2021

Process Mining in Manufacturing:

MEASURING AND IMPROVING ASSEMBLY LINE PERFORMANCE WITH PROCESS MINING TECHNIQUES

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Introduction

Today's highly competitive business environments enforce organizations to stay ahead of their competitors by any means necessary (Mahendrawathi et al., 2018). Companies in the manufacturing industry are no exception. Improving processes to meet customer demands, producing better quality products at a higher volume, shorter cycle times, and less downtime per machine are all examples of requirements that manufacturing companies put a lot of effort and investments in (Nugroho Yahya, 2014). With the rise of industry 4.0, our capability to generate and store data produced by machines has increased significantly. In the manufacturing environment, production machines are connected to each other and have the capability to generate continuous on-line production data. This opens up the possibility for managers to make more accurate decisions, given that they use the right tools to infer knowledge and insights from the data (Choueiri et al., 2020). Moreover, many activities and machines in the production process are either monitored or supported by information systems. Examples of such information systems are Enterprise Resource Planning, Product Data Management, Supply Chain Management, Customer Relationship Management, and Workflow Management systems . Many of these systems support the underlying business processes while recording the data in a format that can be used for further analyses (Rozinat et al., 2009).

However, not all processes are recorded in detailed and structured event logs. Most systems only produce raw data which needs severe pre-processing to make it usable for further analysis (Fani Sani, 2020). Some machines only produce sensor data (Sidorova et al., 2016), while other machines produce data which is stored as textual values in, for instance, CSV format. These machines have in common that they produce data which first needs to be pre-processed, otherwise the analysis results will not represent the actual production process (van Eck et al., 2015). Data pre-processing is an important part of most process mining projects (V. der Aalst, 2012), and is therefore a crucial part of this project as well. After the raw machine data is pre-processed, it should be useable for process mining.

Process mining is a research discipline that tries to discover, monitor, and improve real processes which are performed by information systems, people, and machines (van der Aalst et al., 2012). The emergence of process mining is fueled by the developments in generating and storing data, and can thus be used to assist managers in decision making. In the context of manufacturing, process mining extracts knowledge from the event logs that are produced during the production process of a product (Son et al., 2014). Because of this knowledge extraction to assist decision making, process mining serves as a crucial link between data mining and business process modeling and analysis (van der Aalst et al., 2012).

Process mining has been successfully applied in various domains over the years, including healthcare, education, software development (Intayoad & Becker, 2018), financial services, and telecommunication (Mahendrawathi et al., 2018). Most applications and implementations have been used for the service industry (Nugroho Yahya, 2014). Examples of specific purposes for which process mining has been used in these domains are internal fraud mitigation from procurement SAP data, the completion of X-ray machines and high-end copiers, developing web services, and improving care flows in hospitals (Rozinat et al., 2009). Process mining has also been applied in the manufacturing domain, albeit not that much. Examples are modeling and analyzing material movement and incoming raw materials for warehouse business improvement (Mahendrawathi et al., 2018), and the improvement of test procedures in wafer scanners (Rozinat et al., 2009).

The evaluation and improvement of the efficiency of the production line and its individual machines has always been an important topic for discussion and research in the manufacturing domain. The Overall Equipment Effectiveness (OEE), coined by Nakajima (1988), is a metric that measures the effectiveness of individual machines and enables companies to benchmark and monitor their progress and improvement (Nayak et al., 2013). It can also indicate in which areas the biggest improvements can be achieved. Since the OEE can only be calculated for individual machines, without taking operators into account, it might not be the best method for companies with more complex production lines with operators. That is why researchers have proposed new and extended versions of the OEE (Stadnicka & Antosz, 2018), such as the Overall Resource Effectiveness (ORE) proposed by Eswaramurthi & Mohanram (2013). The ORE differentiates between different kinds of downtimes, such as absence of operators, planned downtime, and facility downtime. The calculation of OEE needs input data such as the uptime and downtime of machines, and amount of good items produced. The ORE needs additional information such as the absence time of operators, lack of material, the line order, and other kind of domain knowledge. Most of this data is available in ERP systems, which can be combined with domain knowledge to get an idea of how well the line is performing.

With all that being that, the implementation of ORE is not as simple as one might think. The problem that companies in the manufacturing domain face is that the analyses are performed based on only the data recorded by the individual machines. The results of the analyses are then used as input for problem mitigation projects, in order to improve the overall line efficiency (Li et al., 2009), often expressed in terms of OEE (Stadnicka & Antosz, 2018). Most of these analyses are throughput analyses, which have their limitations. Oftentimes the data is recorded by each machine individually, and therefore the analyses are also only done for each machine individually. By doing this, the input flow and output flow for a specific machine is overlooked, leaving out important information for the analysis. This gives an incomplete overview of why a machine is e.g. standing still, or performing well. The data is available at each machine individually, but the problem is that most companies are missing the means to connect those individual pieces together, which is often a challenge in itself because of information incompleteness and inaccuracy. Next to this, the actual routes that the products take change over time, or even per product, and the behavior of operators also influences the analysis. All of this crucial information for the correct production line analysis is present in the event-logs, however, techniques from the manufacturing domain have so far not been able to correctly utilize this information (Li et al., 2009). This presents limitations to the production line analysis that require assistance from techniques outside of the manufacturing domain.

Because of the process-oriented nature of process mining, process mining should be capable of solving the aforementioned challenges and limitations. However, process mining without any domain knowledge can lead to confusion and incorrect insights. Therefore, in order to reduce the limitations of the manufacturing domain and the limitations of the process mining domain, both domains need to be combined.

The aim of this research is to get a better understanding of how process mining can be utilized to correctly calculate the OEE for individual machines, and the ORE when surrounding machines and operators are needed to be taken into account. A framework will be designed that indicates which data and information is needed for which kind of analysis or calculation, and whether this information can be found in the event-logs by using process mining, or whether it needs to be extracted from other domain/case documents or meetings. Adding to this, the main goal of the ORE is the indicate when and why each machine in the production line is not processing an item. In order to do so, operators and machines that are working together through the operators, need to be taken into account in the calculation and analysis. Process mining techniques such as process discovery will be used to extract the necessary data for the calculations. After the calculations have been performed, it is important to find out where exactly the line is performing poorer by using visualizations, and thus to identify where the client should invest time and money in.

As mentioned, there are various process mining studies within the manufacturing domain, and the OEE is studied extensively, which produced a lot of extended variants of the OEE such as the ORE. However, the combination of process mining, OEE and ORE, and other information from the manufacturing domain has not been researched before and therefore presents a gap in the literature that this research aims to fill.

The following research questions have been formulated:

Main Research Question:

- *Which types of data are required in order to make decisions on possible production line improvements?*

Sub Research Questions:

1. Which types of data are required in order to calculate the line effectiveness?
2. Is the OEE metric elaborate enough in order to be used as input for production line improvement?
3. Can the combination of process mining and a machine effectiveness measurement indicate why machinery is behaving a certain way?
4. How can different information needs be visualized so that it is useful for analyzing a production line?

This paper expects to contribute to the literature by filling in the gaps that are missing regarding process mining in the manufacturing domain and the use of process mining for measuring and improving machine effectiveness, indicating when and why a machine is inactive, and the creation of a framework which has not been done before. The results of the paper are expected to help the client to improve the efficiency of the production line, and to enrich the research area with framework that can be used to see which data is required for production line analysis. The remainder of the paper is organized as follows: Chapter 2 will describe the related literature, chapter 3 contains the research method and the way this research is conducted, chapter 4 consists of the results, the conclusion is presented in chapter 5 and the paper ends with chapter 6, which is the discussion.

Related work

Process mining in manufacturing

The power of process mining can be harnessed in almost any domain and the manufacturing domain is no exception. Manufacturing companies produce products that are made step-by-step in the production line. This production process can be explained as a series of activities in sequence that transforms raw materials into a finished product (Park et al., 2015). Business processes in manufacturing are often highly complex and dynamic (Intayoad & Becker, 2018). The production line contains many machines that all produce different products, or work together to create a more complex product. Next to this, several operators handling the machines and unforeseen events are also needed to be taken into account. Moreover, business processes often change over time because of managerial decisions that impact the original business process. In order to stay ahead of competitors in the market, businesses strive to increase process efficiency and performance, and to gain knowledge that will give them the upper hand over competitors and to improve their own future processes. A thorough way of getting these insights is by using process mining (Intayoad & Becker, 2018).

Process mining can be used to analyze the (production) process in three different perspectives; the process perspective, the resource perspective, and the case perspective (van der Aalst et al., 2007). The *process perspective* encapsulates on the control-flow, i.e. the order that the activities are in. The objective is to find all possible paths and portray them in a process model, often visualized using a Petri net. This activity is called *process discovery*. Based on this process model and the event-log, the model can be verified, which is called *conformance checking*, and/or enhanced, which is called *enhancement* (Nugroho Yahya, 2014). The *resource perspective* analyses the performance of organizational entities executing the activities during a process. A resource can be different kinds of things; one machine, a group of machines, one person, a group of people, or an information system. The goal of the resource perspective is to map the roles and/or units that are present in the organization, and to reveal the performance of, and relations between individual resources, roles, units, and activities. This can be achieved by building a social network using social network analysis and organizational mining (Nugroho Yahya, 2014; van der Aalst et al., 2007). The *case perspective* focuses on individual cases and tries to make sense of any connection and relation between the different individual properties and characteristics of a case by seeing it as a whole. Properties of a case include their path in the process, the originator and performers of the case, the elements and values related to the case, and the activities being executed. Using the case perspective, it is for instance possible to correlate the size of the order and the time it takes to manufacture (van der Aalst et al., 2007, 2012).

There are a few challenges that need to be taken into account when performing process mining in manufacturing. First of all, low quality of the event logs. This is mainly due to the complex and dynamic nature of the production processes, the frequent changes, and the short product life cycles. The data generated by machines is often not ready for process mining and needs to be pre-processed (Intayoad & Becker, 2018). Secondly, issues which are related (but not limited) to event logs from the production process, are incompleteness and noise. We can only monitor processes that are recorded, which implies that some interactions may not be visible in the log and some low probability paths are often not even detected. As a result, not all possible behavior is captured making the log incomplete. Noise (incorrectness, exceptions) can originate because of human or technical errors, work which is not logged by the system, and the occurrence of unusual events. This noise, which is often incorrectly recorded information, is not part of the main process. Thirdly and finally, for some organizations there are privacy issues. It may be easy to see which resource (human) is responsible for a delay in the process, but labor contracts and other agreements may prevent that information from being analyzed (van der Aalst et al., 2007).

Measurements for machine effectiveness

If process mining is to be used to propose improvements and suggest different ways of working in the production line, then there is a need to quantify these improvements. According to Nachiappan & Anantharaman (2006), metrics for analysing and measuring productivity and efficiency of manufacturing facilities have been studied extensively for a long time. It is indicated that measurement is needed to identify problems and to suggest improvements in regard to productivity, and to quantify these improvements. That is why the *Overall Equipment Effectiveness* (OEE) was launched by Nakajima (1988) as part of the TPM paradigm. TPM stands for Total Productive Maintenance and is an approach to maintain effective equipment, eliminate breakdowns, and to help operators work autonomously throughout their day-to-day activities (Nakajima, 1988). Since its release, it has been widely accepted and used as the industry standard for measuring the productivity of individual machines in factories' production lines. The OEE consists of three contributing factors: Availability, Performance, and Quality. The *availability* factor measures the percentage of time that the equipment was running (Operation Time) compared to the time it should have been running (Planned Production Time). This includes unplanned downtimes, planned stops, set-up times, recurring maintenance, and absence of operators. The *performance* compares the actual output (Total Pieces/Operating Time) to the theoretical output (Ideal Run Rate), in other words, losses that occur when the equipment is not utilized optimally in terms of speed. The *quality* factor measures the number of good parts (Good Pieces) to the total number of parts (Total Pieces), to see how much loss occurs due to defects (Nayak et al., 2013). The formulas are as follows:

$$\text{Availability} = \frac{Operation\ Time}{Planned\ Production\ Time}$$

$$\text{Performance} = \frac{Total\ Pieces/Operating\ Time}{Ideal\ Run\ Rate}$$

$$\text{Quality} = \frac{Good\ Pieces}{Total\ Pieces}$$

$$\text{OEE} = Availability\ x\ Performance\ x\ Quality$$

However, the OEE is not always measured and calculated in the exact same way by different companies. According to Stadnicka & Antosz (2018), there have been numerous extensions, variants, changes, and improvements to the original OEE. The calculation heavily depends on the factory, personal preferences, whether the line works with human operators, whether you want to know the OEE of the whole line or per machine. Therefore, it may be difficult to compare the OEE results between companies if they use different calculations. However, when a company decides on a way the OEE should be calculated, it can compare its own improvements over time.

Calculating the OEE is useful, but does not add value if it still does not indicate where improvements can be made. That is why Nakajima (1988) linked the three contributing factors to the Six Big Losses. These *Six Big Losses* indicate which factor is experiencing trouble and this can be used as the input for a mitigation process to fix the problem (Nachiappan & Anantharaman, 2006). The Six Big Losses are widely used in the literature and can be described as follows:

Losses	Definition	Factor
Equipment failure	Losses caused by failures in machines, which results in downtime	Availability
Setup and Adjustments	Stoppage losses that occur when machines need to be recalibrated because of the production of a new product, and other setup related losses	Availability

Minor stoppage and idling	Losses caused by temporary equipment stoppages or idling, often due to jamming, actuation, or due to an external factor	Performance
Reduced speed	Losses that occur when the actual equipment speed is slower than what was designed	Performance
Defect/Rework in process	Losses caused by reworking and defect products	Quality
Reduced yield	Material losses due to a difference in input and output weights	Quality

Table 1. Six Big Losses

Using the OEE and its individual contributing factors, it can be seen which of the Six Big Losses is causing the biggest loss, and can then be mitigated if needed.

The reason that over the years a plethora of new variants have been designed, (Stadnicka & Antosz, 2018) is because the original OEE has some limitations. It is designed to be calculated for one individual machine and does not take the properties of a whole line into account. An apparent property is that the output of a previous machine is the input of the next machine (Nachiappan & Anantharaman, 2006). When the process starts with 100 products, and the first two machines cause 10 defects, then the input for the third machine should be 90 products, not 100. The original OEE does not take this into account. Another property is that it is possible for production lines to work with human operators who have to manually move the products from one machine to the next. When an operator is not fast enough, there will be a lot of availability losses due to the absence of an operator (Eswaramurthi & Mohanram, 2013). This loss is not taken into account in the original OEE, where all the availability losses are calculated only with one formula and it not split into smaller categories.

Because of these reasons, Eswaramurthi & Mohanram (2013) came up with a new variant of the OEE, called the Overall Resource Effectiveness (ORE), which extends the original OEE with more specific factors that address different kind of losses seen in manufacturing lines, which can then be targeted to initiate improvements. The proposed method includes new factors described as Readiness, Availability of Facility, Changeover Efficiency, Availability of Material, and Availability of Manpower. The first factor, *Readiness,* takes planned downtime into consideration. *Availability of facility* calculates the losses caused by equipment breakdowns and unplanned downtimes such as a certain machine not being ready in time to receive the next item. *Changeover efficiency* covers losses due to setup and adjustments. *Availability of material* decreases when there is a non-availability of material which results in downtime. *Availability of Manpower* takes the operators into consideration and decreases when the machines are inactive because there is no operator that can feed the machine the next product. Performance efficiency is like the normal OEE, which are losses due to speed. Lastly, the Quality losses are also just like the normal OEE, which takes defects into account (Eswaramurthi & Mohanram, 2013; Garza-Reyes et al., 2008; Garza-Reyes, 2015). Figure (1) below visualizes all of these losses that need to be taken into account to calculate the ORE.

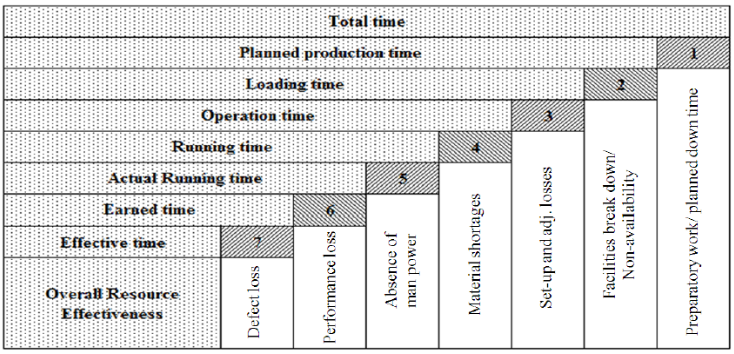

Figure 1. Overall Resource Effectiveness. Taken from Eswaramurthi & Mohanram, (2013)

The calculations of different ORE factors are as follows:

Factor	Formula	Loss
Readiness (R)	$\frac{Planned\ Production\ Time}{Total\ Time}$	*Total Time* = Shift Time or Time as decided by management *Planned production Time* = Total Time – Planned Downtime
Availability of Facility (A_f)	$\frac{Loading\ Time}{Planned\ Production\ Time}$	*Loading Time* = Planned Production Time – Unplanned Machine Downtimes
Changeover Efficiency (C)	$\frac{Operation\ Time}{Loading\ Time}$	*Operation Time* = Loading time – Setup and Adjustment time
Availability of Material (A_m)	$\frac{Running\ Time}{Operation\ Time}$	*Running Time* = Operation time – Time lost due to Material Shortages
Availability of Manpower (A_{mp})	$\frac{Actual\ Running\ Time}{Running\ Time}$	*Actual Running Time* = Running Time – Manpower absence time
Performance Efficiency (P)	$\frac{Earned\ Time}{Actual\ Running\ Time}$	*Earned Time* = Cycle time/unit X Quantity produced
Quality rate (Q)	$\frac{Quantity\ of\ products\ accepted}{Quantity\ of\ products\ produced}$	*Quantity of parts accepted* = Quantity produced-Quantity rejected
$ORE = R * A_f * C * A_m * A_{mp} * P * Q$		

Table 2. Overall Resource Effectiveness formulas

Input data for process mining

More and more machines and information systems support the generation of data, and therefore enable the option to be analyzed and be used for process mining. Large amounts of raw data is recorded daily by all kinds of machines and information systems, which in turn is stored in large databases. However, organizations are still struggling to extract knowledge from this data (Choueiri et al., 2020). The reason for this is that to successfully perform process mining, the input should be an event log, and not the raw data generated by the machines. Therefore, generated data needs to be pre-processed into usable event logs first (Fani Sani, 2020). Event logs are used as the starting point for all process mining activities, e.g., process discovery, conformance checking, enhancement, and concept drift detection. The algorithms used during process mining are able to produce perfect results using clean, structured, and complete event logs. However, real-life data is often noisy, incomplete, and imprecise, which leads to poor process mining results. Using pre-processing, it is possible to improve the quality of these results (Jagadeesh et al., 2013). The process mining manifesto (van der Aalst et al., 2012), seems to agree with this, as it lists five maturity levels based on the quality of event logs, ranging from one star to five stars. The goal is to pre-process the event logs so that the quality is increased, and the results, which are based on the event logs, are improved. There is a substantial amount of papers related to pre-processing of event data and event logs, most of which describe techniques and guidelines for pre-processing (van Eck et al., 2015). The amount of quality issues in event logs and the pre-processing techniques to tackle those issues is almost endless, and heavily depends on the data generated by the machines (Suriadi et al., 2017).

Structure of event logs

In process mining terminology, an event-log contains multiple events, and an event is characterized by three main properties. As described by W. M. P. van der Aalst (2015), the first property is the *Case ID*, which refers to the case (also called process instance) that the event is a part of. If the event is relevant for more than once case, the event should be linked to those cases as well. The second important property is the *activity* that the event relates to. Each event refers to an activity instance, which means that a certain activity takes place when the related event occurs. The third main property is the *timestamp*. Timestamps are used to order the events and to calculate the duration and measure the performance. Besides these main attributes, the event can contain all kinds of optional attributes, such as the *resource* that executed the event, the *type* (start, complete, suspend, resume, etc.), the *costs* of the event, the *customer* for whom the event is executed, and many more. The kinds of attributes that the event contains or needs for process mining depends heavily on the questions that need to be answered (van Eck et al., 2015). Since each event is associated with a case (because of the Case ID), these can be ordered to get a trace. A trace is a finite number of events in a given sequence, such that each event only appears once in the sequence and is ordered by increasing timestamps. When you take a few traces together, you get an event log. In other words, an event log consists of traces, which consist of cases, which are linked to events that perform activities (Choueiri et al., 2020). In order to store such event logs, dedicated process mining formats like XES or MXML have been developed (W. M. P. van der Aalst, 2015). However, most process mining tools are able to handle CSV files nowadays as well.

Input data for production line analysis

For the analysis of production lines, different kinds of data can be used as the input. The type of input depends on the domain, the situation, and the type of output information that is desired. Examples of input data are failure causes such as mechanical or electric failures, defects, repetitions (Ahmad et al., 2018), different kinds of costs such as raw material costs, human force costs, sales distribution costs, (Bahremand, 2015), labor costs, energy costs, rent costs, (Ebumüslüm & Paşayev, 2013), valuable knowledge such as who is the best person to contact when material is running short (Harding, Shahbaz, & Kusiak, 2006), or other kinds of information such as shift periods, work rhythms, amount of equipment and workers at production lines, and the target production amount (Ebumüslüm & Paşayev, 2013). These examples should give an idea as to the range of different types of input data that can be used for the analysis of production lines. This data can be obtained through the company's business plan documents, their website (Ismael, 2021), production reports, interviews (Ahmad et al., 2018), databases (Harding et al., 2006), and meetings. All in all, there is considerable variability in the type of input data and the way it can be collected, and it heavily depends on the specific analysis situation at hand that determines which data and information is actually required.

Research Methods

Chosen Research Methods

For this research a case study approach has been taken as the research method. The goal of this research is to gather, process, and analyze quantitative data collected by an organization, in order to improve their production line. Gerring (2017) defines the "case study method" as an intensive study of an individual unit with the aim to use the results of that unit to generalize the approach, method, tool, or any other artifact that was designed to a larger set of units. The goal of the project for which this research is conducted is to extensively study a production line in a factory, and to use the results of the study to design a framework that can be used to analyze other production lines for the organization, and preferably also production lines from other companies. This is in line with the definition of a case study provided by Gerring (2017). Another reason why a case study has been chosen as the research method, is the fact that in the domain of process mining, a case study is the single most used method when process mining is applied to data gathered from an organization or company. Some examples of papers that use a case study that have been cited in this research paper are (Eswaramurthi & Mohanram, 2013; Mahendrawathi et al., 2018; Park et al., 2015; Rozinat et al., 2009; Sidorova et al., 2016; Son et al., 2014; Suriadi et al., 2017; van Eck et al., 2015), and together provide a solid foundation for the application of process mining on production line data. In order to prove that the designed approach can in fact help organizations derive to results that were not possible to derive to before, the approach will be validated using expert interviews.

While applying process mining during the case study, a process mining methodology called PM2 has been used. The reason why it was used is because PM2 is an established methodology in the process mining domain. The methodology was proposed by van Eck et al. (2015) and it guides organizations in, for instance, achieving improved process performance or an improved compliance to regulations and rules. PM2 translates the goals of a process mining project into concrete research questions, which are refined in an iterative way at each stage of the process. The results are findings that form a solid basis for process improvement. PM2 consists of 6 six stages in total. The first two stages are (1) planning and (2) extraction, which is when the research questions are formulated and the extraction of data takes place. After the initiation stages, data analysis is performed, which consists out of (3) data processing, (4) mining & analysis, and (5) evaluation. These stages can be executed one or more times and can happen in parallel or sequential. Each iteration of analysis focuses on answering a specific research question, for which different kind of process mining activities are used. Lastly, if satisfactory findings have been found, then (6) process improvement & support can be executed. Figure 2 below visualizes all of the stages and indicates the input and output of each stage.

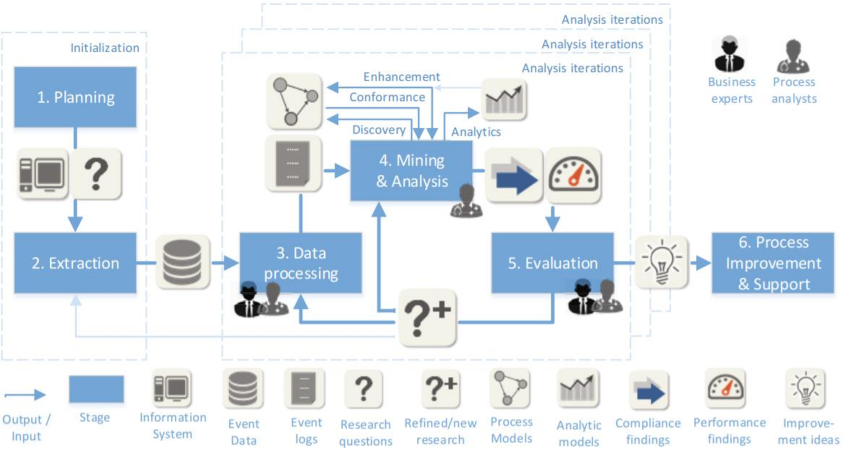

Figure 2. PM2: A Process Mining methodology. Taken from van Eck et al. (2015)

The context of the case study

The case study will be conducted at one of TNO's clients, which is a technology provider in industrial automation, healthcare, and electronic components. The client has a production line that is connected to an ERP system, which stores data generated by the machines that is ready to be preprocessed and analyzed. The client is a good place to conduct this study, since it is already clear what the order of activities must be (the machines have a predefined order, but this still needs to be discovered with process mining to use as input for the script), the production line engineer can apply tests and improvements on short notice, real-life changes to the production line are documented, and next to the event-logs the client has provided a lot of additional information in terms of domain knowledge.

The client has multiple production lines, which in turn can produce several different products. The two lines in question, the NX-A and NX-M, produce Programmable Logic Controllers (PLCs), which are electronic devices with a microprocessor. These PLCs use programmable memory to store instructions, such as logic, sequencing, and timing. With these instructions, the PLC is able to use the ingoing/input information in order to control the outgoing/output information (Lashin, 2014). The PLCs can have different amounts of pins (8, 12, or 16) and can be designed for different purposes. In total, the two lines are able to produce 38 different PLCs and new ones can be added at any time. Every PLC has a unique itemnumber, and each itemnumber consist out of a certain amount of serialnumbers. So, each itemnumber is a generic predefined item (in this case a manufactured item, which the client sells to their customers), and a serialnumber is a unique number for one piece of an item.

Both lines consist out of 16 machines that take a Printed Circuit Board (PCB) as input, and have useable PLC as output. The 16 machines are divided into 4 categories: machines that record no data at all, machines with data but no tracing, machines with pcb tracing only, and machines with data and tracing. The first two machines, *start scanner* and *De-Paneling robot* produce no data and are therefore not able to be analyzed. The third and seventh machine, *Board Programming* and *Assembly stage 2* only have pcb tracing, which means that the products can only be traced between those two machines. When a product has been handled by these machines, it will receive a new serialnumber when it has reached the first machine with normal tracing and can therefore not be traced completely throughout the production line. Another reason why a product can't be traced throughout the whole line is because the fourth, fifth, and sixth machine only produce data, but no tracing. This means that the event logs indicate that the machine has run, for how long, and for which itemnumber, but it does not indicate which serialnumber it has handled, which means there is no tracing. These machines are the *Pin Stitcher*, *Assembly stage 1*, and *Automatic Soldering*. The last group of machines all produce data and tracing information, which means the event logs indicate which serialnumber a machine has processed and for how long. The machines with data and tracing are *In-line lasering*, *Connector cleaning 1&2*, *Pin inspection*, *Bus inspection*, *Final inspection 1*, *Final inspection 2*, *Final inspection 3*, and the *Packing and connector inspection*. For each product only one Final inspection machine is used.

The lines do not only consist out of machines, but need two or three operators (per line) to pick up the product from one machine, and insert it into the next machine. This is called 1-piece flow. There are also no buffers in the line, which means that if there is no material yet for a specific machine, the machine simply has to wait for the previous machine to be finished with the required material. The operators are also needed at the *assembly stages* and the *packing and connector inspection* stage, because it requires manual work to process the items at those stages. The fact that the line is 1-piece flow and needs operators to handle the products and machines makes the analysis with OEE quite difficult, which is one of the reasons why the ORE is also used. The client claims that the operator is king, which means that the operators can decide which action to perform and when, so this makes the behavior of the line very unpredictable. Figure 3 shows the line with the operators.

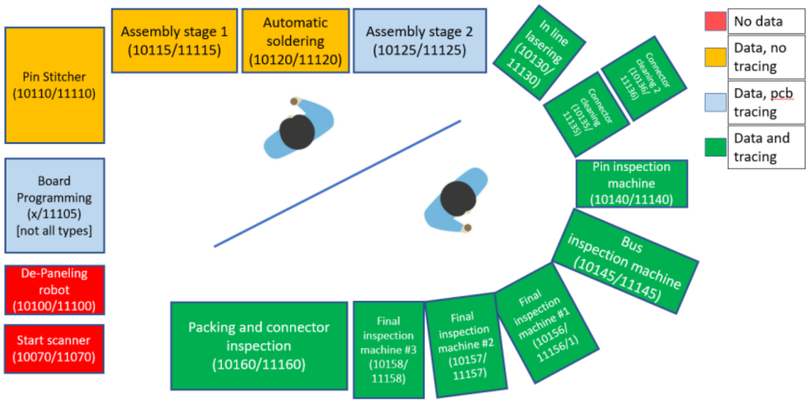

Figure 3. Both of the client's production lines with two operators

Lastly, both lines should be active, at the same time, during weekdays from 06:00 until 23:45 and occasionally for a few hours on the weekend. One working day consists out of 2 shifts of around 9 hours, and each shift has a planned break of 1 hour. There is planned maintenance on the lines every 4 weeks for 2 hours on a Wednesday morning. Next to these planned occurrences, there are occasional downtimes when machines are jamming or have breakdowns. The last two important factors to take into account are the defect and reworked products. At any of the stages a product can be found to be defect, and will be removed from the line. When it is repaired after some time, it will be re-inserted back into the line. A product can be reworked when an inspection machine indicates that the checked item did not pass the test and needs to be checked again. This double-occurrence of the same serialnumber is called a rework and influences the effectiveness of the machine and line.

Besides the aforementioned characteristics of the line, it is important to note that there is a lot of data variation. The previous sections have already indicated the amount of different machines, unpredictable behavior of the operators, difference in shifts, two lines, different types of recorded data, a broad range of different products/itemnumbers, and different amount of serialnumbers per product. Furthermore, the cycle time for a machine varies per itemnumber. Out of the 38 itemnumbers, 18 groups of itemnumbers with the same cycle time can be found. This constrains the analysis, because the conclusion for one machine and itemnumber(group) might not hold for other itemnumbers for that same machine. In fact, there are 2 lines, 14 machines with data, 18 different cycle times, 2 shifts per day, and 3 factors for OEE or 7 factors for ORE. This amounts to 3024 and 7056 potential different calculations per day (if all itemnumbers would be produced in *one* day). This is of course not feasible to calculate and also just way too much information for the client to work with. Therefore, three filters are needed in the script. One filter indicates the itemnumber for which the ORE needs to be calculated, the second filter indicates the date and the third filter indicates the time range. The combination of these filters should give only one OEE or ORE number. Changing any of the filters will of course change the OEE or ORE value.

All of the mentioned variations in data described by the previous section is the reason why this study aims to create a framework that encapsulates which kinds of data and information is required for a successful analysis of a 1-piece flow production line. The amount of input data that is available to use can be overwhelming, or it can happen that there is not enough input data available. That is why the framework can assist in deciding which kinds of data and information is necessary to have in order to fulfill certain information needs that practitioners or production line engineers might have. This way, before actually trying to do the analysis, it can be established which data and information is already present, and therefore also, which data is still missing. This data can then be gathered before doing the analysis, in order to make the analysis work.

The means of data collection

There are two main ways of data collection: requesting event-logs required for the script via e-mail, and bi-weekly meetings where the progress of the project is discussed and new information and ideas are shared. At the end of the project, there is a third data-collection phase where semi-structured expert interviews are conducted in order to validate the results.

In order to analyze the production line and to create the framework which indicates the data that is required to fulfill the information needs, event-logs are required. Event-logs for the client consist out of the necessary information for process mining: start -and end dates, start -and end times, serialnumber, machine code, and some additional attributes are all present. Since the data is all stored in their ERP system, the desired data needs to be requested so that it can be exported from the ERP system into a CSV file. The only thing that the client needs to know for this is the start -and end date. In the requested timeframe, all of the information that is present needs to be included in the CSV file. The reason for this is that excluding some information for whatever reason could influence the eventual data analysis. That is also why manual pre-processing this data is limited to converting the machine codes to actual activity names, splitting the CSV into two files, one for the NX-M line and one for the NX-A line, and changing the times and dates into the correct format so that the script does not result in any errors. After this, the event-log collection should be finished, meaning that it should be ready for the script. More pre-processing will be done by the script itself.

Next to the event data, domain knowledge and case knowledge is needed for the framework. Domain knowledge is, in a broad sense, information that applies to the whole manufacturing domain and/or factory of the client. This includes the usage of machines, whether machines needs to be in parallel, and the standard break times, among other things. Case knowledge is information that is more specific in the sense that it only applies to one line, one itemnumber, one group of operators, or one certain process. Examples of case knowledge is the planned maintenance for a specific production line, the cycle times that differ per itemnumber, and whether an employee is experienced or not. All of this information is gathered during the bi-weekly meetings with the client. New findings from the two weeks before are presented to the client, and a discussion is initiated about whether this is the direction that the client wants to move forward in. The bi-weekly meetings are conducted for a period of 6 months, and almost every meeting results in new domain or case knowledge. This new information is then added to the script, new analyses can be performed, and new plots can be generated. If the new analyses or plots prove to be adding value over the already existing plots, then the new domain/case knowledge will be added to the overall framework.

At the end of the project, the designed framework and its implementation on the client's data that has been gathered needs to be validated. In order to do so, semi-structured interviews need to be conducted. The focus of these interviews will be to understand whether the generated plots add any value to the experts' analysis, compared to how the experts did their analyses in the first place. For each plot, a couple of questions will be asked, and there should be plenty of room for additional discussion. During the interviews it should become clear which (parts of the) plots are informative and valuable, and also which plots will probably not be used that much (yet). It can also happen that during these interviews, new domain knowledge or wishes/ideas come to light, which then can be implemented in the framework and script or they can be described in the future work. In order to be able to look at the same plots on one screen, the interviews will be conducted at the factory of Omron. After the interviews have been conducted, the implementation of the framework should be validated, and if successful, the value of the framework itself will also have been proved.

The means of data analysis

The data will first be explored and analyzed in Disco using process mining techniques, and after that the data will be loaded into a script that will do more analyses. The reason why Disco is used first, is because it is fast and easy to use, and already gives a lot of options for some preliminary data analysis and validation for the script. Overall, it can transform the unclear raw event-logs into an easy to understand process model that can be used to discover the line order and points of interests for further analysis. Disco uses the Fuzzy Miner technique to compose a process model (Dakic & Stefanovic, 2018). After the initial analysis has been done and the order of the line has been discovered and validated, a script is needed that calculates the OEE/ORE for the machines in the line. Next to this, different kinds of visualizations can be generated in order to visualize the information that is gathered by using the framework. The reason that this script has to be developed is because the Disco tool does not offer the in-depth analysis that is needed to properly calculate the OEE/ORE for a production line, and also does not offer the possibility to visualize the data in different ways. Next to this, the script can be handed over the client at some point for further use. Lastly, if coded correctly, a script has better traceability, reliability, and consistency, and additional domain/case-related information can be added.

Threats to validity

One of the fundamental questions in experimental research is how valid the results are. The results should be valid for the population that the experiment was conducted on, but also for a broader population if the aim is to generalize the results. Wohlin et al. (2012) have described four kinds of validity: *conclusion validity*, *internal validity*, *construct validity*, and *external validity*.

Conclusion validity

Threats to the conclusion validity describe the uncertainty of correctness of the relations between the outcome and the treatment of an experiment. In other words, the degree to which the relationships between variables in the data are reasonable or correct. Things to take into account include the type of statistical test and significance level that was chosen, deliberately looking for a specific result, the way measures and treatments are (consistently) used, random irrelevancies such as noise from another room, and the similarities or differences of treatment subjects that might influence the result. Since this case study uses quantitative data from a production line, some threats, such as noise from another room, are not applicable. The data does include information about operators, so it could be that some products or machines are not scanned and therefore not recorded in the data, which need to be taken into account. No statistical tests are used, so those threats are also not applicable. The sample data will be of the same length each time and the only difference is the exact date from which the data has been taken from, but this is something that is required, because the script needs to be applied to different kinds of datasets. Lastly, the threat of deliberately looking for a result might be something to watch out for. Reason for this is that eventually the client wants see an increase or decrease in the OEE/ORE if a certain change has happened, but other factors could also influence this OEE/ORE. The way this threat can best be tackled is by performing the calculations numerous times and knowing at all times which factors could influence the result.

Internal validity

This threat to validity is of concern when causal relationships are influenced by another factor next to the independent variable, without the researcher’s knowledge. Things to look at for this threat are the days on which the experiments have taken place or the data has been taken from, and the subjects that have participated in the study. The subjects (operators) that have participated in the study should all have had the same training and therefore have the same knowledge. If there are inexperienced operators in the line, this will be indicated by the client. The difference in the data that can occur if data from different days has been taken is tackled by taking the same timeframe for the data, and if certain days need to be compared, the same day of the week with the same operators should be taken. Other factors that could influence the results have all been indicated by the client, and can therefore be taken into account for the analysis.

Construct validity

This threat to validity looks at the way the results of a chosen method can be generalized to the theory that is behind the method. In other words, whether what is studied aligns with what the research questions need in order to be correctly answered. Things to take into account are the sample size, the theory behind the method, amount of observations, testing with the same subjects, subjects with different kinds of experiences that could influence the results, whether the chosen method is the correct one, and other types of social behavior of subjects. As already mentioned, threats that have anything to do with subjects are not applicable for this case study. One important threat to construct validity is the whether the correct method has been chosen compared to what the client already uses, or any other method that could do the same. This threat is taken into account by the fact that the client does not have a method to calculate the OEE/ORE yet, and that one of the purposes of this research is to find out a method to do so. That being said, there is always a chance that there is another better method to calculate the OEE/ORE, however, according to Stadnicka & Antosz (2018), it does not matter that much which method has been chosen, as long as it is used consistently over time.

External validity

This aspect of validity is concerned with the generalizability of the findings and results, and to what extent these results are interesting to people outside of the investigated case. Things to look out for are having an under-representative population, not using the right tools for the subjects during the treatment, and the timing of the case study. The case study takes place over a period of approximately six months, so that should be enough time to make sure that timing does not influence the results. Next to that, other than the usage of Disco for data analysis, no tools are used for treating the subjects during the case study, so that should also not influence the results. Under-representative population should also be no problem, since data from the same machines will be used each time. One thing to take into account however, is the fact that this line is 1-piece flow and has two or three operators handling the products and machines. The results are therefore not generalizable to all lines, but only to lines that are comparable to the client's line.

Results

The framework

The main result of this study is a framework that can assist researchers and companies in the manufacturing domain to see which data and information is necessary for a thorough analysis of similar production lines. Certain information needs have been identified and extracted from meetings with the client, and have been summarized in a table (table 3). The desired plots to visualize the information needs have also been extracted from the meetings. Based on the gathered information needs and the desired plots, the framework has been created. The framework indicates for each element of data, which overarching data 'type' it belongs to. This can be event data, domain knowledge, or case knowledge. This distinction is important to make, because it shows whether the data can be found in the event-logs, or whether it has to be provided during meetings or through documents from the company.

It must be noted that when using this framework, not all of the information is always needed to create a certain plot. That is why, in the implementation, additional smaller tables have been incorporated that indicate which information is required to create the plot, and which information needs are fulfilled by it. This work can be used by researchers and companies to find out which information needs are desired by looking at table 3, and then looking at the implementation to see how those information needs can be visualized, and in order to do so, which data is required.

Case Study

In order to illustrate the creation, usage, value, and results of the designed framework, a case study has been performed in combination with the PM2 methodology, as mentioned before. However, even though PM2 originally indicates that step (1) *planning* and step (2) *extraction* should only be executed once at the beginning of the project, this project executed all but the last step in an iterative manner. The reason for this was that the meetings took place bi-weekly for over 6 months. During every meeting new wishes and information came forward, as well as new event-logs now and then. That is why not everything could be planned from the start, but had to be discovered during the duration of the case study.

Stage 1: Client meetings

According to the first stage of the PM2 methodology by van Eck et al. (2015), a couple of meetings with the client have to be conducted in order to set up the project to find out which information needs they have, how the client wants to visualize those needs, and to answer the research questions of this paper. As said, these meetings took place over a time period of 6 months, and during every meeting new information needs arose, which required different data and visualizations. At the beginning of the project, the most important information needs were the process model and the OEE per machine. However, as the project went on, it became clear that the provided event-data, in combination with domain knowledge and case knowledge, could provide for many more opportunities to fulfill other information needs and to perform other kinds of analyses. All information needs presented in this section were discussed during the meetings in an iterative manner. The plots that have the potential to visualize the information needs have been discussed with the client during the meetings, and will be used for the implementation of the framework later on.

Before presenting the table with information needs and plots (table 3), the main purpose of each plot is explained to get a better understanding why each plot is desired by the client.

- *Process Model*
  For the client it is important to find out the line order, anomalies, and missing data. The line order should be consistent, but it can happen that one machine is often skipped, without the client even knowing this. This is important information for further analysis. Anomalies and missing data are important to detect early on, otherwise they might influence other analyses/plots. A process model should be the right visualization technique for this goal.

- *Classification chart*
  There needs to be a plot that shows for every machine in the line what is happening and why. This means that is should show whether a machine is standing still because of the absence of material, a lack of facility, the absence of an operator, or any other reason. If done correctly, the classification chart can best be used to find points of interest which are interesting to zoom into using the other plots. The format of the classification chart prevents this chart to be used to draw conclusions from, since it does not focus or zoom into one specific part.

- *ORE boxplot*
  The client wants to quickly see which ORE values are the lowest, and compare them with other machines. The client also wants to see if the ORE values are consistent or not. A boxplot does just that, and is therefore a requested plot to visualize these needs. If done correctly, it can best be used to quickly find out which machines have the lowest ORE values and therefore should require attention.

- *Minutes-lost Bar chart*
  Since operators might also want to use the plots every now and then, it should be easily understandable why, and for how long, a machine has been standing still. That is why a bar plot with the minutes lost per factor per machine is desired. Because of the nature of the line, this plot should also clearly visualize any bottleneck that might occur.

- *ORE Pie charts*
  The plots described up until now focus mainly on the absence of material, lack of facility, and absence of operator. Since there are other important factors, a chart is desired that clearly shows which of the six factors has caused the most time lost. After discussion, a pie chart is requested to visualize this data. The pie chart should clearly show the biggest/smallest losses.

- *ORE factors Pie/Bar charts & Cycle Time plots*
  The client wants to get some indication of why the performance might be good or bad, and therefore the theoretical cycle times need to be compared to the actual cycle times. A bar chart and histogram can generate bars that represent the cycle times, which can then be compared to the theoretical cycle times. Next to this, the client wants to have some kind of indication as to which machine/factor they should focus on first. That is why a bar chart visualizing the availability of all factors is desired, along with a line that indicates how much the ORE can be improved.

- *Production Rate Bar chart*
  In order to find out how much each machine can still be improved before reaching its theoretical maximum production rate, a plot is needed that visualizes the actual production rate and the theoretical production rate. This comparison should make it clear which machine can still be improved, and which ones are already maxed out. A bar chart where one bar is on top of the other should give the effect that is desired.

- *Line charts*
  It can happen that one group of operators is faster than another group, or one machine is getting slower at the end of the shift. In order to see such occurrences, the development/fluctuation of the factors should be visualized. Line charts can visualize this easily. If a factor increases or decreases over time, this should be easy to spot.

Table 3 below presents a summary of all individual information needs and which plot could visualize each information need.

Plot type / Information need	Process Model	Classification chart	ORE Boxplot	Minutes-lost Bar chart	ORE Pie charts	ORE factors Pie/Bar charts & Cycle Time plots	Production Rate Bar chart	Line charts
Line order*	X							
Machines with no tracing	X	X						
Machine utilization	X	X		X	X			
Defects (quality)		X			X	X		X
Reworks (quality)		X			X	X		X
Potential bottleneck	X	X		X				
Unreported breaks		X						
Machines suitable for improvement		X	X	X	X	X	X	X
Absence of material**		X		X	X			
Absence of operator		X		X	X			
Lack of facility		X		X	X			
Patterns		X		X			X	X
Average ORE value			X			X		
ORE value distribution			X					X
Time lost due to individual factor (in minutes)				X				
Time lost due to all factors (in minutes)				X				
Time lost due to factors (in percentages)				X	X			
Total processing time (in percentages)					X			
Performance losses					X	X	X	X
Availability of material**						X		X
Availability of manpower						X		X
Availability of facility						X		X
Potential ORE increase after improvement						X		
Theoretical ORE						X		X
Theoretical vs. Actual Cycle Time						X		

Cycle time distribution						X		
Hourly production							X	
Unknown parallel machine identification	X	X					X	
Factor development over time								X

Table 3. Individual information needs that are visualized by certain plots

*Some plots use information extracted by other plots. The line order is a good example of this. In order for the classification chart to work correctly, the line order needs to be indicated.

**The difference between absence of material and availability of material is that absence indicates how much time was lost due to the factor, and availability indicates how much of the time it was available. It can be seen as the inverse of each other. When there is a high absence, there is a low availability. The reason why availability is needed is because performance and quality are calculated in terms of availability, so in order to visualize all six factors in one plot, the absence has to be converted to availability. The same explanation goes for facility and operator/manpower.

In order to fulfill this long list, there needs to be some way of knowing which data is needed in order to correctly visualize all of the information needs. That is why a framework is designed that presents an overview of the data and information that is required in order to perform a such a production line analysis. This will be elaborated upon in the following section.

Stage 2: Data extraction

Now that it is clear which information is needed and how that should be visualized, the required data should be gathered and extracted. This is done in the second stage of the PM2 methodology. There are three types of data: event data, domain knowledge, and case knowledge.

Event data is all the data that comes straight from the ERP system and machines. This event data includes the start -and end date, start -and end time, the serialnumber and itemnumber that is being processed, and the JIGs. The event data also directly indicates which machines do not have tracing, how many defects and reworks there are, and how many times each machine has executed an activity during the chosen timeframe. The timeframe of the event data that was provided by the client spans over 10 days. Without event data, no process mining activity can take place, and none of the plots can be generated. It is therefore a crucial part of the data extraction.

Domain knowledge is everything that needs to be known from the manufacturing domain and the whole factory, in order to fulfill the information needs. This is information that is not present in the event data. In fact, the domain knowledge needs to be used in conjunction with event data, otherwise incorrect conclusions could be derived, or the data might not even make sense. First of all, domain knowledge includes the start -and end times of breaks, shifts and planned maintenance, the OEE factors, and the ORE factors which have both been explained before. Next to this, the line type needs to be communicated by the client, since that is crucial information in order to make sense of certain plots, to identify bottlenecks, and to interpret patterns. The line of this case study is 1-piece flow non-continuous, which should be analyzed differently than, e.g., a continuous line. Another important piece of information to have is whether a machine/stage is manual or automatic, in order to make sense of the cycle times and possible improvements. Lastly, the nature of the machine needs to be known. For some machines it makes sense that it takes a while, for some machines it doesn't, for some machines it makes sense to have a lot of defects/reworks, for some other machines it might not make sense. Without this domain knowledge, incorrect conclusions and insights could be derived.

Case knowledge looks a lot like domain knowledge, but is more specific in a sense that it focuses on the work situation at hand. This means that it encompasses information that is relevant only for a certain line, group of operators, itemnumber, or process, while domain knowledge applies to the whole factory or domain. Case knowledge includes the conversion of JIG numbers to the correct activity names, whether there are any buffers, the designed line order, how many operators are working during a specific shift, which machines are in parallel, and the theoretical cycle times. It is also useful to know whether some machines handle one serialnumber multiple times, otherwise it might look like a parallel machine. That is also what happened to the *Connector cleaner 1&2* before the client had communicated this piece of case knowledge. If case knowledge is not present, the same cycle time would be used for all itemnumbers, parallel machines could be seen as bottlenecks because they produce less products, and the overall analysis would just not represent the line that is being analyzed.

Event data is extracted from the provided event-logs and domain/case knowledge is extracted from the client meetings and/or documents provided by the client. The combination of these three types of information should be sufficient for all of the information needs and visualizations stated in table 3. In order to make an artifact about this, that can be used for the analysis for other similar production lines, the event data, domain knowledge, and case knowledge have been merged into one overarching framework which can be seen in figure 4 below. This framework includes all of the data and information that is required for a production line analysis, where the purpose is to fulfill all of the information needs as described in table 4. This means that if all of the data and information named in the framework is present, the analysis of the production line should be successful.

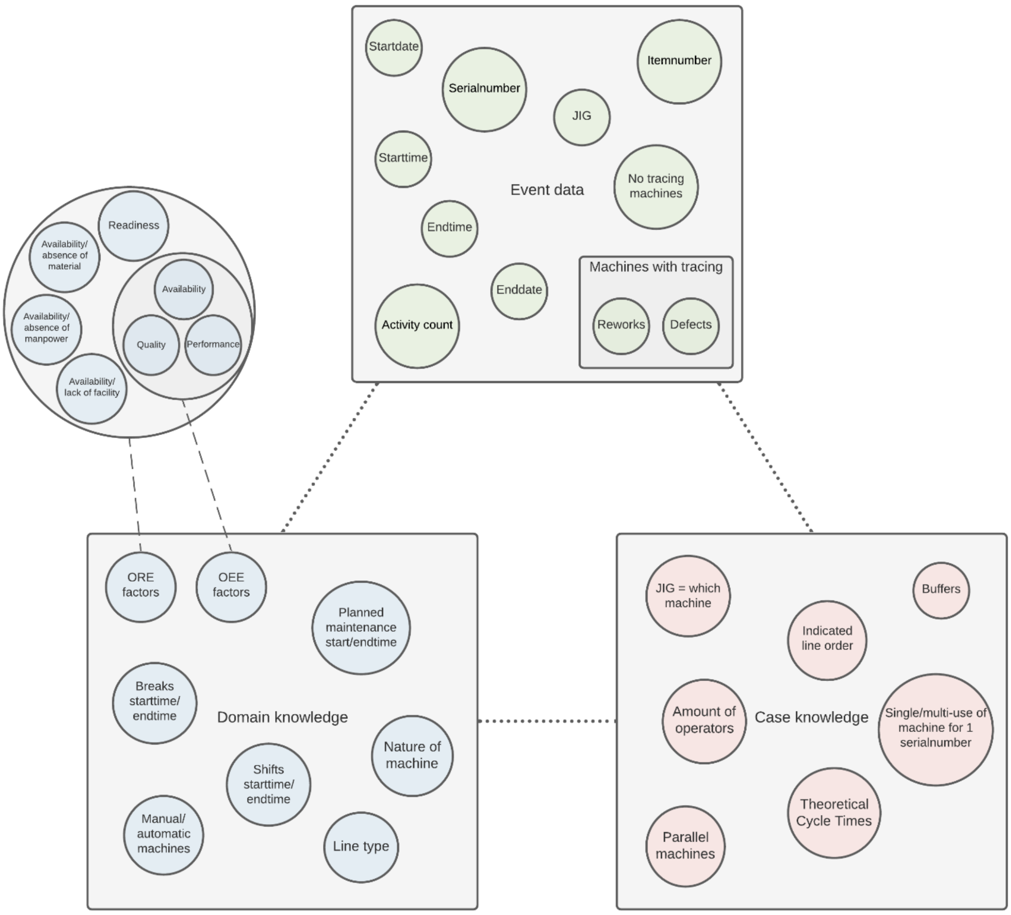

Figure 4. Framework displaying data required for production line analysis. Combination of event data (green), domain knowledge (blue), and case knowledge (red)

Stage 3: Data processing

Now that the data has been extracted by using the framework in stage 2, the extracted data needs to be pre-processed and processed in order to prepare it for further implementation. The client's data is recorded quite complete and noise-free in the ERP system. The only manual pre-processing that needs to happen is the conversion of JIG numbers to actual activity names, changing the dates to the correct format, and splitting up the CSV file into two smaller CSV files: one for the NX-M line and another for the NX-A line. The CSV is now ready for the script. The script consists of 4 sub-scripts. The first sub-script pre-processes the CSV file to drop unused columns, and to mark defects and reworks. The output of this sub-script is in a compatible format for the second sub-script. The second sub-script processes the CSV file to calculate everything that is needed for the visualizations. This includes the OEE, ORE, absence of material/manpower/facility, durations, and every other piece of information that is required for the plots to work. This sub-script is where most of the work is done, and also uses the third sub-script that contains some helper functions. After the process sub-script is done, there should be a CSV file ready for the fourth sub-script. The fourth script contains all of the functions needed to visualize the information needs, and makes sure that the plots are interactive. These four sub-scripts can be used to implement the framework and to create plots that fulfill the information needs of the client.

Stage 4: Framework implementation

The fourth stage is where the framework is being put to use. The client has indicated the information needs during the meetings in the first stage, in stage 2 research has been done into which data is needed to fulfill these information needs and based on that a framework has been created, and the third stage has prepared the event data to be ready to be visualized in stage 4. As said in the previous section, the fourth sub-script contains all of the code for the plots that the client has requested and that are needed to answer the research question. The only plot that is not visualized (yet) in the script, is the process model. This has been done in Disco. The reason why it was not visualized in the plots is because of a lack of time. With all this being said, this section will present each plot individually, and show in a table which data from the framework is needed for it, and which information needs are fulfilled by it. Since all plots need all the event data, the overall 'event data' will just be stated in the tables, and each type of necessary domain/case knowledge will be stated individually. In the tables, the left items do not directly fulfill the items directly right to it. It is simply a list of inputs and a list of outputs.

Process model

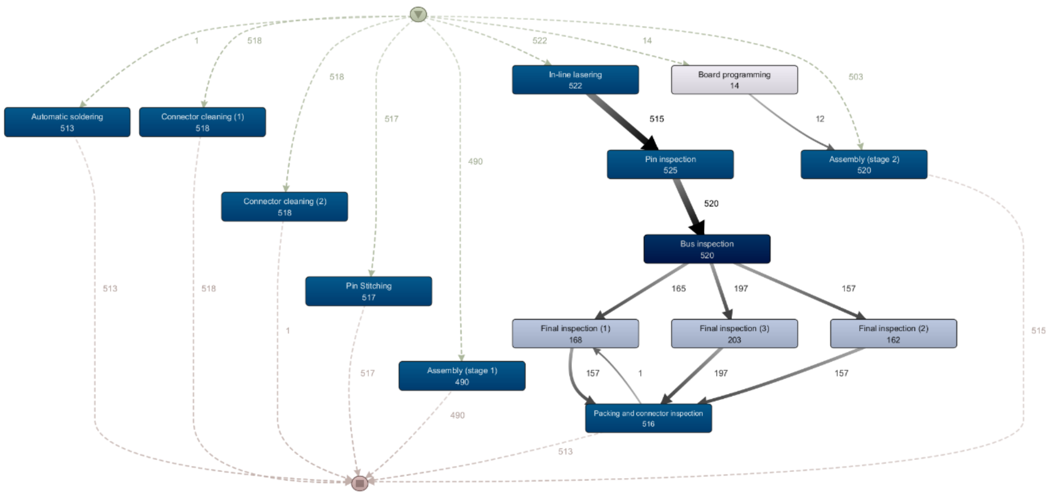

Figure 5. Process model of the NX-M production line

The process model is the first discovery and visualization of this implementation, which can be seen in figure 5. The process model gives a clear overview of the structure of the line, and which paths the serialnumbers follow. Unfortunately, since some machines do not have tracing, the process model is not complete. The 5 activities on the left (*Connector cleaning 1&2, Automatic soldering, Pin Stitching,* and *Assembly stage 1*) and the two activities in the upper right corner (*Board programming, Assembly stage 2*) all do not have correct tracing information. That is the reason why those machines cannot be included in the middle part, which shows the actual line order. The input data (which data from the framework) and the output information (fulfilled information needs in table 3) are indicated in table 4 below.

Input data	Output information
Event data Nature of the machine Line type JIG = which machine Indicated line order Parallel machines Single/multi-use of machine for 1 serialnumber	The order indicates which machines have *tracing information* or not The numbers under the activity names indicate the m*achine utilization* The *line order* is displayed (albeit incomplete for this data, because not all activities have tracing) If one machine has too many serialnumbers to process it will show up as a p*otential bottleneck* Activities with less executions indicate the presence of *(unknown) Parallel machines*

Table 4. Required input and obtained output for the process model

Classification chart

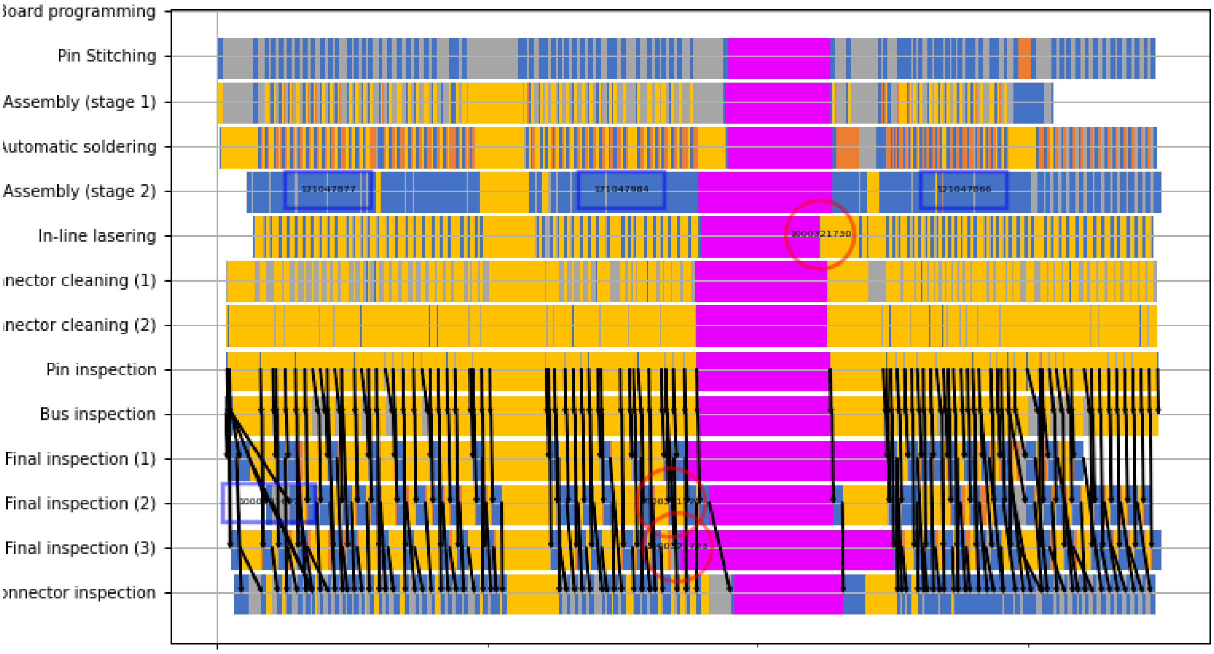

Figure 6. The classification chart showing a timeframe of 4 hours of data from the NX-M line

The second plot that has been created by implementing the framework is the classification chart, which can be seen in figure 6 above. The classification chart is a top-down view of the production line that shows for each point in the chosen timeframe what each machine is doing. Yellow is when a machine is waiting for material (input flow), orange is when it is waiting on the next machine the be finished (output flow), grey is when it waiting for the operator, blue is when it is processing an item, and purple is when the machine is standing still because of a planned break. Defects that have been found are indicated with a red circle, and reworks with a blue square. For the machines with tracing, arrows have been added that show the path of individual serialnumbers. The main point of this chart is to show points of interest such as bottleneck and patterns, and give an overall idea of how the line is behaving. Using the other plots, these points of interest can be zoomed into. Table 5 below indicates which data is required for this chart, and which information needs are fulfilled by it.

Input data	Output information
Event data	Arrows show which machines have *tracing information*
ORE factors	The blue blocks indicate the *machine utilization*
Breaks starttime/endtime	*Defects* are displayed in red circles
Planned maintenance start/endtime	*Reworks* are displayed in blue squares
Shifts starttime/endtime	A *potential bottleneck* can be seen when there is a suddenly a lot of
Line type	absence of material
JIG = which machine	*Unreported breaks* can be seen when there is a gap for all machines
Indicated line order	*Machines* with a lot of yellow/orange/grey are suitable *to improve*
Parallel machines	Colors show the *Absence of material/operator, lack of facility*
Single/multi-use of machine for 1 serialnumber	*Patterns* can be discovered by looking at the colors
Buffers	*Unknown parallel machines* will have way less blue blocks

Table 5. Required input and obtained output for the classification chart

ORE Boxplot

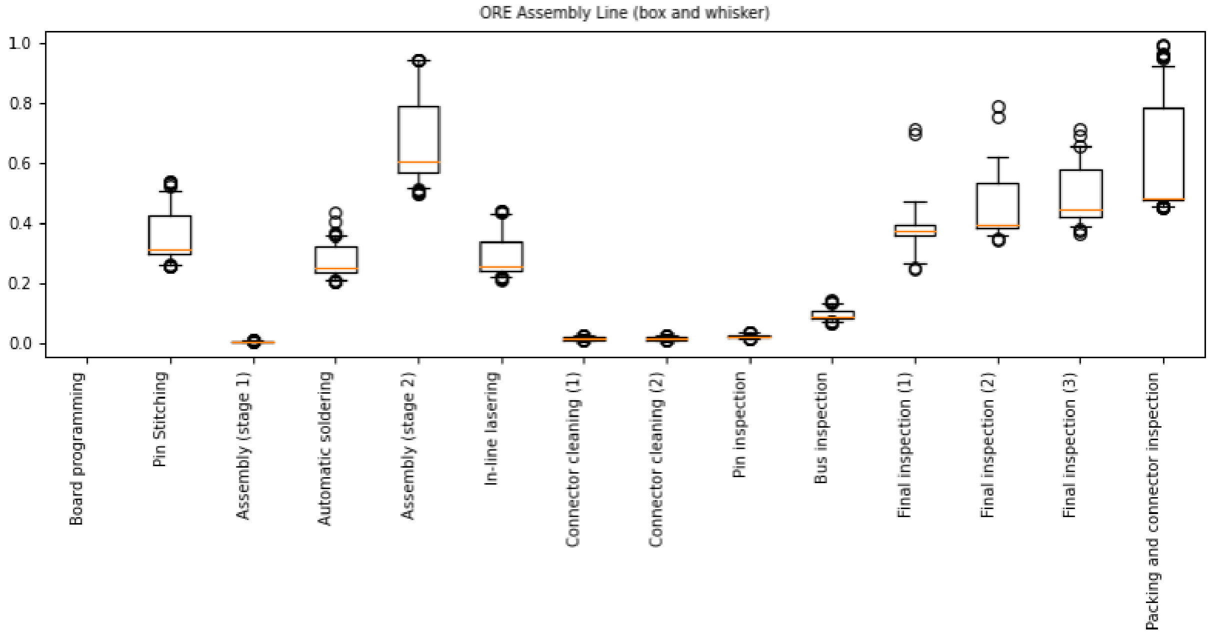

Figure 7. The distribution of OREs per machine shown in a boxplot

The ORE Boxplot in figure 7 above makes it possible for the client to easily and quickly compare the ORE of every machine. The orange line is the median of all ORE values for one machine, the box around it represents the 25% of values higher and lower, and the whiskers have been configured to represent 95% of values higher and lower than the median. The remaining percent are the circles, which are considered outliers. The main purpose of this plot is to give an idea of which machines are performing the worst according to ORE standards, and which machines are performing better. Since the ORE also includes the performance and quality, machines that seem to be processing a lot in the classification chart in figure 6, can see show up with a low ORE here. This plot should only be used to confirm which machines require attention, and not for conclusive answers. The reason for this is that the ORE consists out of several factors, which cannot be seen individually in this plot. Table 6 shows which data is needed to create this plot, and which information needs are fulfilled.

Input data	Output information
Event data ORE factors Manual/automatic machines JIG = which machine Indicated line order Theoretical Cycle Times Parallel machines Single/multi-use of machine for 1 serialnumber	Low values indicate *machines suitable for improvement* The orange line shows the *average ORE value* The box, whiskers, and circles show the *ORE value distribution*

Table 6. Required input and obtained output for the ORE boxplot

Minutes-lost Bar chart

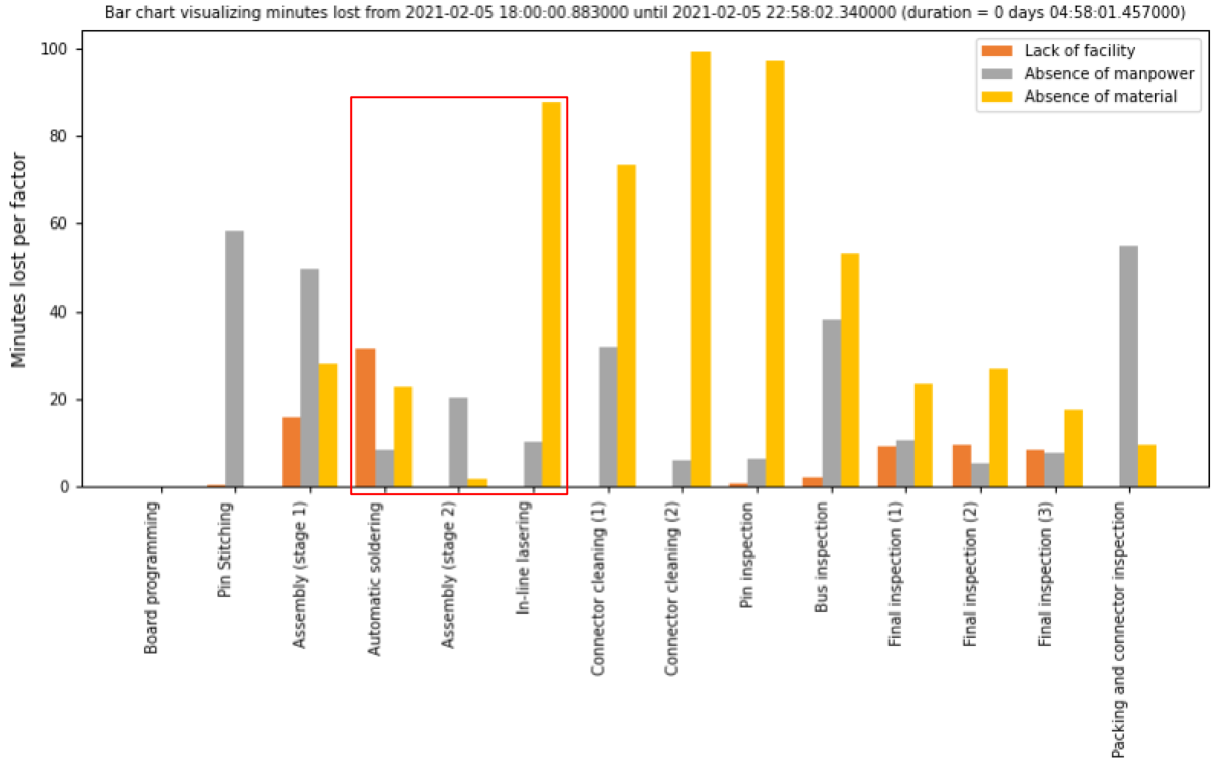

Figure 8. The amount of minutes lost due to a factor per machine visualized in a bar chart

The minutes-lost bar chart is an easy-to-understand graph that quantifies how much time has been lost due to a specific factor, and can be found in figure 8. The factors that are included are the absence of material, absence of manpower, and lack of facility, which have the same colours as in the classification chart: yellow, grey, and orange respectively. The y-axis indicates how many minutes are lost in the timeframe that was chosen. The timeframe can also be found in the title. The main purpose of this chart is to make it clear which machines are standing still the most, and because of which reason. This is valuable information for potential improvement projects. This graph also excels in showing where the bottleneck is located. In this plot, the assembly stage 2 is the bottleneck stage, which can be seen in the red square in figure 8. The bottleneck machine can be identified by looking at the machines before and after it. The machine before it has to wait for facility a lot, which means that the assembly stage 2 is making it wait. The machines after it have to wait for material a lot, which means that, again, assembly 2 is not producing products fast enough. Two variations of this plot can be found in Appendix A. Figure A1 shows the time lost in percentages, and figure A2 shows all three factors stacked on top of each other. Table 7 shows which information is required for a bar chart, and which information needs are fulfilled by it.

Input data	Output information
Event data	The amount of losses indicate *how much each machine is used*
ORE factors	The structure of the losses indicate a *potential bottleneck*
Line type	The amount of losses indicate which machines is *suitable to improve*
Nature of machine	Bars show the *Absence of material/operator, lack of facility*
JIG = which machines	The size of the bars can be used to identify *patterns*
Indicated line order	The y-axis shows the *time lost due to all/individual factor(s) in minutes and percentages*
Buffers	
Amount of operators	
Parallel machines	

Table 7. Required input and obtained output for the bar chart

ORE Pie charts

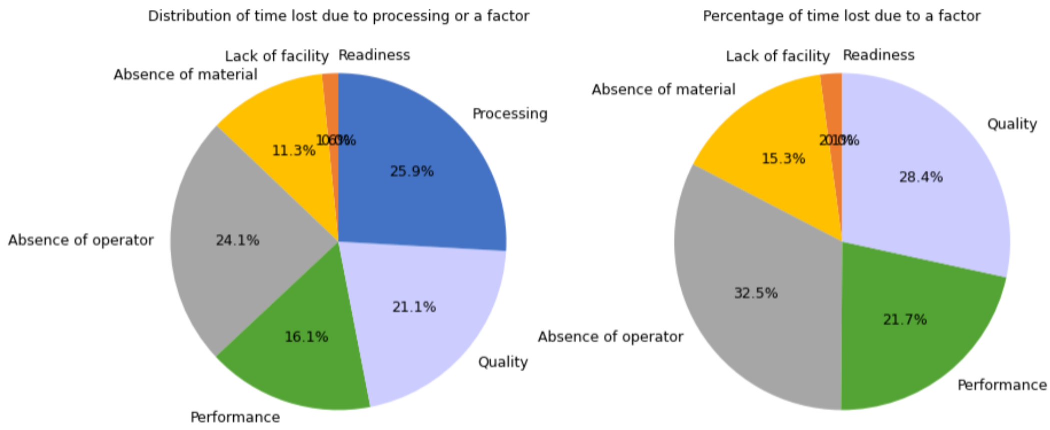

Figure 9. Percentage of time lost due to an ORE factor displayed in a pie chart

The next plots that have been created using the framework are pie charts displaying six ORE factors and the processing time, as can been seen in figure 9 above. The pie charts show a percentage for each factor that indicates the amount of time that was lost due to that factor. The difference between the left and right figure is that the left figure also includes the time that the machine was busy processing, while the right one focuses on only the factors of the ORE. The main purpose of these plots is to include the performance and quality losses in the analysis as well, as the previous plots had not done that yet. From these plots it is still easily visible whether the absence of material, absence of manpower, or lack of facility has caused the most time lost, but now it can also be seen whether the performance and/or quality are causing time losses. Thus, these plots give additional information compared to the previous plots in that all six factors are now included and can be used to identify why a machine is not effectively using its time. The changeover efficiency, which is also part of the ORE, is not included in figure 9, figure 10, and figure 12 below, because according to the client, there is no time lost due to changeovers. In order to create a pie chart for the ORE, certain information is need which can be found in table 8 below. The fulfilled output information is also stated.

Input data	Output information
Event data	The blue part indicates the *machine utilization*
ORE factors	The light blue (quality) part indicates the *defects* and *reworks*
Planned maintenance start/endtime	*Machines* with high percentages for losses are *suitable to improve*
Breaks start/endtime	The colors indicate the amount of *absence of material, absence of manpower,* and *lack of facility*
Manual/automatic machines	
Nature of machine	The *percentages* show the *time lost due to all/individual factor(s)*
JIG = which machine	The green part indicates the time lost due to *performance* issues
Theoretical Cycle Times	
Parallel machines	
Amount of operators	

Table 8. Required input and obtained output for the pie charts

ORE factors Pie/Bar charts & Cycle Time plots

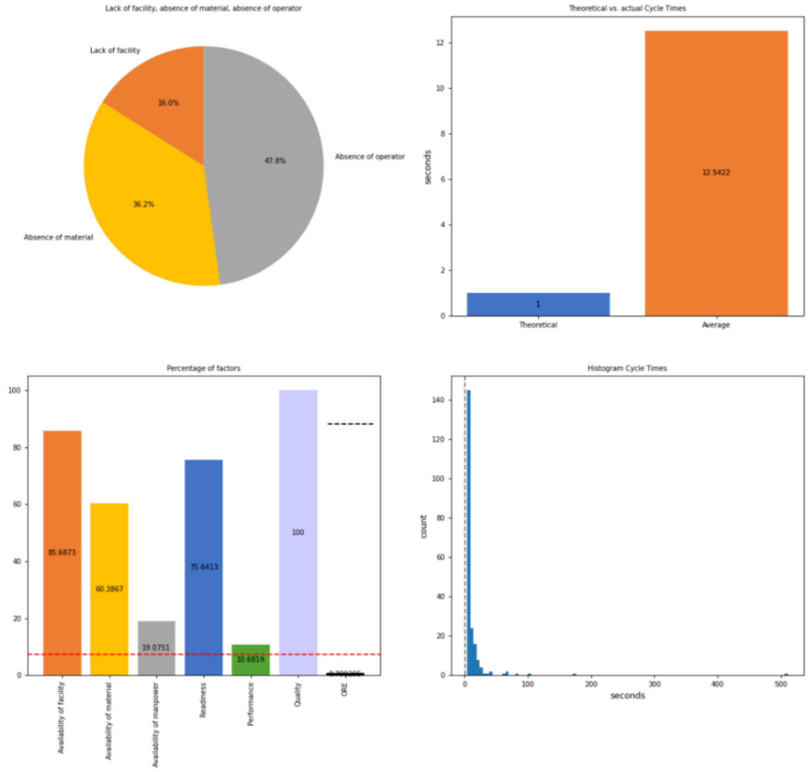

Figure 10. Pie chart and bar chart displaying the availability of ORE factors, and two plots for the cycle time

The four visualizations shown in figure 10 are plotted together because they are useful to use in conjunction. The top left corner shows a pie chart that indicates which loss is the biggest. This plot has been included because the classification chart in figure 6 is quite cluttered and does not always clearly indicate which loss is the biggest. The lower left corner then shows the availabilities of all factors, along with a red and a black dotted line. The red dotted line indicates how high the ORE would be if the worst performing factor would be improved until a 100%. In figure 10, the worst performing factor is the performance. If the performance would be improved until a 100%, then the ORE would be as high as the red dotted line. The black dotted line indicates the theoretical ORE, which shows how high the ORE would be if all of the factors would be 100% and you would only have the mandatory breaks left. The plot in the top right corner visualizes the theoretical cycle time against the average cycle time. This is a useful plot when wanting to find out why the performance is a certain value. The plot in the lower right corner shows the distribution of cycle times, and can be used to check if there are any outliers, such as the cycle time around 500 seconds in figure 10. In order to create these four visualizations, certain data is required again. This is included in table 9 below, along with the fulfilled needs.

Input data	Output information
Event data	The light blue quality bar shows if there are any *defects* or *reworks*
ORE factors	All bars together indicate which *machine* is most *suitable to improve*
Planned maintenance start/endtime	The black bar shows the *average ORE value*
Breaks start/endtime	The green bar indicates the *performance* losses
Nature of machine	The yellow, grey, and orange bars show the availability of material, manpower,
JIG = which machine	and facility respectively
Theoretical Cycle Times	The red dotted bar shows the *ORE increase after improvement*
	The black dotted line shows the *theoretical ORE*
	The plot in the top right corner shows the *Theoretical Cycle Time vs. Actual Cycle Time*
	The plot in the lower right corner shows the *cycle time distribution*

Table 9. Required input and obtained output for the ORE factors Pie/Bar charts and Cycle Time plots

Production Rate Bar chart

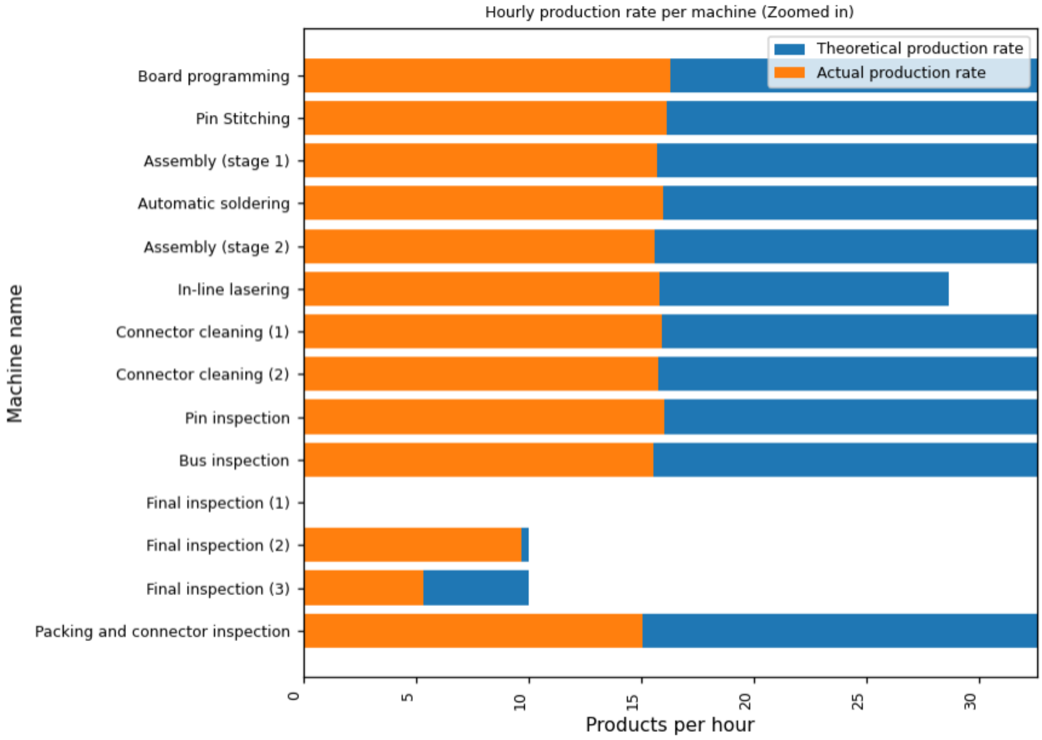

Figure 11. Hourly production rate per machine compared to the theoretical production rate

The second to last plot that has been created to satisfy the information needs of the client can be found in figure 11. The plot visualizes the theoretical production rate (blue bars) against the actual production rate (orange bars). This comparison is done to indicate how much each machine can still be improved. Looking at figure 11, we can see that final inspection 2 is producing almost as fast as theoretically indicated. It would therefore not make sense to focus on improving the performance of that machine, but rather to add an extra final inspection machine. For the other machines there is still a lot of performance improvement possible. This is a 1-piece flow production line, so there will never be a big increase/decrease in products, since the whole line will produce as much as the bottleneck machine. Therefore, bottlenecks cannot be identified in this plot. The plot in figure 11 is zoomed in, a zoomed out version of this plot can be seen in figure A3 in Appendix A. Table 10 indicates which data from the framework is required, and which information from table 3 it fulfills.

Input data	Output information
Event data	The blue bar indicates which *machines* are still *suitable to improve*
Nature of machine	A slow decrease of the orange bars would indicate a *pattern*
Line type	Small orange bars indicate *performance losses*
JIG = which machine	The orange bar depicts the *hourly production*
Indicated line order	*Unknown parallel machines* can be identified if the hourly production
Single/multi-use of machine for 1 serialnumber	rate is suspiciously low
Theoretical cycle times	
Parallel machines	

Table 10. Required input and obtained output for the Production Rate Bar chart

Line charts

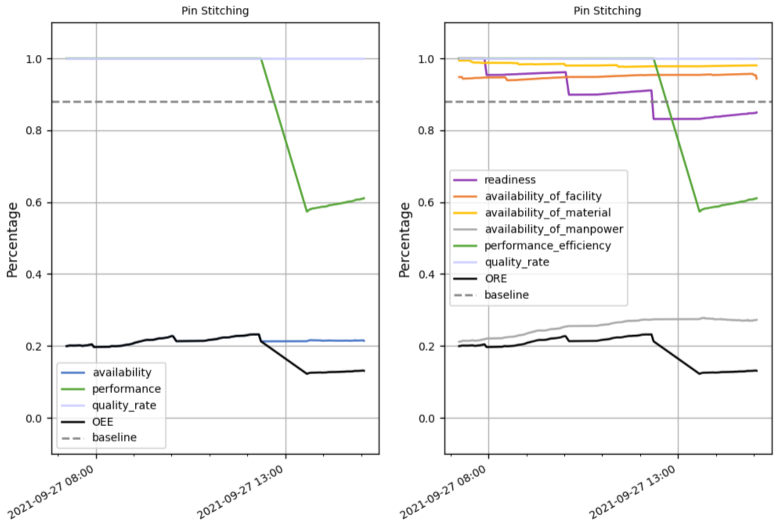

Figure 12. OEE and ORE line charts displaying the development of individual factors over time

The final charts that have been generated for this case study using the framework are the line charts, which can be found in figure 12. These line charts show the development over time of each factor for the OEE and ORE. This clearly shows whether the availability of a certain factor was better or worse at the beginning of the timeframe, compared to the end of the timeframe. The big difference between both plots is that the left plot, which depicts the OEE, only has one line for the availability, and the plot on the right, which depicts the ORE, has three lines for the availability. In figure 12 it can be seen that the availability for the OEE is quite low, around 20%. However, this does not say much, because it is not indicated why it is 20%. The lines in the ORE plot do in fact indicate this, because the orange and yellow lines are high, and the grey line is low, meaning that there was a low availability of manpower. Thus, in order to improve this machine, the focus should be on the operator being more present at this machine. This shows the added value of the ORE over the OEE. All of the required data and fulfilled information needs are shown in table 11 below.

Input data	Output information
Event data	The light blue line shows the quality which indicates how many *defects* and *reworks* there are
OEE factors	*Machines* with low lines are *suitable for improvement*
ORE factors	*Patterns* such as lines going down at the same point in time every shift can be identified
Breaks start/endtime	The *distribution of ORE values* over time can be seen
Planned maintenance start/endtime	The green line indicates the *performance losses* over time
Nature of machine	The yellow, grey, and orange lines indicate the availability of material, manpower, and facility respectively
Manual/automatic machines	The grey dotted line is the ‘baseline’, which is the *theoretical ORE*
JIG = which machine	The fluctuation shows the *factor development over time*
Amount of operators	
Theoretical Cycle Times	

Table 11. Required input and obtained output for the line charts

Implementation sidenote

The implementation of the framework shows what is possible in terms of analysing production line data. However, before conducting such an analysis, it must be clear what the goals of the analyses are. Reason for this is, as the tables at each figure show, there is not one plot that can fulfil all information needs by itself. For that reason, table 3 must be advised to see which plots are needed to fulfil specific information needs. Some information needs are only fulfilled by one plot, while others are fulfilled by most of the plots. The same goes for the required data, some data is always needed (such as all of the event data), while other data is only required for only one or two plots.

Stage 5: Framework evaluation

In order to validate the usefulness of the framework and whether the fulfilled information needs that are visualized in the plots are valuable to the client, three semi-structured expert-interviews have been conducted in the fifth stage. This section contains the results of said performed expert-interviews, where for all three experts can be seen what their opinion was for each one of the plots. Since these plots have been created on the basis of the data and information gathered by using the framework, this is also an indirect evaluation of the usefulness framework. Since this was a semi-structured interview, some questions have been skipped for one or two experts. When that is the case, there will be no answer in the table for that expert/question combination. The evaluation can be found in table 12.

The process model is the only plot that is not evaluated. The reason for this is that the process model is not part of the script, and the initial idea was to evaluate only the plots in the script, since those were made from scratch. The process model is one of the visualizations that can be created by using the framework, but it is not part of the script/tool that will be delivered to the client, and is therefore not interesting for the client to evaluate.

Experts / Questions	Rene	Wouter	Joost
Classification chart			
Understandability	Easy to understand	- Easy to understand - Had some trouble with the color choices	Easy to understand
Overall impression	Difficult to say from this plot alone	Difficult to say, however, gives idea where to look next	
Found bottleneck	Yes	Yes	Yes
Results expected	Yes	Yes	Yes
Patterns identified	- Machines with most losses - Bottleneck	- Machines with most losses - Bottleneck	- Machines with most losses - Bottleneck
ORE Boxplot			
Understandability	- Did not understand completely - Confused ORE with cycle time	Easily understood	Easily understood
Correct machines fit for improvement identified	Drew incorrect conclusions due to confusion with cycle time	Spotted well / poor performing machines	Spotted well / poor performing machines
OREs expected		Yes	Had some trouble understanding why some OREs were low
Where to focus first identified	Lowest values	Lowest values	Lowest values
Minutes-lost Bar chart			
Understandability	Easy to understand	Easy to understand	Easy to understand
Machines with most losses identified	Correct machines identified	Correct machines identified	Correct machines identified
Most occurring loss identified	Correct loss identified	Correct loss identified	Correct loss identified
Losses expected	- Yes, losses before and after bottleneck makes sense - High absence of material at final inspection machine do not make sense (*actually a mistake in the plots*)	Yes, losses before and after bottleneck makes sense	- Yes, losses before and after bottleneck makes sense - High absence of material at final inspection machine do not make sense (*actually a mistake in the plots*)

			- Intrigued why the first part of the line has a lot of absence of operator
Points of interest identified	- Bottleneck machine identified - Machines with most losses identified	- Bottleneck machine identified - Machines with most losses identified	- Bottleneck machine identified - Machines with most losses identified
ORE Pie charts			
Understandability	Could only be understood after elaborate explanation	Could only be understood after explanation	Could only be understood after elaborate explanation
Provides additional valuable information	- Too detailed / low level - May be useful in the future	Yes, especially the performance and defects	- Yes, the performance - Easy to grasp which factors are biggest
Sparks ideas what to focus on first	No, need more context		
ORE factors Pie/Bar charts & Cycle Time plots			
Understandability		- Easy to understand - However, could use some context	- Easy to understand - Visualizes the OEE the same way himself
Biggest loss spotted		Yes	Yes
Surprises / points of interest		No	Nice that it splits up the availability bar into more detailed bars
Thoughts on Histogram		Very useful because you can also see the malfunctions (when a cycle time is taking way too long)	
Production Rate Bar chart			
Understandability		- Easy to understand - Did not immediately understand the graph type	Easy to understand
Derived insights		- None of the machines has reached their potential, could produce more - You can see that one final inspection machine is preferred	- Which machines are performing well - Which machines can benefit from improvement - Not all machines can be improved in the same manner
Influence on line when one machine reached theoretical production rate			That machine then needs to be improved, otherwise it will be the bottleneck
Machine closest to theoretical production rate identified		Yes	Yes
Line charts			
Overall impression	- Again, really detailed and low-level - Not ready for this plot yet	Performance decreases for one of the machines	- ORE is pretty consistent - Some values increase of decrease - Could be used to find patterns/consistent behavior over shifts
Surprises / points of interest	You can clearly see that an employee was trained	Makes sense that the performance and absence of manpower are intertwined	- Could use these plots to identify good operators, and teach their ways to other operators
First factor to focus on		The lowest values, however, depends on which machine you are looking at and the context	
Added value of ORE over OEE	- No, not right now		- No, not right now

	- First fix the ‘big’ problems, only after that this plot will be interesting - Plot will be interesting for ‘mature’ lines		- OEE is sufficient right now for line chart - You would want to go to ORE, but right now not ready yet
General questions			
Most useful plots		- ORE Pie chart - Classification chart - Minutes-lost Bar chart - Cycle time histogram	ORE factors Bar charts
Least useful plots		Line chart	Right now, the line chart. Too low-level
Overall analysis becomes clearer or more confusing		- Clearer - Gives good pointers as to where to look next	Clearer
New information		Assembly stage 2 having 11% performance loss in the chosen timeframe	The actual reason for low/high availability
Changes to current plots		- Add processing time bar to Minutes-lost bar chart	Add information for ORE of whole line
Recommendations for future plots		- Plot that shows the performance per machine	Add data for malfunction machines (*data not available*)

Table 12. Evaluation of the visualizations

The most important insights that can be derived from these expert-interviews are that the information gathered by using the framework does indeed add value to the analyses of the experts. All plots are easy to understand to all three experts, albeit that some plots need a small one-time explanation. Machines that are performing the worst and best can easily be identified in the Classification chart and the ORE boxplot. The Minutes-lost bar chart and ORE Pie chart then extend this view by showing which factors are causing the low ORE values. This could all be easily identified by all three experts. The remaining plots show where and how much improvement can be achieved for each machine, which was clear to the experts as well. All three experts were very much under the impression that this information could help them with further analysis, more than they could do without these plots. There was only one plot that the experts agreed on not using right now, which was the line chart. The reason that they would not use this plot is because it is too detailed for where they are right now, and not necessarily because the plot was unclear or contained insufficient information. With all that being said, all three experts agreed that the information in the plots is valuable for future analysis, that they would all use most of the plots, that new information was acquired, that it made their current analysis clearer, and that it provided added value. It can thus be concluded from these interviews that the framework is useful in regard to fulfilling the information needs from the client and for the visualization of said information needs.

Stage 6: Process Improvement & Support

The last stage of the PM2 methodology by van Eck et al. (2015) concerns the improvement steps that can be taken based on the previous stages. During the implementation of the framework in stage 4, a few things came to light that the client can use for process improvement. For instance, the bottleneck machine has been discovered, which means that in order to improve the production rate of the line, this will be the first thing the client needs to focus on and improve. Another example is that the amount of losses per machine has been visualized. This information can be used to improve the path that the operator walks and/or remove some of the inspection machines. However, this research ends with the implementation of the framework and the visualization of the information needs. The production process improvement needs to be undertaken by the client itself.

Conclusion

This research aimed to identify which types of data are required in order to sufficiently measure the machine effectiveness, find out why machines are standing still, and based on that information, make decisions on production line improvement. Based on the meetings that have been conducted with the client, the process mining activities performed with Disco, and the creation and implementation of the script, it can be concluded that the required data is divided into three types: event data, domain knowledge, and case knowledge. The combination of different elements contained within these three data types should provide enough input in order to successfully fulfill most of the information needs that can arise when analyzing a production line that uses a 1-piece flow structure with operators. In order to summarize and visualize the different elements that might be required for certain production line analysis activities, a framework has been created. Researchers and experts in the field can use this overarching framework to identify which data and/or information is already present to be used for their production line analysis, and therefore also which data is still missing in order to complete their analysis. It must be noted that not all data in the framework is always required for every analysis and fulfillment of an information need, and to show this, this study has also included an implementation of the framework. In this implementation it can be seen which data elements are required in order to visualize a certain aspect of the line, and therefore fulfill some of the information needs.

Two important elements in the framework are the effectiveness metrics OEE and the ORE. In order to derive to correct conclusions for production line analysis, the use of the appropriate effectiveness metric required. This study has shown that the OEE is a useful metric for measuring the individual machine effectiveness, but that the OEE is lacking when analyzing a line where the input flow, the output flow, and the operators need to be taken into account. That is why the ORE metric was used. During the implementation of the script, plots were made to utilize the additions that the ORE provides, in order to prove the added value of the ORE over the OEE. This has been done by implementing plots that show when and why a machine is standing still, which clearly indicates to the end user where the focus for improvement should be. This is information that the OEE cannot provide, and thus proves the point that ORE is a better metric to use in a 1-piece flow production line than OEE.

This research helps to solve the problems that companies in the manufacturing domain experience when trying to analyze production line data, by not only looking at individual machines, but by also taking the input and output flow into consideration, as well as the operators, and changing routes that the products can take throughout the line. By using the framework to combine event data extracted and processed with process mining, domain knowledge, case knowledge, and the appropriate effectiveness metric, it should now be possible for companies in the manufacturing domain to utilize all of the information present in the event-logs for a thorough analysis of the production line. This paper and accompanying framework provide the means necessary to find out what is needed to connect all of the pieces together by combining techniques and knowledge from both the manufacturing domain and the process mining domain. The paper has also filled a gap in the research by creating an intersection of the OEE, ORE, process mining, and domain knowledge, which had not been done before.

Discussion

The main purpose of this study is to find out how individual data elements and pieces of information from different domains can be combined in order to derive to results and be visualized to get new insights, as well as to find out whether the OEE metric is an appropriate measure of effectiveness for a production line with operators. This study demonstrates that in order to improve the analyses performed by companies in the manufacturing domain that are struggling to utilize event-logs and in-house expertise, certain data elements need to be combined. The client's event logs contain certain columns that are necessary for process mining, and the information gained through process mining is important for further analysis. Other types of data are gained through meetings or documents containing information that is only relevant for a specific line (case knowledge) or for the whole domain and/or factory (domain knowledge).

While many studies (Ahmad et al., 2018; Bahremand, 2015; Ebumüslüm & Paşayev, 2013; Harding et al., 2006; Ismael, 2021) mention the data that was collected for the production line analysis and acknowledge the presence of there being multiple types of data that needs to be extracted by using different means (through interviews, meetings, documents, etc.), none of the studies specifically focus on the required data for the analyses. The studies all briefly mention which data has been gathered and for which purposes, but none of them provide information about which data is necessary or required in order to reproduce their analyses. That is why this research differentiates itself from the other studies done in the same domain. This research focuses on the information needs and the data that is required to fulfill those needs, while other studies focus mainly on answering some other kind of question, whereby the 'data collection' or 'data gathering' parts are just a small by-product; something that needs to happen in order to get to the main result. In this study, the framework that is designed and that indicates which data and/or information is required, is the main result. This study also clearly divides the data into event data, domain knowledge, and case knowledge, while the other studies do not. Event data is oftentimes not even mentioned, let alone which columns are necessary for the analysis. Domain knowledge and case knowledge are for the most part considered as the same thing.

With that being said, there are of course also some things that the other studies have already discussed, or things that the other studies did include, while this research this not. First of all, Bahremand (2015) and Ebumüslüm & Paşayev (2013) both include cost information, which this study did not include. Reason for that is because it was not provided by the client. Secondly, Ahmad et al. (2018) discuss the different types of line failures that can be used as input. This study has not included failures in the framework, since, again, this data was not provided by the client. Thirdly and lastly, Ismael (2021) and Ahmad et al. (2018) both describe ways to gather information from business plan documents, the company website, and daily production reports, all of which were not used for data gathering during this study. Reason for this is that communication took place via one employee of the client, who gathered all of the data internally and then sent it all at once in an email with a CSV file. All in all, the framework includes data and information in a summarized way, but is not complete enough to be used for every situation. Therefore, the advice is to use the framework in conjunction with other types of internal domain knowledge/documents that were not discussed during this research.

The study also shows that the OEE in itself is not the appropriate metric to be used for a 1-piece flow production line with manual processes and operators handling the machines. The OEE factors are too limited in the sense that they in fact indicate when a machine is standing still, but not why. Especially the answer to the "why" question is very useful information for companies, because this forms the basis for an improvement project to eventually increase the production line performance and overall effectiveness. The ORE metric does in fact answer the "why" question, and can therefore, together with domain knowledge and the input from process mining, indicate why each machine is behaving a certain way.

These results build on existing evidence by Eswaramurthi & Mohanram (2013), Garza-Reyes et al. (2008), and Garza-Reyes (2015), who indicate that the OEE is not the correct metric to use in manual and low rate speed production processes, and if OEE is used nonetheless, the results will be insufficient on its own as a performance indicator and improvement driver for these types of processes. Next to this, the authors state that the factors of ORE were more elaborate in measuring the performance than the factors of the OEE. Lastly, the authors stated that in practical terms, the data and elements for the proper calculation of ORE are easily available and collectable.

This study partially agrees with these findings, and partially contradicts these findings. The study agrees with the findings that the added factors included in the ORE make the metric and the overall effectiveness measure more complete, meaningful, and feasible compared to the OEE. Next to this, it agrees with the statement that the OEE is not an appropriate metric to be used for a low-rate production line, with manual assembly stages and operators controlling the machines. Ignoring the behavior of the operators, the input material, and the availability of the machines results in an insufficient performance indicator that cannot be used for process improvement. Furthermore, it agrees with the notion that the factors of ORE suggest a wide applicability range and therefore has the potential to be used in a wider range of processes than the OEE. However, this study also agrees with the previous papers in that the OEE is definitely still useful in other processes. The OEE is by far the most used and researched metric and reported cases in the literature have established that OEE can be used successfully in a wide range of environments. The script and the framework that have been created during this research also still include the OEE. Therefore, this work must be seen as a demonstration for production engineers that the correct measure, whether this be OEE, ORE, or any other metric, must be chosen on the basis of the characteristics of the production line and the processes therein.

On the other hand, this study contradicts the findings by Eswaramurthi & Mohanram (2013), Garza-Reyes et al. (2008), and Garza-Reyes (2015) in that the data and elements required for a successful calculation of ORE are not easily available and collectable. In fact, this study showed that the incompleteness of the data resulted in a limited analysis. The ORE is significantly better and more elaborate than the OEE when all of the data is available, however, when data such as the serialnumber is missing, ORE loses a lot of ground. The case study showed that it was not possible for the client to deliver serialnumber tracing for almost half of the machines in the production line. Therefore, the process model was incomplete, and thus the input data for the ORE script was deficient. Because of this, the ORE calculation was impacted for those machines. Classification in why the machines were inactive was still possible, but could not use tracing information, making it error prone to some extent. According to the client, some machines cannot record serialnumbers that easily, so this makes the data collection difficult. Because of these reasons, this study does not agree with the fact that the easy-to-collect data part of this metric can be used as an argument to suggest it as an alternative to OEE.

Limitations

The study and framework have a few limitations that need to be discussed. First of all, the generalizability of the results is limited by the fact that the framework was created based on the data and meetings with only one client during this case study. Because of this, the problems that the case study experienced, the results that it produced, and usage of the framework can only be generalized to companies with production lines that are similar, and want to fulfill the same information needs. That being said, the study was performed using multiple datasets from the client, to make sure that the framework includes a wide variety data and information. In order to make sure that the results are generalizable and the framework can be validated to work and be helpful for other production lines that are not similar, more case studies need to be performed.

Secondly, not all organizations have the same structure of data and most organizations do not have all of the data readily available, and a lot of pre-processing is needed. This limits the applicability of the framework. In order to successfully use the script, or similar scripts, the framework should actually also include which format each element from the event data should have. However, this is not something that has be done due to the fact that the study does not suggest to only use this framework in conjunction with the script that has been made. The framework should be used to check which data and information is required for similar analyses, and the script, or another script/technique can be used to utilize that information. Each organization has a different database with different kinds of attributes and information. This needs to be converted in the right format, whether this is done by the organization themselves, or researchers using this framework, is not predetermined.

Thirdly, since only data and information from one client is used, the framework does not contain all information that is possible to use as input for production line analysis. Certain things such as costs, failures, and specific domain/case knowledge will differ per organization, and can therefore not be expected to be included in the framework. With that being said, the paper indicates which kinds of plots can be visualized using the data in the framework and which information needs will be fulfilled, so if a user of the framework wants to fulfill any other information need, there might be a chance that the required data is not included in the framework.

Fourthly, the framework does not describe many ways of gathering the required information and data. The described case study predominantly used meetings and event-logs sent by the client to gather information and data, however, there are many other ways of acquiring the required data for certain analyses. Be that as it may, the main result of this study is the framework, which indicates which data and information is required for certain analyses, and not how this data should be gathered. This is something for the user of the framework to determine.

Fifthly and lastly, the paper does not go into too much detail of how the data and information listed in the framework should be implemented. This study created a script that can take some of the data/information in the framework as its input, and some information/data from the framework should be taken into account while looking at the plots (so this is not actually used as input in the script) to derive to the correct conclusions. Hence, someone using the framework should determine his/her own way of implementing the required data/information listed in the framework.

Future work

First of all, as already discussed, further research is needed to extend the framework with more elements that can be used as input. This could be done by performing case studies at more and different kinds of companies. Only then can something be said about the generalizability of the framework. The additional case studies should not be exactly the same as the case study that was already performed, to make sure that the framework includes different kinds of information from various scenarios and production lines. It should be tested on lines whose order constantly changes, on lines with more manual assembly stages, on lines with more machines, and on lines with different amounts of operators. The presence of serialnumbers in all of these cases would be most beneficial.

Next to this, focusing on the limitations of the paper, the process mining part and the ORE calculation and visualization is done separately. Disco is used for process mining to discover the process model and thus the order of the machines. This information is then given as input to the script, which in turn performs the rest of the analysis. Something for future work would be to implement the process discovery in the script itself. PM4Py is Python library that makes it possible to perform process mining in Python, so that could be used at the beginning of the script. This line order will then be re-discovered each time the script is executed and used as input to the rest of the script. This would make the script a lot more flexible and adaptable, because it can automatically notice when the order of the line has changed (a machine has been added or removed, the order of a few machines has changed, etc.), and immediately give this as the input for the script. This way, the calculations would still be done correctly, and not using the wrong order. Right now, this 'order discovery' needs to be done manually using Disco, but with this implementation it could be done automatically, saving a lot of time and effort.

Furthermore, the script uses the ORE to calculate the machine effectiveness per machine, or actually per group of machines. The required information for that is included in the framework. However, it would also be useful to be able to calculate the effectiveness of the whole line. This way, an increase or decrease in the effectiveness of the line can be seen when comparing different shifts with each other. Deriving to a value for the whole line is not as simple as taking the average of all OREs, so something for future work would be to find a new metric that can convert the ORE values into one value for the whole line and include this in the framework.

Lastly, the script can always be improved with new additions, but the most important ones are related to the ORE and manufacturing lines. In the literature, the ORE has a seventh factor, called the changeover time. This is the time lost when a new product needs to be produced, for which the machines and/or operators need time to prepare. Since the client in the case study has no changeover time, this was not included in the framework and calculations. Another addition that would be beneficial for the script and framework is the inclusion of data required to deal with robots in the production line. Right now the line uses operators, but it might very well be that these will be replaced by robots in the future, and the framework/script should be able to adapt to that.

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Appendix A

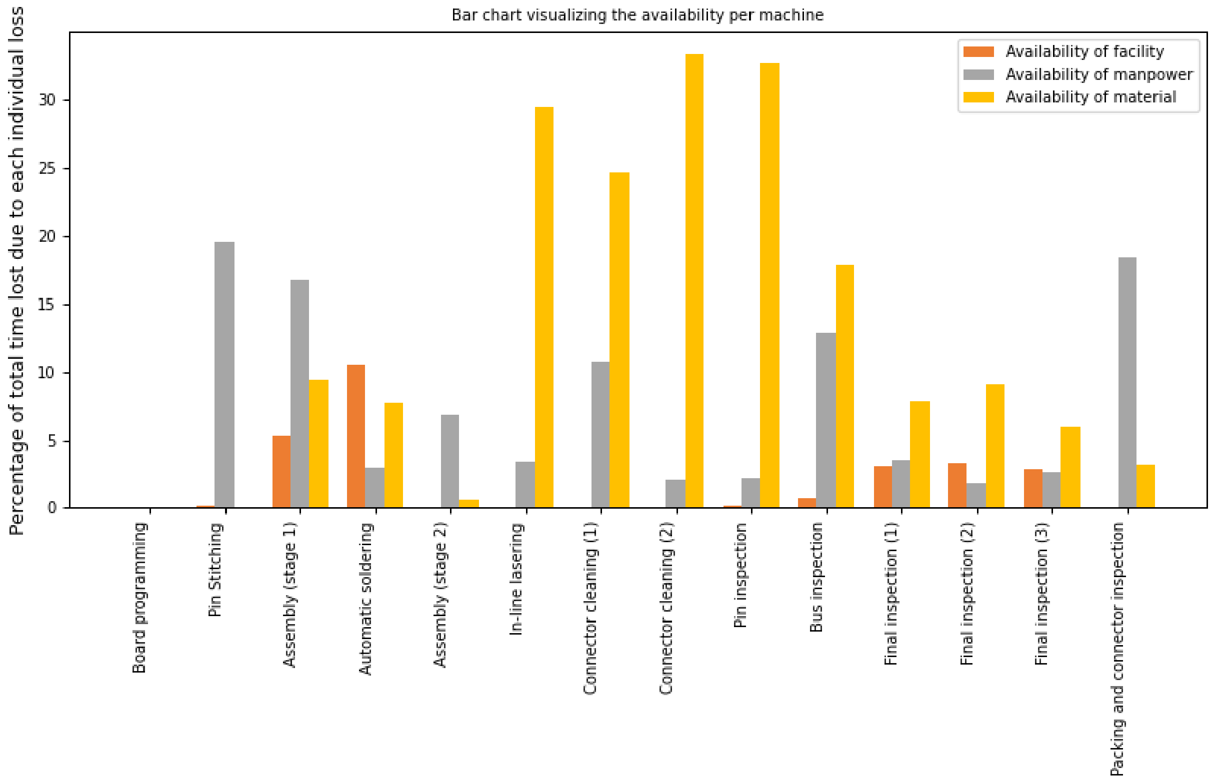

Figure A 1. Minutes lost per factor for each machine, displayed in percentages

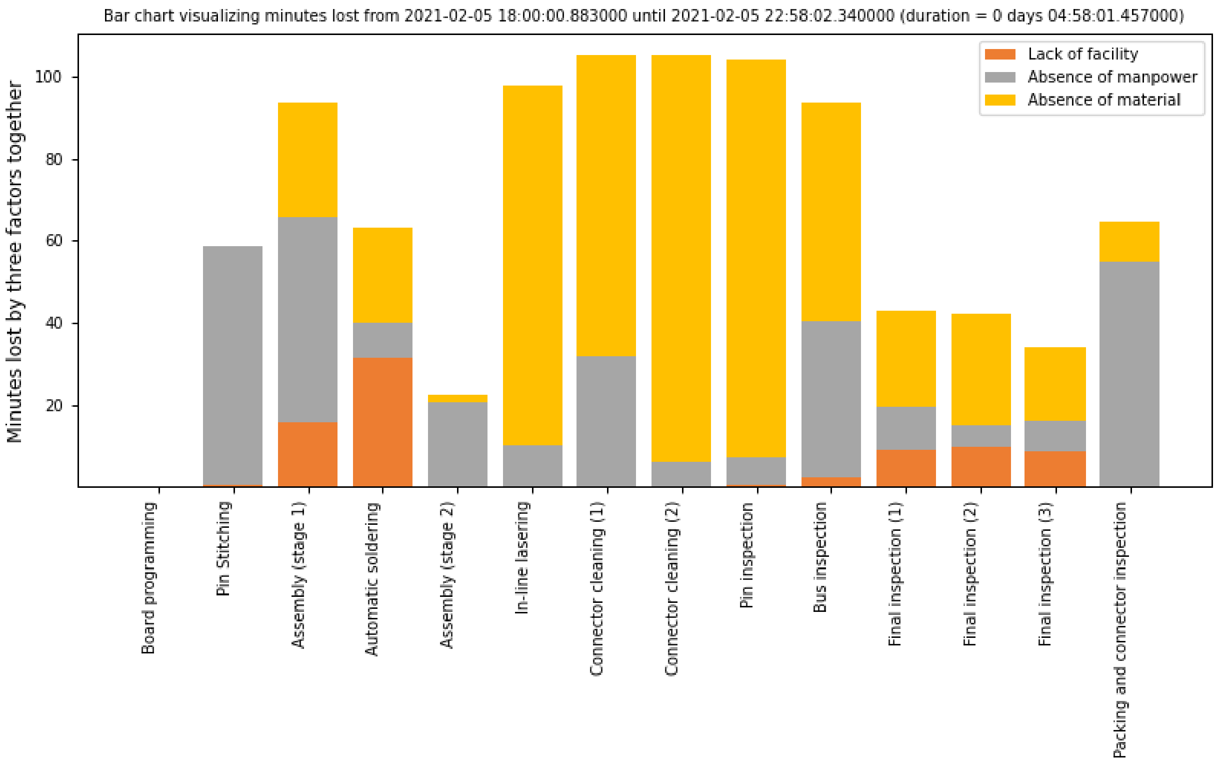

Figure A 2. Stacked bar chart displaying the total minutes lost by all three factors in the chosen timeframe

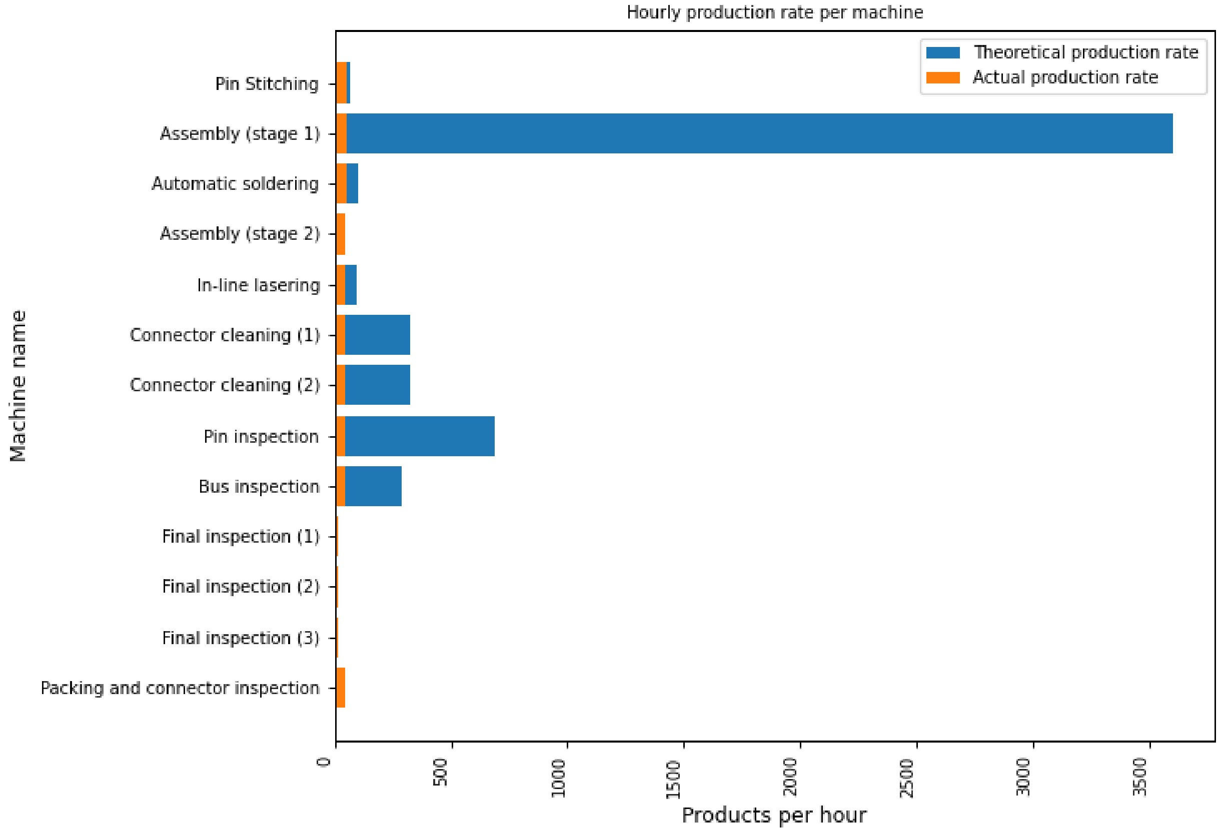

Figure A 3. Actual Hourly Production Rate vs. Theoretical Hourly Production rate