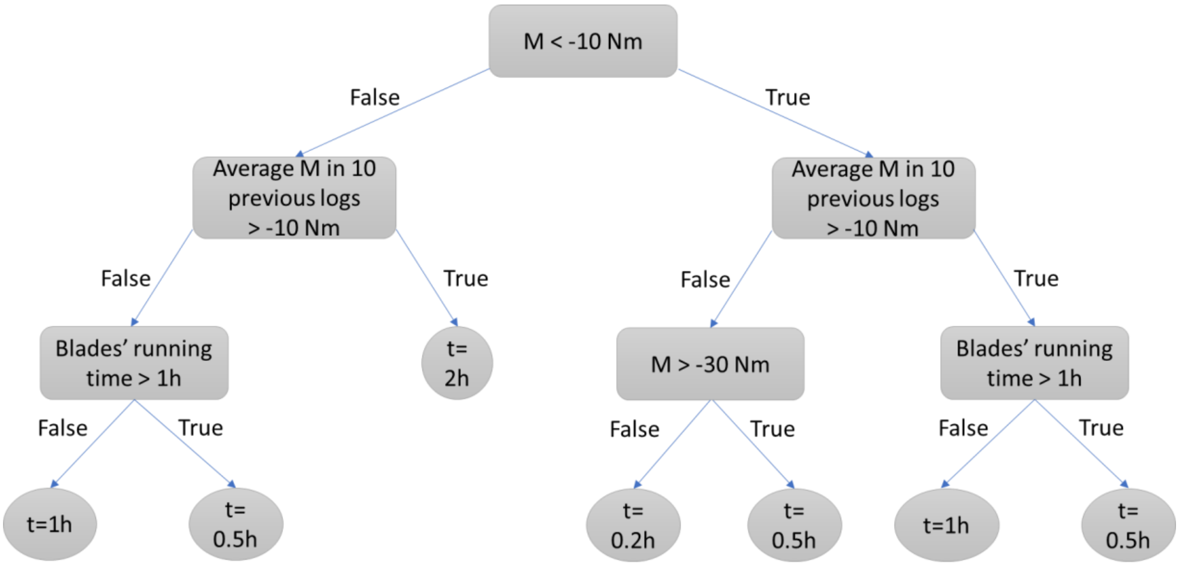

Figure 14. RF-analysis decision tree using servo torque values.

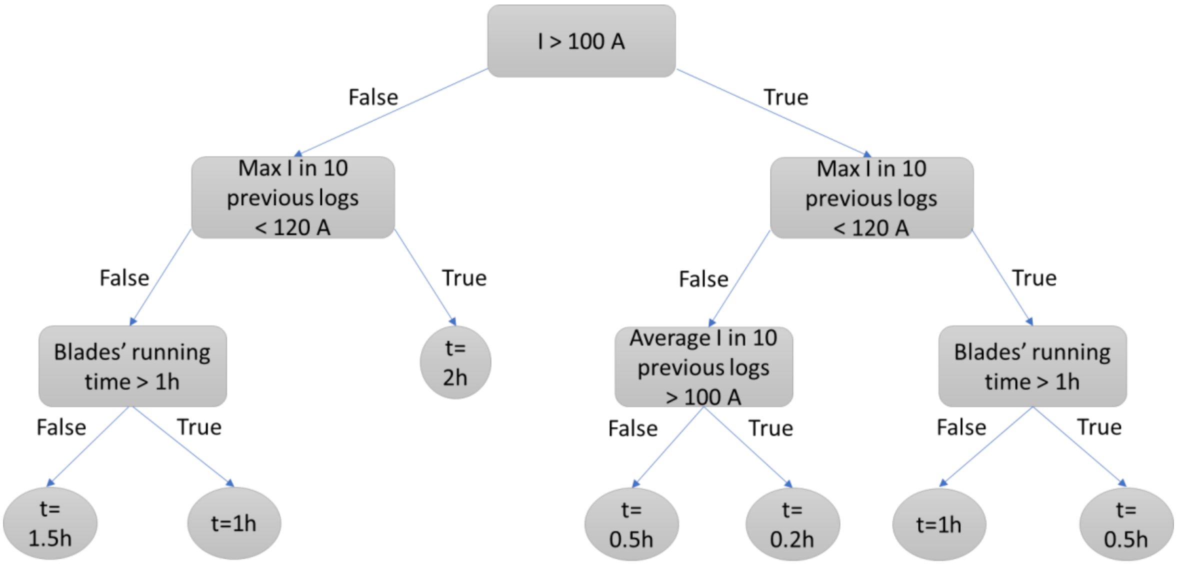

Figure 15. RF-analysis decision tree using motor current values.

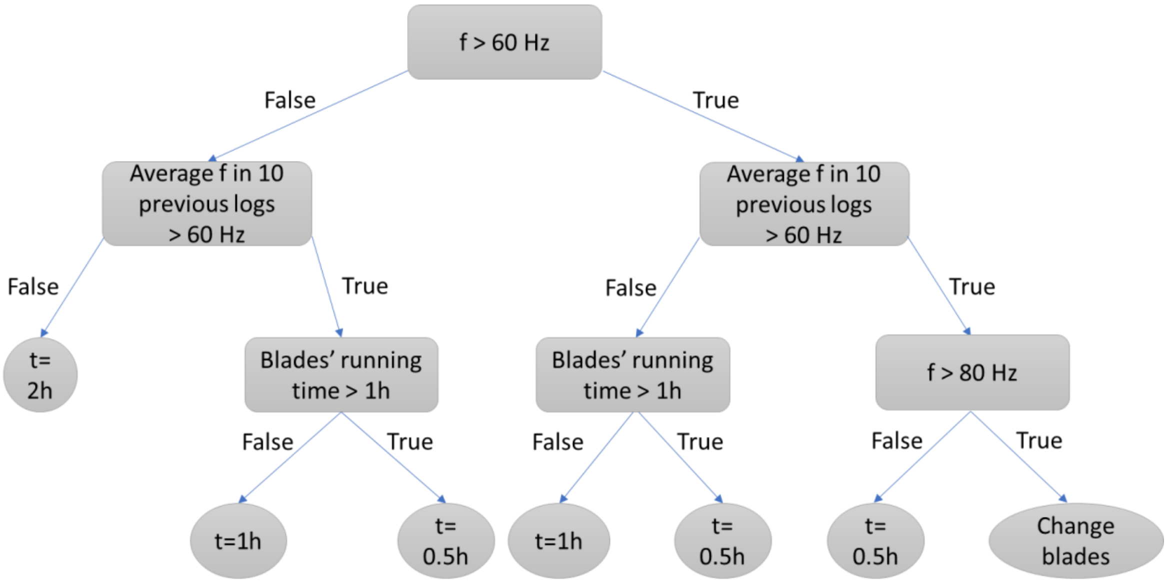

Figure 16. RF-analysis decision tree using accelerometer values.

3.6.3 Overview of the data analytics concepts

The two data analytics concepts use same data acquiring and data storing methods, in which log ID, line speed, chipping head rotation speed, chipper canters left and right side currents, chipper canters left and right side servo torques, chipper canters left and right side vibrations, top end diameter, cutting areas from left and right side, and time stamp are stored first in short term cache from which they are transferred to cloud service for analysis purposes. All the variables are linked to the log ID for easier data handling as the measured values can be traced to their roots. Values of the variables which do not have only one value per log are calculated averages of the values measured from the length of the log. All the other values except vibrations are only measured while log is in the chipper canter, as vibration values may give useful information even without log inside the chipper canter.

After the values are measured and data collected, analysis tools are used to determine blade wear and energy consumption. This is the phase in which the concepts vary from each other. Alarm limit concept uses only basic statistical analysis and alarm limit without simulation possibilities and RF-analysis concept is equipped with simulation capabilities as well. However, even alarm-limit concept can be programmed to ensure possibility for proactive blade change planning. RF-analysis concept is equipped with possibilities to constantly predict future blade wear and energy consumption to ensure more tools in production and maintenance planning.

When analysis is executed, the analysis outcomes should also be visible for the machine operator and maintenance crew. In this first phase of data analytics concept, this is done with the co-company's software which is also providing sensors and other data handling services for the concepts. From this dashboard all the relevant information can be gathered to maintain productive chipping process.

In the table 3, this overview of the two data analytics concepts are shown in table format from which their minor differences can be clearly seen. Shortly, the two concepts are mostly similar and work alike, but the data analysis and simulation functions vary depending on the concept.

Table 3. Overview of the two different data-analytics concept and their main functions.

	Alarm limit concept	RF-analysis concept
Data collection	CC, PLC, and accelerometers	CC, PLC, and accelerometers
Data storing	Short-term cache and cloud storage	Short-term cache and cloud storage
Analyzing	Statistical analysis (alarm limit)	Statistical analysis (alarm limit) and RF
Simulation	Warning-alarm limit method	RF
Visualization	Independent dashboard software	Independent dashboard software

3.7 Tests with example values

In this early phase of data analytics concept development, not all the relevant data is yet accessible. Thus, tests regarding the usability of these two data analytics concepts developed will not be complete after these early tests and they only represent an example of the capabilities of these concepts. In this example test couple of the final variables are used to proof-test the two concepts. These variables accessible and used are servo torques and main motor currents. With these values, the usability of the concepts can be tentatively determined and their suitability for real-life tests verified. Also, a comparison can be carried out between the two concepts to find their primitive strengths, weaknesses, and differences.

The test values from servo torques and main motor currents are gathered by remote monitoring one of Heinolan Sahakoneet chipper canter in real-life environment. The values are saved to wanted file by automated computer program, which detects when either the torque or the current value changes and saves this time and the changed value. At this point the values are not linked to any other variable or specific log, so advanced suppositions cannot be made regarding blades' lifetime or cutting area, because of this, averages for every log cannot yet be calculated and the data is only a list of individual values. Also, the values gathered are from limited time spans and constant long term trend cannot be inspected, rather just using values from one predetermined log batch, in this case the batch size is 17 logs.

The test environment is general sawmill equipped with Heinolan Sahakoneet circular sawline. The sawmill uses sugi (Japanese cedar) as raw material wood and saws with many different cutting patterns, even within one log batch as the sawmill is not equipped with log sorting. Also, the log dimensions vary greatly as related to the lack of log sorting process, but logs are divided in their respective classes regarding length, diameter and conicity, thus avoiding great variation between the logs. Within this test batch, the cutting pattern is however kept constant, and it is shown in the figure 17. Log temperature and humidity are not available to measure at this point, but as air temperature is over 0℃, the logs are not frozen, and this will not affect the measured values. The parameters and log classes used in this 17 log test batch are:

- Sawline speed: 80 m/min
- Log diameter class: 185 mm
- Log length class: 4000 mm
- Log conicity: 20 mm/m
- Log quality: A

Part of the example values measured is shown in the figure 18. The complete data set of almost 5000 lines and 100 pages is not fully presented in this paper other than as a trend chart in the results section.

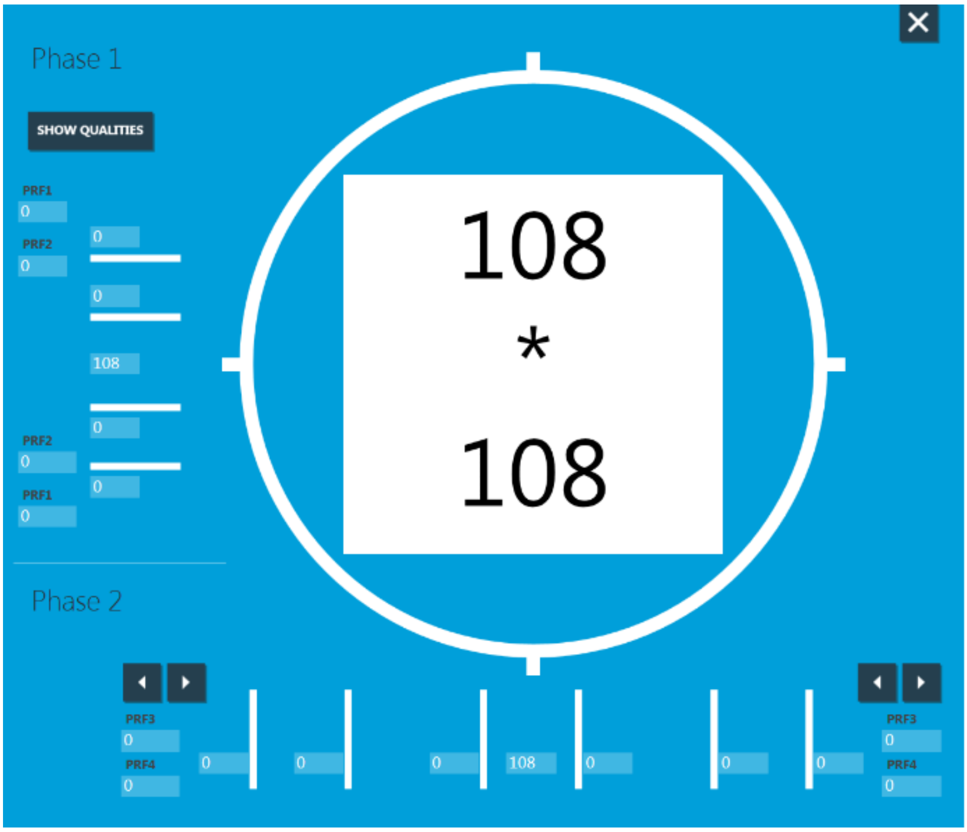

Figure 17. Cutting pattern used in gathering the example data (Vuorela 2019).

Timestamp	Torque left	Torque right	Current left	Current right
20191004 14:59:07.058	-0.60	-0.50	0	0
20191004 14:59:07.058	-0.60	-0.50	52	51
20191004 14:59:07.105	-0.70	-1.00	52	51
20191004 14:59:07.105	-0.70	-1.00	52	51
20191004 14:59:07.167	-0.70	-0.40	52	51
20191004 14:59:07.183	-0.70	-0.40	52	51
20191004 14:59:07.214	-0.50	-0.60	52	51
20191004 14:59:07.229	-0.50	-0.60	52	51
20191004 14:59:07.277	-0.70	-0.60	52	51
20191004 14:59:07.292	-0.70	-0.60	52	51
20191004 14:59:07.323	-0.90	-0.30	52	51
20191004 14:59:07.339	-0.90	-0.30	52	51
20191004 14:59:07.386	-0.70	-0.40	52	51
20191004 14:59:07.401	-0.70	-0.40	52	51
20191004 14:59:07.433	-0.70	-0.50	52	51
20191004 14:59:07.433	-0.70	-0.50	52	51
20191004 14:59:07.495	-0.90	-0.80	52	51
20191004 14:59:07.511	-0.90	-0.80	53	51
20191004 14:59:07.542	-0.70	-0.80	53	51
20191004 14:59:07.558	-0.70	-0.80	52	51

Figure 18. Example values of the data gathered. Torque unit is Nm and current unit is A.

In the example test alarm limit cannot yet be determined, thus the measured values are only used to test the RF-analysis concept. In the RF-analysis concept servo torques and motor current trees are used as accelerometer values are not accessible. The questions are slightly modified as the average values can be calculated only from the whole 17 log batch. The RF-analysis is carried out with the final log of the batch as the test log to ensure there is information gathered also before it. As the logs cannot be detected from the data specifically, the final “bump” in the data is used as reference point for being the log. From this “bump”, the minimum (servo torque) or maximum (motor current) value is used in answering the questions. As blades’ running time is unknown, decision is made to use 1 hour as their value. This decision can be made as these tests are only used to inspect these analysis tools’ usability and not to make any predictions.

With this example data, data analytics concepts’ usability is tentatively tested. After the test executed, evaluation form is filled for the concepts based on the results. The evaluation form used is shown in the figure 19. With this evaluation form, concepts and their usability are more profoundly studied, and their comparison is more transparent and reliable. The evaluation form is constructed based on the requirement list, so it would portray thoroughly the requirements set for the wanted data analytics concept and are they met with these two concepts developed. In this form the data analytics concepts are given scores based on their features. The scores are given on a scale from 1 to 3, 1 being the worst and 3 being the best. The evaluation criteria are described more profoundly in the following list:

- Monitoring and collection possibilities: Amount of data that can be collected and which variables does the collected data cover.
- Data storing: Amount of data that can be stored for further analysis and ease of future use of this stored data.
- Amount of data required: How much data is required for functional data analytics concept.
- Connectivity between different data: Is there links between different variables, such as log ID and servo torque value and how many links there are.
- Blade wear monitoring: Is it possible to monitor detect blade wear with the concept.
- Energy consumption monitoring: Is it possible to monitor energy consumption with the concept.

- Mechanical failure detection: Is it possible to detect mechanical failures with the concept.
- Simulation possibilities: Is it possible to simulate and predict blade wear or energy consumption with the concept.
- Compatibility with other sawline processes: Can the concept be used with other sawline processes as well.
- Dashboard accessibility: Where and how can one access the dashboard of the data analytics concept.
- Need for further research: How much further research is needed for the concept to be in real-life production process use.

This evaluation form is constructed to be used in future tests as well with all the data, thus in this state not all the evaluation forms criteria could be used due to lack of information. All the results of the example test calculations and filled evaluation forms are presented in chapter number 4.3.

Evaluation form		
Concept / Evaluation Criteria	Alarm Limit Concept	RF-Analysis Concept
Data Collection:		
Monitoring And Collection Possibilities		
Data Storing		
Amount Of Data Required		
Analyzing:		
Connectivity Between Different Data		
Blade Wear Monitoring		
Energy Consumption Monitoring		
Mechanical Failure Detection		
Simulation Possibilities		
Compatibility And Visualisation:		
Compatibility With Other Sawline Processes		
Dashboard Accesibility		
Need For Further Research		
Total		

Figure 19. Evaluation form used in comparison of the two different data analytics concepts.

4 TEST RESULTS

In this chapter the example test results and calculations are revealed and evaluated to compare the data analytics concepts for sawline chipper canter. The test results are thoroughly inspected, and evaluation form is used in evaluating the different concept models. All the calculation results are presented in the respective subchapter of the concept and all evaluation forms in their own subchapter. First, trend diagrams of the measured data are shown for comparison of the left-right servo torques (figure 20), left-right motor currents (figure 21), and servo torque-motor current for both sides individually (figures 22 and 23). These diagrams show the complete data set gathered for example test in compact and easy-to-read form. Also, the maximum, minimum, and average values of measured data set for every variable are shown in table 4.

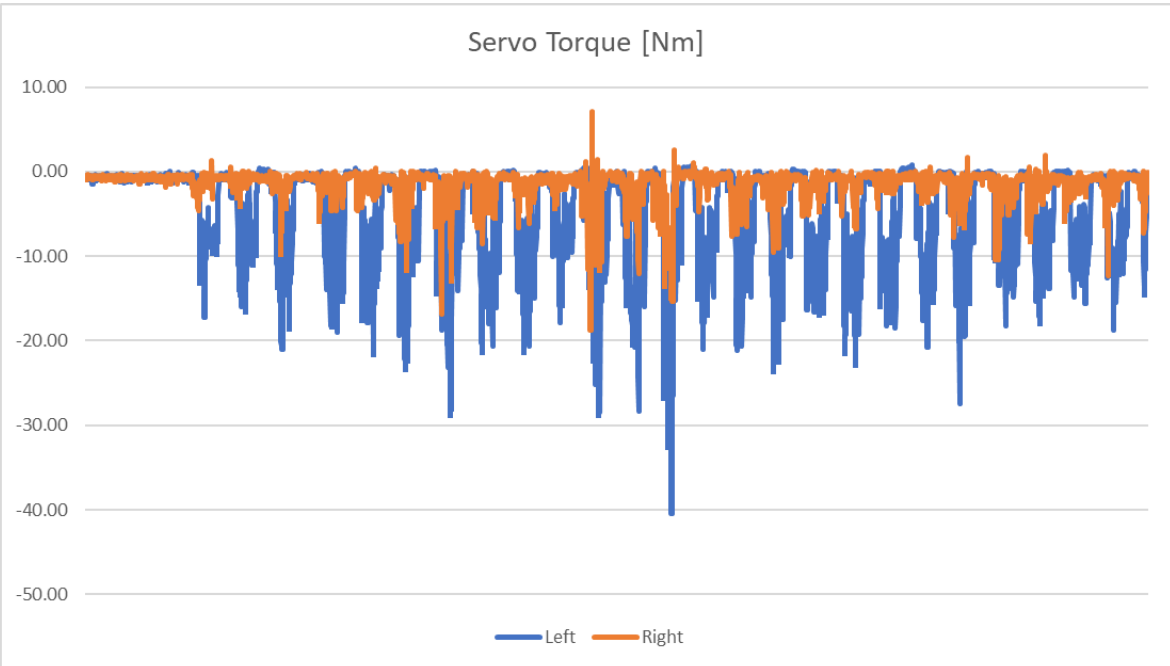

Figure 20. Measured servo torque for left and right side of the chipper canter.

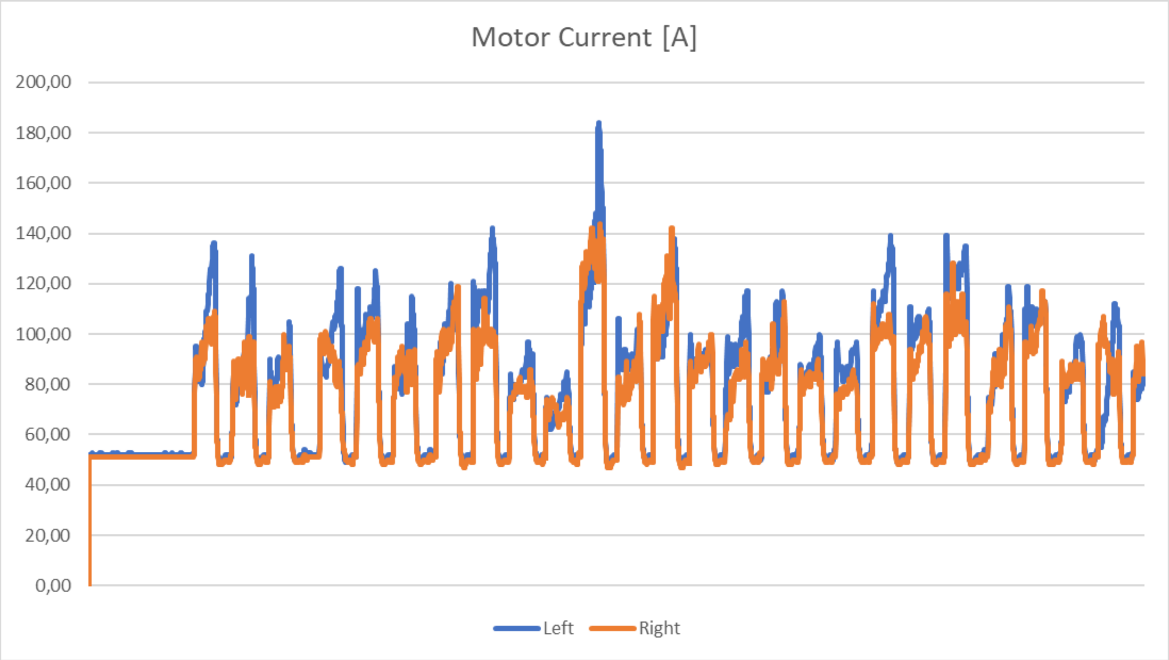

Figure 21. Measured motor current for left and right side of the chipper canter.

Figure 22. Comparison of the left side servo torque and motor current.

Figure 23. Comparison of the right side servo torque and motor current.

Table 4. Measured max, min, and average values of servo torques and motor currents.

	Max	Min	Average
Servo Torque Left [Nm]	0.80	-40.50	-5.32
Servo Torque Right [Nm]	7.10	-18.80	-1.46
Motor Current Left [A]	184.00	0.00	76.81
Motor Current Right [A]	144.00	0.00	72.77

4.1 Alarm limit concept

As alarm limit concept does not include any formulas or calculations, this example test does not give further information on the concept. The trend chart is also too short and lack of information on the blades make it impossible to do any assumptions on the alarm limit or warning limit levels. Thus, the result regarding alarm limit concept is only verification of the possibility to draw trend chart from all the values measured, which can be then inspected for further information and alarm and warning limit level detection.

4.2 RF-analysis concept

The RF-analysis results are shown divided into four figures. In figures 24 and 25 left and right side servo torques are shown and in figures 26 and 27 left and right side motor currents are shown. The accelerometer values were unavailable, so their RF-analysis was not carried out. In the figures, the path and final prediction of analysis is shown with green accent color. The predictions for effective blade running time with these trees were 1h or 0.5h for the left side and 2h or 0.5h for the right side.

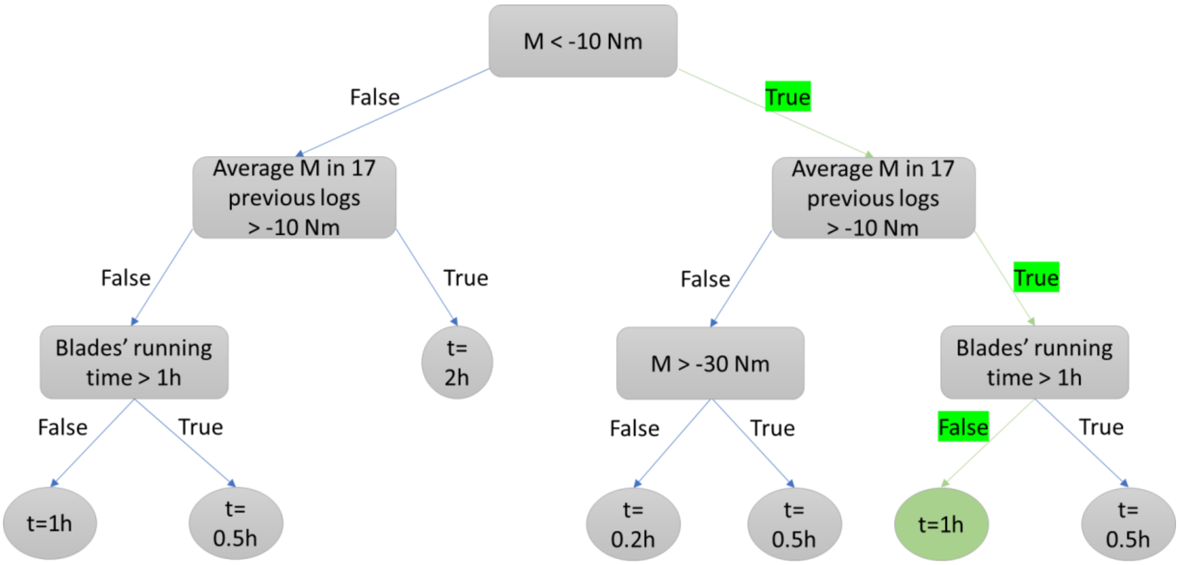

Figure 24. Left side servo torque RF-analysis.

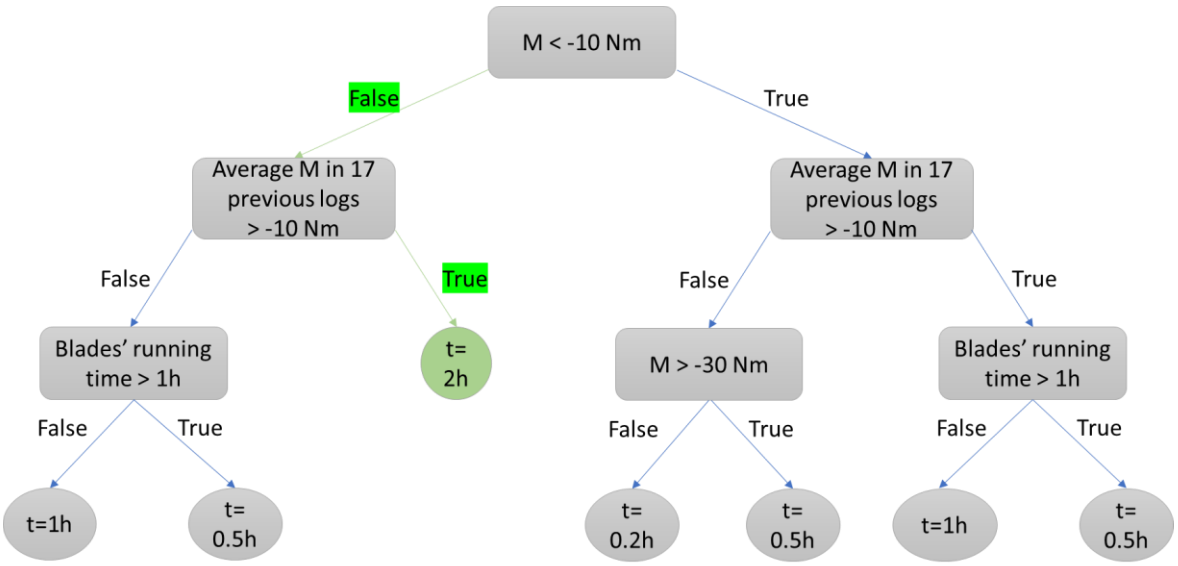

Figure 25. Right side servo torque RF-analysis.

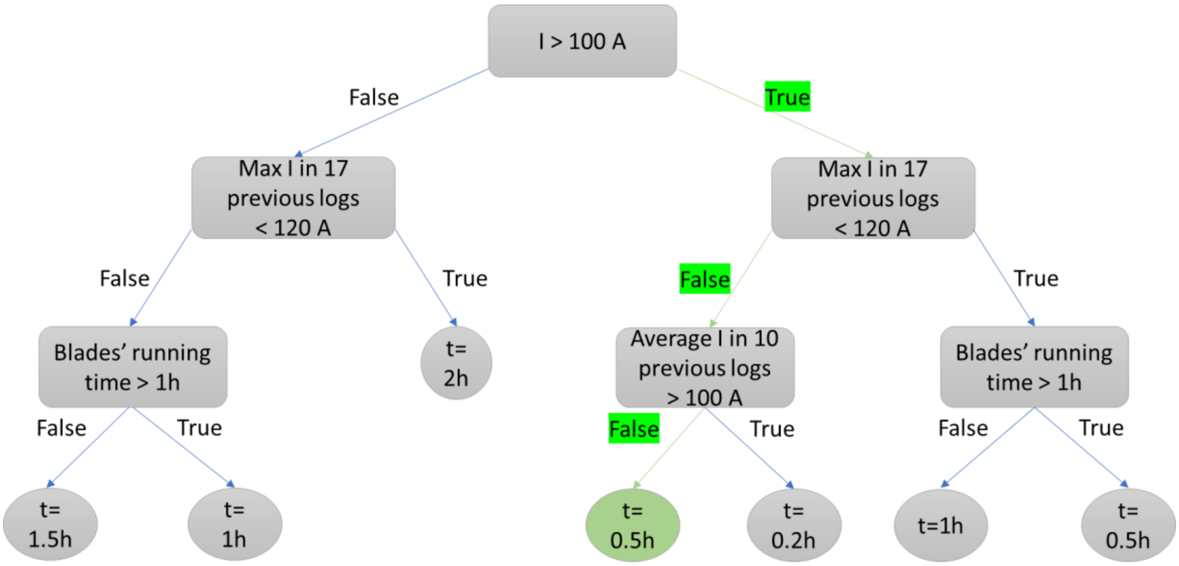

Figure 26. Left side motor current RF-analysis.

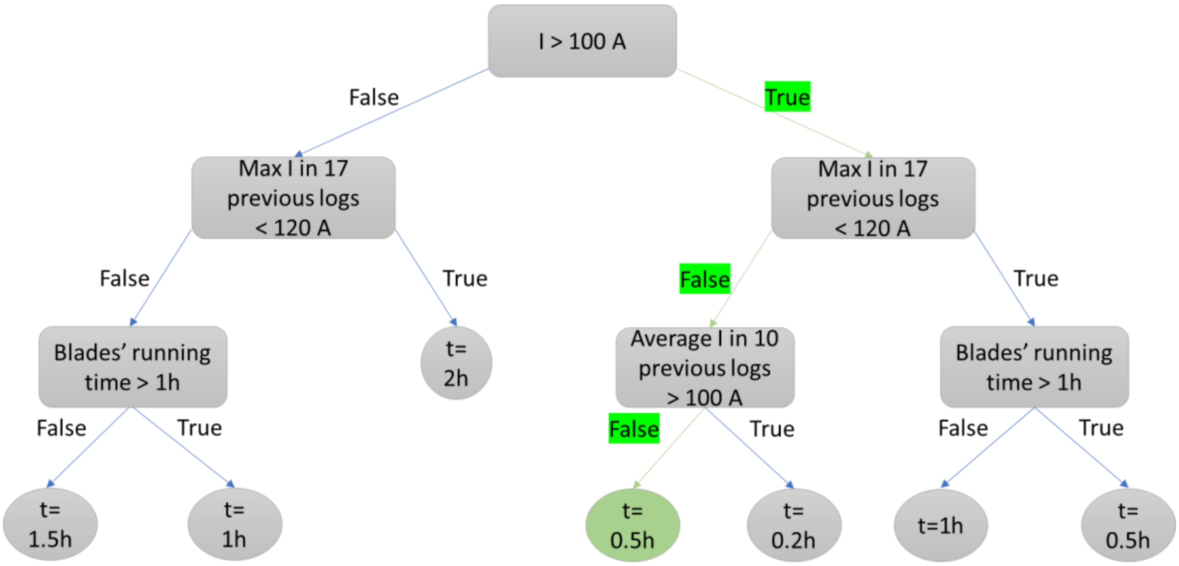

Figure 27. Right side motor current RF-analysis.

4.3 Evaluation form

The filled evaluation form is presented in figure 28. The form is filled based on background research and example test results. The detection section and their scoring cannot yet be determined as more information is still required. Based on current information, alarm limit concept is better by 1 point compared to the RF-analysis concept. This difference is mainly due to simplicity of the alarm limit concept.

Evaluation form		
Concept / Evaluation Criteria	Alarm Limit Concept	RF-Analysis Concept
Data Collection:		
Monitoring And Collection Possibilities	2	2
Data Storing	2	2
Amount Of Data Required	3	1
Analyzing:		
Connectivity Between Different Data	2	2
Blade Wear Monitoring	-	-
Energy Consumption Monitoring	-	-
Mechanical Failure Detection	-	-
Simulation Possibilities	1	3
Compatibility And Visualisation:		
Compatibility With Other Sawline Processes	3	3
Dashboard Accesibility	2	2
Need For Further Research	2	1
Total	17	16

Figure 28. Filled evaluation form for the two different data analytics concepts.

5 DISCUSSION

First inspecting the collected data, some interesting observation can be done. The collected data shows that servo torque values are mostly negative, which is caused by the orientation of the servos being opposite to their moving direction towards the log. However, this does not affect the calculations as absolute values can be used in the formulas. When inspecting the comparison charts more conspicuous observation is the great variation between left and right side values. From the figure 21 and table 4 can be seen that the values measured from the left side are constantly lower (if absolute values are used, they are higher) than those from the right side. As the left side min value of the torque from the entire data set is -40.50 Nm, right side min value is only -18.80 Nm. Also, the average values have significant difference, average of the left side being -5.32 Nm and right side being -1.46 Nm. The highs and lows however follow each other fairly evenly between the two sides, which indicates the great difference is not occurring because of logs fed into the chipper canter unevenly. Rather the possible reason being log's curvature or incorrect alignments. Whether the reason, this great variation could possibly indicate the left side blades dulling much faster than the blades on the right side.

When motor currents are inspected, not as great variation has occurred during the test batch. Within this batch the difference in max values was 40 A (184 A on the left side and 144 A on the right side) and the percentual difference in average motor current was 5.3 % (compared to the 72.6 % with the servo torques). However, even with motor current the left side values are noticeable higher than those on the right which could be caused by the same factors discussed previously.

From the comparison between left side servo torques and motor currents and right side servo torques and motor currents the most significant observation is the interaction between these two variables. As motor current increases, servo torque decreases (or increases if using absolute values). This would indicate that if either one of these variables could be used in blade wear or energy consumption monitoring or simulation, the other one could also be used in the same manner, as their values interact. However, the max and min values have still some variation in their occurring time, which would indicate that these two variables are not directly proportional to each other.

Inspecting the trend of all these four variables during this 17 log test batch, the difficulty of detecting and simulating blade wear or energy consumption can be seen. Even if this batch is small compared to long term production process, the variation within the test is great. Thus, there might be difficulties in seeing constant trend of increasing (or decreasing) values which can indicate blade wear. Within this batch the max (and min) values occurred in the middle of measurements. If this occurs a lot within bigger batches as well, the difficulty to detect the "too high" values may cause problems. However, any profound assumptions regarding this cannot be made yet and more testing and bigger batch sizes are needed to inspect the long term trend and any information it may produce.

When inspecting the test results of the two concepts it is still difficult to make assumptions on their usability as not all of their functions could be thoroughly tested. Regarding alarm limit concept, its' usability could be determined only when more information is gathered, especially from the blades and their wear process. However, during this example test no problems occurred. If the data can be gathered and sufficient amount of data is available regarding the whole process, there should not be any difficulties in utilizing this concept. The only drawback may be caused by the heterogenous of the logs, which can hamper the limit level setting process.

RF-analysis in the other hand showed possibilities to be utilized even as a simulation tool for chipper canter blade wear or energy consumption. When enough information is gathered and right questions and formulas are developed, this concept could give profitable information on the process. However, the difficult part is to develop these correct questions and decision trees and it may take some time. Thus, the usability of both of these concepts were verified, but future research is still required.

Comparing these two concepts with evaluation form is also difficult for the same reason. As more information is required to inspect all the capabilities and usability of these concepts, determining the better concept is currently not possible. However, based on the evaluation form, these two concepts may be evenly functional although they have different analysis tools. As alarm limit concept does not have more than very basic simulation capabilities, it still scores more points because it is simpler and requires less data and future work to be functional in real-life environment. Its advantage may however vanish when RF-analysis concept is fully trained and can use all its functions. As RF-analysis uses both, current information and predictive capabilities, it is predicted to score better points in blade wear, energy consumption, and mechanical failure detection.

5.1 Replicability

Exact replicability of this example test carried out is challenging. When the test material is heterogenous, the exact same environment and test circumstances are hard to obtain. Even within this test with few example measurements, variation in logs fed through the chipper canter was great and the measured values also varied greatly. Also, in this test the log temperature, humidity, and other material properties could not be measured further than determining the logs are not frozen and what are their rough dimensions and log grade, so the exact same log properties are almost impossible to replicate. However, in this type of test and with this kind of production process, the circumstances and work pieces will never be homogenous. Thus, it is not even reasonable to assume that tests carried out with homogenous material and in real-life environment would be fully replicable. Of course, homogenous and strictly regulated test pieces would give an overall picture of the capabilities of these data analytics concepts, but real-life testing would still be required to completely determine their usability, and these real-life tests will never be identical.

Regarding the process parameters, this example test is reasonably replicable. As cutting pattern, sawline speed, log diameter class, log length class, log quality, and log conicity are known and the chipper canter used can be used in the future tests as well, process could be replicated with the same environment and parameters in the future as well. Also, the measurements can be done with the same automation program and remote monitoring as in this test, which would produce comparable data with this test. However, as the chipper canter and sawline used in this test does not have log sorting system, the variation in the logs could be great in future tests. Thus, this example test carried out could be replicated in reasonable scale, but exact replication is difficult due to the test species, logs, being heterogenous.

5.2 Future work and tests

As mentioned earlier multiple times, there are many measurements left to make and inevitable need for future research as. The main focus is on implementing all the planned measurements, as this first phase only included a couple of those. Also, the idea of detecting blade wear based on the data is still to be determined, as only some example values were collected and predictions made, and continuous monitoring could not be carried out. In the following paragraphs, ideas and guidelines for future tests are presented.

Regarding the basis of the data analytics concept, all the necessary principles are presented in this paper. The requirements for future are to bring these into use. The sensors have to be installed, network and needed software have to be programmed, and the dashboard designed to include all the information and alarms, for operator and maintenance crew. However, these will also still need testing to be fully functional and used in the final production version. One possible development for the basis of the data analytics concept should be the automated blade change time detector already mentioned, which would not require man power in storing information regarding the blades. Within this blade information, possibility to identify every blade individually would also bring beneficial information on which blades sustain the wear longest and how the blades should be sharpened for optimal lifetime and product quality. This information could also be used to determine ideal blade-blade and blade-log grade pairs to prevent unnecessary blade changes where one of the multiple blades is dull while others could still be used. Rather the optimal and desired circumstance being situation in which every blade has the same effective lifetime with their pairs. Also, the implementation of the analytics dashboard into the Heinolan Sahakoneet automation program should be considered.

When the basis of the data analytics concept is installed and ready to use, the most important future work and test phase can be launched. In this phase the measurements for the variables presented in this paper should be carried out and data collected for analysis purposes. This phase of data collection should cover all the possible production circumstances, for example frozen logs, defrost logs, different wood species and different cutting patterns. Thus, the data collection phase should last at least one year in which most of the possible circumstances are covered. As data analyzing is constant learning process for people and computers, sufficient amount of data over long period of time is necessity for successful data analytics concept. In this data collection phase, the previously mentioned use of average values for every log should be tested and utilized as the amount of data would otherwise be difficult to handle and store. As the example data collected and used in this paper from 17 logs was almost 5000 lines and 100 hundred pages long, it would be multiple times greater when the data is collected from hundreds or thousands of logs.

Simultaneously with this data collection phase, blades should be monitored as well to actually determine the usefulness of the presented data analytics concepts and their formulas. Even if there is no implementation of automated blade change detector, then this should be executed by man power to detect any correlations in blade wear and measured values. The blade wear itself should be measured after every blade change to determine the wear occurred within that usage time. These values should then be saved for analysis purposes to determine, when the blades are actually dull and comparing this information on that collected from the chipper canter to find correlations. In the beginning of seeking the correlations, one might notice the values of measured data will not show any change within the blade change time as now the blade changes are usually not driven by blade wear. If this occurs in the beginning of data collection phase, the test chipper canter operators should be informed to lengthen the blade change intervals.

After data acquiring methods are validated and necessary data collected, the data analytics concepts should be tested in real-life environment with real-life data. In this phase the correct data is already known, and thus the data analytics concepts could be tested and finalized. With the correct data (known correlation between blade dullness and high/low data values), alarm and warning limits could be set to right levels, and their variation depending on the log species, cutting patterns, et cetera could be also set after analyzing the measured data and blades and finding possible correlations between these two regarding blade wear and energy consumption. Regarding RF-analysis concept, the continuous machine learning process (such as the one shown in figure 2) should be carried out to determine if it is a usable tool in simulating and detecting blade wear and energy consumptions. Necessary to this is constructing more RF-analysis tool questions and validating those as more information is available and the questions presented in this paper are only examples of the possible questions and their models. For example, the cutting area data could be used to determine effective areas cut for every blade, which could be utilized in constructing new questions.

During the machine learning process data is fed for RF-analysis tool to be analyzed and letting the computer make assumption on the blade wear and energy consumption based on the calculations and checking if the assumptions are correct. If they are, this process should be continued with different data sets to determine the usefulness of the simulation in all circumstances.

If the formulas or questions presented in this paper or the assumptions are not correct, changes in the formulas or constructed RF-questions should be considered to correct the models. However, when changing the models, one should be aware that variation in the measured data may as well cause incorrect assumptions. There is also possibility for these data analytics concepts to be totally unsuitable for this kind of data and process, thus limiting the possible data analytics tool for the alarm limit concept only. For this reason, within this test phase, these two data analytics concepts should be compared to each other constantly to determine the more suitable one for sawline production. Also, if there is a case of the concepts being unsuitable, new data acquiring methods could be considered. Such as audible sensors may give extra information and prove to be useful in blade wear detection. Dull blades may produce sounds that indicate blade wear, which could be detected by correct sensors. Other possibilities include developing totally new data analytics concepts. For example, SVM tool already mentioned in this paper is used in tool wear prediction for metallic materials and thus may be suitable for sawline production as well.

When the most suitable data analytics concept and correct data are determined through tests and comparison, duplication process of this data analytics concept for other sawline processes should begin. However, if one of these concepts seems more suited than the other, this phase may be started even before the final decision is done to shorten the process of equipping the whole sawline with data analytics. In the duplication phase, the chosen data analytics concept is attached to every machine on the sawline from which data is wanted to be analyzed. At least all the machines using blades could be equipped with the chosen data analytics concept. As both of these data analytics concepts are developed to work with all the sawline machinery, only installation of the required sensors and programs is required for beginning the data analysis. With every machine the test phase should be carried out to determine suitable limit levels and/or formulas and questions for the exact process for successful data analysis. After all the adjustments are done, the data analytics concept should be connected to the network and wanted user interface. With these procedures data analytics concept covering the entire sawline is ready for use. Illustrative timeline of all these development phases to be carried out after this paper is shown in the figure 29.

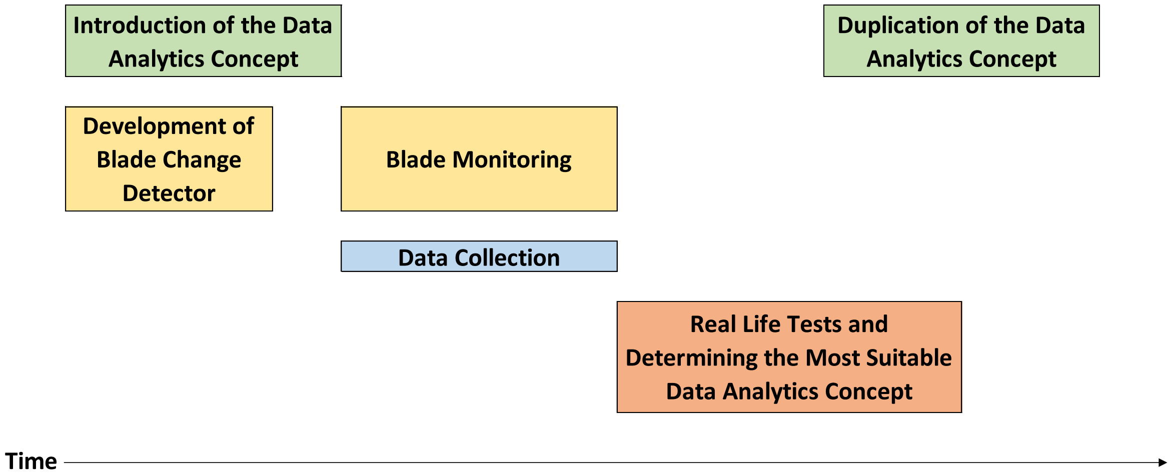

Figure 29. Timeline for the main future tests and development.

After fully functional data analytics concept is put into service, one should consider making use of it more than just detecting blade wear and energy consumption. This should consider for example making use of the known effective blade lifetime as the maintenance department could introduce predictive maintenance plans for blade changes and production planners could use this information in more effective production planning with maximized blade usage and minimized idle times due to blade changes. Also, the total energy consumption could be reduced when knowing the patterns of it and detecting the logs or cutting patterns that have alarmingly high consumption. For example, changing cutting patterns slightly may reduce the energy consumption as the process is carried out more energy efficiently. With these kind of improvements to the production process, energy costs could be decreased, and environmental friendliness increased. Both valuable assets in this day’s world.

Regarding predictive maintenance, also possibility to detect machine break downs could be utilized. As data is collected and analyzed, deviations in this data can be used to detect break downs before they occur and could be seen with human eye preventing long repair times. For example, detecting deviations in accelerometer measurements may direct to changing one bearing (taking approximately 20 minutes of repair and idle time) as opposite to not detecting any deviations and continuing the production process causing the entire motor to break down. This causes changing the entire motor (taking approximately one day of repair and idle time). The difference could be even greater depending on the availability of replacement components. This example also shows only the benefits achieved with idle times, not even considering the possible cost savings. This kind of data is beneficial to both, the sawline user and sawline manufacturer who supplies the maintenance.

The sawline manufacturer can also benefit from the data analytics concept by studying their machinery in use and detecting development targets. For example, if one component seems to break down more often than others, this component could be changed to more durable. Also, the manufacturer could use the data to detect inappropriate usage of their machinery in case of user claiming false advertised achievable production values. Related to this, the claims for these values may also be revised based on the data collected. The data regarding blades could also be very helpful for blade manufacturers as they could develop their blade designs and materials based on the data.

Further development of data analytics concept and IoT within sawline would consider more automated production processes. Such as automated measurements after every process could produce benefit as the previous process could be constantly optimized. For example, if sensors after chipper canter detect variation in wanted cant measurements, the automation program could adjust the chipping process without human input, as is now usually required. These kinds of automated adjustments could increase yield and final product quality. Thus, even the sawline processes and machines being automated already, implementation of IoT could bring benefits to these processes even further than just detecting and optimizing blade wear and energy consumption. Even fully automated sawlines with no human workers could be a possibility with IoT.

6 CONCLUSION

Beginning of this research, research problem and research questions were set. Research problem being “How collected data from a sawline process can be utilized to optimize the chipping process?”, the research questions were used to determine if this problem is solved after the research. The first question was “What are the ways to collect data?” and based on the literature review the main ways are different sensors attached to the machine. Other way is using computer program to monitor the signals within the machine, such as motor current. The second question was “What data is collected?” and in this application data collected was decided to being servo torque, motor current, vibration, log ID, sawline speed, chipping head rotation speed, log top end diameter, cutting areas, and time stamp. The third question was “Which available and collected data is relevant?” and based on the limited example test and literature review the most relevant data include servo torque, motor current, and vibration. The fourth question was “What are the ways to analyze the data?” and statistical analysis tools found within the literature review were numerous, but the most suitable tools for these circumstances were the alarm limit method, RF-analysis and SVM-analysis. The fifth question was “How the analyzed data can be utilized?” and it was determined this data would be used in monitoring blade wear and energy consumption. The sixth question was “For who is the collected and analyzed data beneficial?” and the answer is for all the parties working with the process and machine, whether it being the manufacturer or end user. The final question was “How can the process’ productivity and energy efficiency be increased with data analytics?” and the answer is mainly by optimizing the process regarding idle times, process parameters, and maintenance planning. As answering all these questions, the main research problem is solved as collecting data from a sawline process produce information on the correlations between variables, which can be utilized to optimize idle times, energy efficiency, and maintenance planning.

Regarding the research process, even it being successful by answering the research questions and solving the research problem there is still room for development. As stated in the previous chapter, future work is inevitable. Because the example test being concise and not including all the relevant data on the blade wear, the usability and all the functions of the data analytics concepts developed could not be tested thoroughly. Because of this, the results and answers to some research questions should be considered with caution as new information on the blade wear could change the conclusions made based on this research. For example, the possibility introduced earlier that the concepts developed would not be able to detect blade wear or energy consumptions could be reality after further research as the production process on heterogenous wood is difficult to duplicate or predict.

However, based on this research the data analytics concepts developed are capable to detect blade wear and energy consumption if enough data is used in machine (or human) learning process before actual introduction of the concepts. If this data is used to build the base knowledge on different process circumstances and variable value correlations between blade wear and energy consumption, both the concepts should be functional in their desired use. Alarm limit concept as a simple tool to detect blade wear and indicate effective blade change time before it is too late and RF-analysis concept in also predicting effective running times for blades with different process circumstances. And when they are functional, parties gaining profit and the benefits gained are numerous as these concepts would shorten idle times, maintenance breaks, and optimize the process regarding process parameters, production planning, and energy consumption to develop the process being more productive and environmentally friendly.

7 SUMMARY

IoT and its applications have been the greatest development area in industries within the past years. With IoT, companies seek more profitable, productive and effective production techniques to ensure their competitiveness against competitive companies. These advantages reached with IoT include for example automated production processes and data analytic applications. These data analytic applications were also the motivation for this research as Heinolan Sahakoneet aim to introduce IoT capabilities into their sawline solutions. The objective of this research was to study data analytics concept possibilities with sawline chipper canter and develop a data analytics concept to be used in sawline production.

The research was carried out with qualitative and quantitative methods by using triangulation of research methods, in which literature review was used to clarify the background and to find information on the topics regarding data analytics and sawline processes. This information was then used to develop the data analytics concept within systematic design process. In this process, requirements list was composed based on the demands and wishes from Heinolan Sahakoneet. Main demands were possibilities to detect blade wear and energy consumption for information on the process to be used in maintenance and production planning, and in production optimization.

Based on the literature review and requirements list two different data analytics concepts were developed. Both these concepts use servo torque, motor current and vibration values in detecting blade wear and energy consumption. These values are stored log by log with process parameter and log information to cloud service for profound analysis. Based on these values, blade wear or energy consumption could be monitored. The concepts vary from each other by the analysis tool used. The first concept uses only basic statistical analysis and the other one has also simulation possibilities with RF-analysis tool for predictions on the blade wear and energy consumption.

These developed concepts were also briefly tested with example values gathered from real-life production process to study concepts’ usability in real-life environment. In this test servo torque and motor current values were gathered and inspected. From the test results it was discovered that the values varied greatly within the small test batch and the variation would most likely be even greater when bigger batches are studied. This is because sawlines use heterogenous material, log, as work pieces. Thus, the analysis and simulation are difficult as the variable values will not behave linearly. Also, within this test the actual correlation between the measured values and blade wear or energy consumption could not yet be determined as information on the blade wear was not available. The test results were also evaluated and compared with evaluation form.

Because of this limitation within the test, future research is required. Thus, this research included also guidelines and robust timetable for this future work. In this future work, the concepts developed in this paper should be tested with sufficient amount of data gathered from all the possible production circumstances in real-life environment to fully verify their usability. However, despite the limitations, this research was able to answer all the research questions and thus, solve the research problem by developing new data analytics concept for sawline chipper canter.

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