Analysing bottlenecks in production processes with the help of process mining

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Bottlenecks are detrimental to the output rate of a process, causing extended waiting times and increased costs of production. This paper will be looking at process mining, a technique used to create a process model using the event log. Multiple methods will be discussed that will be able to determine bottlenecks in systems, and their precision and recall rates will be evaluated to find the best model. As most studies stay in the detection of bottlenecks, this paper will also explore the methods for predicting bottlenecks. Using predictive process modelling and transition systems, it is possible to predict time left for an item to be finished and if the item is up to quality.

Additional Key Words and Phrases: Process mining, bottleneck, production process, predictive process monitoring

1 INTRODUCTION

Bottlenecks in production processes negatively impact the efficiency in the manufacturing industry. They can lead to stalled production, supply overstock or reduction in morale [19]. These can occur as a result of a number of causes, most of the time being a lower capacity machine in the production line or a non functioning station. With the help of data analysis and other data focused approaches, we can locate the issue and resolve it. An Enterprise Resource Planning (ERP) system is a software system that connects with every part of a business to provide an overview of its functions and their data [10]. Although a lot of companies gather this data, they do not use this data to check their processes for problems and look for improvements [3]. One of the techniques that can be used for this is called process mining.

Process mining is a technique to provide insights into how exactly a system works and what steps have been taken along the way. This technique builds on a combination of multiple approaches that are already used in data science, these being: data mining and process model-driven approaches [17]. However, data mining is too focused on the data itself to provide a good overview of entire processes in an organisation.

Much of the research done on the topic of using process mining for bottleneck analysis only stayed at analysing the system after it has finished. It would be better to tackle the problem beforehand and eliminate it before it can happen. This would speed up the process and save the company costs as they are able to produce more. That brings us to the following problem statement.

2 PROBLEM STATEMENT

First, a decent understanding of bottlenecks and how they can be found is needed. Although a lot of research has already been done on this subject, it can prove useful to go through it again to pinpoint vital strategies we can use in the second research question.

RQ 1. How can bottlenecks be detected in a system?

After this, we can delve into the main part of this thesis, namely to predict bottlenecks,

RQ 2. How can bottlenecks be predicted in a production process?

We will also explore the results that the different algorithms for bottleneck detection give us, to get a better grasp on which technique works best in which setting.

3 RELATED WORK

Process mining can be described as the missing link between data mining and process modeling [18]. Its goal is to use event logs generated by the usage of software or hardware to extract information about the system and to create a process model [17]. Event logs are files that contain timestamps and information of actions taken in a system. There are three main uses of those event logs: discovery, conformance and enhancement. In the subsections below, we look at bottleneck identification and prediction of them. The identification is an integral part as it provides insight into how to predict bottlenecks.

3.1 Bottleneck

We are focusing on bottlenecks in the field of production, here it is defined as a process which capacity is equal to or less than the demand placed upon it [11]. This sub-process can then limit the entire throughput of the production line and cause congestion and decrease efficiency leading to lower profitability.

Finding a bottleneck in a system is a subject that has been researched often [4]. Chompoonoot Kasemset and Voratas Kachitvichyanukul [9] have written a paper on the identification and simulation of bottlenecks. They state 3 main factors that can be checked to look for bottlenecks, these are:

- High value of the machine/process utilisation
- High value of the process utilisation factor
- Low value of the product bottleneck rate

The utilisation factor here means the input/output flow of the machine, where a high utilisation factor means that the machine is used most of the time. The bottleneck rate means the rate of the workstation having the highest long term utilisation. Betterton and Silver have collected 8 bottleneck detection methods that make use of these factors [5]. Beneath, we will discuss these methods.

3.1.1 *Active/Inactive Period method.*

These methods take into account the duration of the periods that the station is active and use this data to pick out the station that has the longest average active period or most inactive for the active and inactive period method respectively. Consecutive active states are defined as one active state in these methods.

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3.1.2 Longest (Average) Waiting Time method. The workstations where the items have the longest waiting times or the longest average waiting times are picked out as the bottlenecks in the system.

3.1.3 Arrow method. This method is more complicated than the last two. This technique finds the bottleneck by giving each station 2 variables: starved and blocked percentages. A station is blocked when the next station cannot take in the items of the previous station. A station is starved when the station has to wait for items to arrive. These terms can be used to calculate frequencies where stations are blocked or starved. If the frequency of blockage of station 1 is higher than the starvation frequency of station 2, the bottleneck is later in the production line. If the frequency of starvation of station 1 is higher than the blockage frequency of station 2, the bottleneck is earlier in the production line.

3.1.4 Turning Point method. The workstation where the blockage and starvation frequencies shift from the blockage frequency being higher than the starvation frequency to starvation being higher than the blockage is referred to as the 'turning point'. The 'turning point' should have the highest percentage of operation time in comparison to the workstations next to it. If no turning point is found with this technique, meaning that for every workstation following the first has a higher starvation than blockage, the first workstation is the bottleneck. If every workstation following the first has a higher blockage, the last workstation is the bottleneck.

3.1.5 Utilisation method. The utilisation of a resource is classified as ratio of the rate of items that enter the machine to the effective production rate. The effective production rate is the maximum rate that a workstation can process accounted for time losses due to errors, setup and other inconveniences. This differs from the raw production rate, which is the theoretical maximum. The workstation that has the highest utilisation is then considered to be the bottleneck, although this only holds for a system where each workstation has the same arrival rate.

3.1.6 Longest Queue method. This method uses the amount of waiting items that have to be processed at a workstation, where the station with the most waiting items is the bottleneck.

These methods are useful to understand how process mining looks at systems and determines the problems within. This information can then be used in other production lines to predict bottlenecks.

3.2 Bottleneck Prediction

The prediction of bottlenecks in systems, in contrary to the identification of them, is a relatively unexplored subject. The technique for this is called predictive process monitoring, where the outcome of the process is predicted by using historical data. Information such as the paths that items have taken or time spent in a machine are used to predict the duration of the process [15]. It is also possible to see if the item will be without errors in its design. More on this topic will be explored in section 6.2

4 METHODOLOGY

This section will cover the methods that will be used to conduct the research. The research starts with the gathering of multiple ways to create a predictive model, a comparison of these techniques using the dataset acquired and afterwards an evaluation of the techniques. The study will be conducted using Cross Industry Standard Processs for Data Mining (CRISP-DM)[8]. It is a standardisation that helps create an easier way for projects to be executed regarding data or process mining by breaking it down into simple steps.

4.1 Business Understanding

To create a good model, there needs to be a deep understanding of the business process behind it. This phase focuses on determining the objectives of the project, what the process should do and what the customer wants to accomplish. For this, the requirements of the project should be noted down. These requirements are already stated in documents attached to the dataset and can thus be directly used.

4.2 Data Understanding

The next step in the process is the understanding of the data. The event logs of the stations used in the steel process factory contain a lot of information, some of which is not required to create the predictive model, such as worker ID. An overview of a single case and its variables will also be made to make it easier to work with.

4.3 Data Preparation

Although the raw data can be used to create a model, trimming down the dataset in regard to the amount of variables can result in a clearer model. Parameters such as worker ID and order quantity are not needed for calculating the bottleneck. The file is in CSV format, which can be directly imported into the program, which converts the data into XES format.

4.4 Modelling

Now that the data is ready, we can begin to create the first model. The program that will be used for this is ProM, a process mining framework [1]. Firstly, a simple model will be created of the production flow of the parts. There are many available algorithms that can be used for the discovery of a process model. This project will make use of the heuristic miner, which has proven to produce the highest precision and recall scores in real life situations out of the other miners [20]. Precision score shows how much the model allows for unrelated behavior, lowering the accuracy of the model[14]. Recall is the metric that shows how much of the model allows for behaviour found in the event log. Both are needed for a model that can predict bottlenecks well. Once a heuristic net is made we can transfer this to a Petri net, a model that displays states, transitions and arcs. This can then be used in conjunction with the event log to get a performance and conformance analysis.

4.5 Evaluation

The evaluation of the different algorithms will be done in two parts. First, the recall and precision of each model will be compared with each other. The algorithm that can create the best fitting model, can also mirror the reality the best. ProM has a built in tool that shows the precision of the models. Secondly, the models are tested for how well they can predict the remaining time left per case. This

Case ID	Activity	Resource	Start Time	End Time
Case 1	Milling	Machine 4	01/29 23:24	01/30 05:43

Table 1. Entry from dataset

	AP	IP	LWT	LAWT	A	TP	U	LQ
U	X	X			X	X	X	
UF	X	X			X	X	X	
BR								
WT			X	X	X	X		X

Table 2. Combination of bottleneck detection methods and their used metrics

can be done via using a plugin in ProM where thousands of cases are entered into the system and average waiting times will be computed.

5 DATASET

The dataset that is used for this project is not a real life example, but a synthetic one [12]. It handles 225 different cases with in total 4544 event logs. Each event log consists of 14 variables only of which 5 are necessary to create a process model. The unwanted variables described in section 4.3 have been removed. An example of a data entry after the removed variables can be found in table 1.

6 RESULTS

This section explains the results found when executing the steps in the section 4. The results have been split up to answer both research questions seperately.

6.1 Locating the bottleneck

Below, a table is made to illustrate the combination of the 3 main factors and the 8 bottleneck detection methods mentioned in section 3.1. Table 2 can be used in the project to see which factors are the most important in our dataset. Waiting time has been added as a metric as it was not mentioned in the factors listed but is needed for a few methods. The methods and metrics are also abbreviated to fit them on a single page, the full words can be found in section 3.1, except for waiting time, which has been shortened to WT.

Finding the bottleneck in the production process proved to be more difficult than thought. Due to the many different items processed in the factory that have different start- and endpoints and unstructured data, a good model could not be created that had a good fitness. The maximum fitness achieved for a heuristic model was 0.16, which is too low to draw any conclusions from.
However, Disco did provide us with a result that we can draw conclusions from. Disco is another process mining tool that is more restricted than ProM but is able to show different results [2]. We can filter the result on items taking more than 20 hours for example, or see how often a machine is used. Loading the csv file into the program, it gives us a process model using the FuzzyMiner, a processing algorithm that is more suited for unstructured data [7]. A small part of the model can be seen in figure 1.

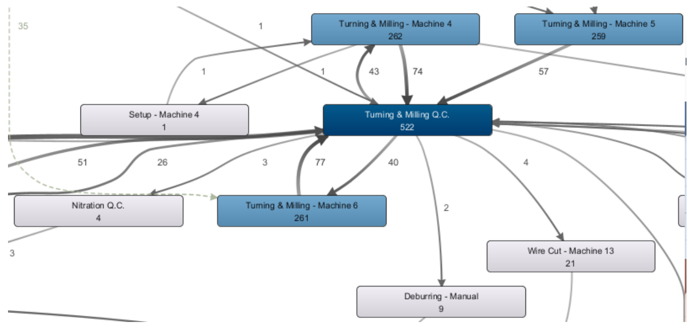

Fig. 1. Example of a process model

The numbers at the lines between the workstations refer to the amount of interactions. For example, 40 items went from Turning & Milling Q.C. to turning & milling - Machine B and 77 items went the other way around. With this data, one can tell the flow of products with relative ease.
The program can also show the performance of each process. Using this performance, we can find bottlenecks in the system. In figure 2, a transfer between workstations can be seen where an example of extreme waiting time bottlenecks are found.

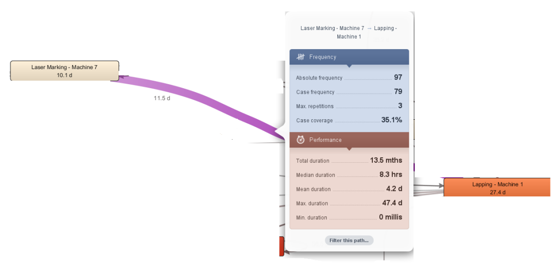

Fig. 2. Example of a waiting time bottleneck

On average, each item has to wait 4.2 days for moving from the laser marking machine to the lapping machine. The maximum waiting time is 47 days. The process can be quickened by looking at why the orders are taking too long to be processed by the next machine.
Another bottleneck can be found in the over-utilisation of machines. In figure 3, an example of this can be found.

The three turning & milling machines are overused and cause significant waiting time when they have reached their capacity. When looked at the other turning & milling machines in the process, they have a lower total operating time than the three shown here. The overusing of the three machines can be solved by redirecting items to the other turning & milling machines.

6.2 Prediction of bottlenecks

Now that we know how to find the bottlenecks, we can start predicting bottlenecks. In section 3.2 it was mentioned that to predict a bottleneck in a system, a predictive model should be created. This

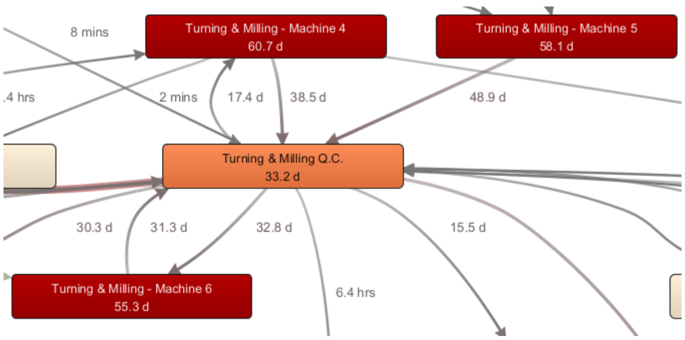

Fig. 3. Example of a overused workstation

model can then predict the time left for a product to finish. This approach is also a part of a branch of process mining called Predictive Process Monitoring (PPM). Predictions made using PPM could be time left until completion, as mentioned before, but also the possible outcome whether the product is conforming with the requirements or the machines the item will pass through [13]. Francescomarino et al. [6] describe the process for creating such a PPM. The information that is used to create the models can be categorised into 4 sections:

- Sequence of events. This means the workstations that the process needs to use to create a particular product (e.g. Turning & milling -> Turning Q.C. -> Final Inspection Q.C. -> Packing).
- Information per event that is available in the event log. In this dataset that would mean the timestamp, the worker who processed the item etc.
- Information not available in the event log. This would refer to the data that the workers themselves have added to the system, for example any remarks made to the item. This is more often used in processes which do not have a set structure such as hospitals where an exam could be added.
- Context information about the process. Workload, queues and availability are important metrics that add extra variables into the mix. If it takes an item longer than average to complete the quality control stage, it could be attributed to a blockage of items in the process, and not mean that that specific stage takes a long time.

There are two main predictive process monitoring approaches: machine learning and model-based techniques. As this paper focuses on process modelling, only the model-based techniques will be discussed here.

In the training phase, a model is constructed out of historical data although it is sometimes readily available. The model is then tweaked using the information from previous cases, such as the time left for an instance at a point in the process. This tweaked model is then used for the implementation phase.

A transition system is used to create a control-flow model, a model that shows the path a product will take. This helps build a model that is used to predict the remaining time for an item to be finished [16]. An example of this system can be seen in table 3.

Case 1	$[TM_0, TMQC_4, LM_7, S_10]$
Case 2	$[TM_2, RG_7, TMQC_12]$
Case 3	$[RM_10, FIQC_15, MQC_17, FIQC_21]$
Case 4	$[FG_0, LM_5, RG_9, FIQC_12]$
Case 5	$[TM_14, LM_20, L_21, FIQC_25]$

Table 3. Example of a transition system

The transition system keeps track of the trace using a representation of the event/workstation. In the graphic you can see that case 1 follows the path of turning machine, turning machine quality control, laser machine. The stations are then annotated with possible variables, such as time remaining until finished like in the example. It makes it easier to also annotate each state in its entirety. For example, the state $[TM_0]$ has 10 minutes to go until it is finished, so it will be adding 10 to the annotation. The state $[TM_0, TMQC_4]$ has 6 minutes until completion and thus will be annotated with a 6. This will be repeated for every state in each case to create a table that the program can then return to. If a trace of a case that is still running is gathered, it can be compared with the outcomes of previous cases with the same trace and then the time left until completion can be returned.

7 CONCLUSION

This paper gives an overview of how bottlenecks can be detected and ways to predict bottlenecks in production processes using process mining techniques. Starting with understanding how bottlenecks can occur, we explored eight different methods for bottleneck detection when looking at four criteria. A literary research was conducted to explore these methods and then were used on the dataset explained in 5. Then another program was used to gather the utilisation of the workstations to determine bottlenecks. Lastly, predictive process modelling techniques were explored to catch bottlenecks ahead of time.

The first research question "How can bottlenecks be detected in a system?" is explored in theory, as the execution of the algorithms on the dataset did not provide us with a decent recall and precision score. A detailed description of methods that are used to determine the bottleneck is however given. Next to that, a second process mining tool (Disco) was used that could visualise the data and show potential bottlenecks in the system. This was done through finding extended waiting times and overused machines within the process. These two metrics proved to be the clearest indicators.

The second research question regarding the prediction of bottlenecks covered the most well known technique, predictive process mining. This showed that it is able to create a transition system using the data from previous finished cases. This can then predict the time left until completion of an item and if the item is up to quality.

This research is limited on the amount of research done on the prediction of bottlenecks in practice as the methods are not readily available in the process mining tools. The dataset can also be seen as a limitation, as it was generated data and not real life data. A study on real-life data can be seen more useful as it steps out of a perfect condition.

The comparison of the different bottleneck detection methods can be done as future work. It would provide an overview of which methods are to be used in different cases. This would require that the methods are to be tested on different datasets, each from a different branch of work. Another possibility of future work can be found in the prediction of bottlenecks. As mentioned in 3.2, not a lot of research has been done on this subject. The implementation of it in programs like ProM, could make it easier for the subject to be explored.

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