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COMBINING SIMULATION AND DATA ANALYTICS FOR OEE IMPROVEMENT

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Abstract
Overall Equipment Effectiveness (*OEE*) is a productivity performance metric widely used in industry to support production control decisions. However, there is still a gap in organisational procedures to systematically identify and address the most promising opportunities to improve the production setup. In this study, we propose and demonstrate a data-driven approach for increasing *OEE* by combining the strengths of discrete-event simulation with data analytics tools and methods, which provides a risk-free test environment that forms the basis for data-driven decisions and supports revealing production interdependencies. Therefore, this approach eases the process for practitioners to proactively identify production losses and forecast the outcome of the most promising selected improvement measures. A case study is performed to illustrate the potentialities of the proposed approach, demonstrating the interdependence between the processes and the improvement measures, and the knock-on effect both upstream and downstream. The results yield substantial insights and facilitate operational decision-making for managers.
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Key Words: Discrete Event Simulation, Data Analytics, *OEE*, Improvement, Industry 4.0

1. INTRODUCTION

The Overall Equipment Effectiveness (*OEE*) is a well-established productivity performance metric that shows how efficient a manufacturing operation is compared to its full potential [1]. Although the measure can be dated back to the 1950s, its relevance has not changed. Additionally, *OEE* is rather nowadays more in focus due to the technologies associated with Industry 4.0, which allows monitoring, maintaining, and improving productivity [2]. Moreover, using *OEE*, it is possible to identify areas for improvement while the Industry 4.0 technologies allow higher accuracy of the *OEE* results. Specifically, Industry 4.0 technologies have supported mass connection of the machinery in production lines, gathering and processing large amounts of data [3], enabling the managers to monitor the production in real-time and thereby make well-founded strategic decisions to improve *OEE* [4].

Simulation and Data Analytics are two Industry 4.0 technologies currently used in manufacturing for improving production systems. Simulation provides the freedom to test out the existing production flow and carry out tests of possible changes in production planning to see how these changes affect the production [5]. This supports managers in predicting behaviour for specific manufacturing system configurations [6]. Furthermore, simulation software provides features for analysing time-series historical data, which supports identifying the most promising opportunities to form the basis tests. On the other hand, Data Analytics tools support data analysis, extracting actionable insights from data stored [7] and improving firm decision making performance [8]. However, Data Analytics tools do not provide the capabilities to test various future scenarios possibilities known from simulation tools. Therefore, this study proposes a data-driven approach that combines the capabilities of discrete-event simulation and data analytics to improve *OEE*.

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The main reason for this research is to provide a way for practitioners to proactively improve productivity using simulation, while data gathered from the production setup supports identifying the most promising opportunities to be tested and pave the way for data-driven decisions. In this study, the approach is exemplified by combining Tecnomatix Plant Simulation as the discrete event simulation tool and Power BI as Data Analytics tool.

The remaining of the article is organised as follows. Section 2 presents a background review on the core characteristics of *OEE* and the interlink between simulation and data analytics. Next, Section 3 describes the various steps for the proposed data-driven approach, while Section 4 exemplifies its use. Finally, implications, contributions, and final remarks are presented in Section 5.

2. THEORETICAL BACKGROUND

2.1 *OEE* – Overall Equipment Effectiveness

Lean manufacturing implies the use of tools and concepts to improve production and efficiency. One of the Lean tools used in the industry is *OEE* which helps to monitor and create a baseline for improvements, indicating where to focus and what to improve next. Therefore, *OEE* is described as a metric to identify losses, benchmark progress, and improve the productivity of manufacturing equipment [9]. As a result, *OEE* is nowadays known as a versatile industry-standard measurement for production efficiency by mathematically identifying the percentages at which the manufacturing time is productive.

OEE consist of three parts: Availability, Performance, and Quality. Today companies often track *OEE* using specific software and methodologies to find the most efficient approach to increase productivity. Hence, much research is focused on finding ways to predict the outcome of production improvements. For instance, Caterino et al. [10] adopted discrete-event Simulation to evaluate the production process parameters, such as working times and operations accuracy, using *OEE* as a metric. Barosz et al. [11] developed a simulation model in FlexSim to determine the real difference in work efficiency between humans and robots at the design stage. Yuan et al. [12] presented a system using machine learning and data analytics for an *OEE* improvement of a CNC machine. Bhattacharjee et al. [13] developed an online dashboard to daily measure *OEE* for blast furnaces root cause identification.

One of the Lean tools usually combined with *OEE* is the Six Big Losses which describe, more detailed than *OEE*, the most common causes of equipment-based productivity loss in manufacturing [14]. These losses are categorised to make a clear division of what type of loss can be the cause for an ineffective production and act as a guide to find efficient countermeasures.

OEE is a valuable tool that can help management unleash hidden capacity and combined with discrete event simulation in combination with data analytics, it is possible to provide a higher degree of control and decrease the risk of costly and ineffective optimisations/ improvements.

2.2 Discrete event simulation and data analytics

Simulation of production lines is widely used to get an overview of the production and monitor the processes. Therefore, it has gained a foothold in the industry, proving its advantages by providing analysis, visualisation, and test optimisation measures [15]. With the ability to map the flow of materials and logistic operations, some simulation programs allow replicating existing manufacturing processes and turning them into a computer model. Hence, simulation is eminent to use in cases were many interconnected variables makes it risky to implement nontested solutions. Hence, simulation allows to test changes and validate them using shop floor data without risking or interrupting production processes.

Discrete event simulation (DES) is one of many simulation options used for experimentation and validation of manufacturing processes. This creates a good basis for production managers to identify bottlenecks or decide on optimisation measures [16]. Furthermore, the simulation programs make it possible to monitor multiple production processes and statistics, generating large amounts of data [17]. However, visualising and creating an understanding of the datasets are challenging. The simulation programs focus on visualising the processes but fail to provide a way to analyse the generated data with a high granularity level in an integrated manner.

Thus, combining data analytics with simulation eases the process of dealing with large datasets needed in simulation. Additionally, it is an option for better treating data before developing the simulation, analysing the data generated by the different scenarios, and to visualise and compare simulation results. Tools like Power BI, Tableau and Plotly are great for interactive visualisation of large datasets [18]. Looking at Power BI, the software is, without experience with coding, easy to setup to communicate with MS Excel, and from there, Power BI will automatically update and treat the data received when data is updated. Visualising the results makes it possible to present progress and suggestions understandable for the decision-makers. Furthermore, it is a good tool for model verification and validation with the strength of revealing patterns, trends, and connections. Moreover, it can be used to illustrate the confidence level at which a simulation model mirrors the real world and thereby reveal the credibility of the data produced.

The integration of simulation with data analytics to improve the *OEE* is described by Abd Rahman et al. [19]. The authors developed a model-driven decision support system for line balancing using data analytics tools and simulation. However, the data analytics tools were only used to collect and organise data for simulation input, not being used after the simulation. Hence this paper goes one step further, using the data analytics tool to help identify and evaluate the most promising improvement scenarios.

3. DATA-DRIVEN APPROACH FOR *OEE* IMPROVEMENT

Following the steps of the simulation modelling process adapted by Stewart Robinson, the data-driven approach proposed in this study combines the well-known simulation development process with data analytics for data processing [20]. Developing a simulation model requires an understanding of the production and data about the core processes. For cleaning and validating the data used in the model, data analytics software proves its potential by verifying and validating the model to ensure accuracy. Additionally, implementing *OEE* monitoring in the simulation model generates data that forms the basis for scenario testing. These scenarios are created based on knowledge about *OEE* and an analysis of the historical data. The data analytics software provides an integrated way to identify promising improvement by visualising data from the current production setup while allowing for further comparison of results. The joint use of both technologies supports both identifying critical points in the current setup and a way to increase efficiency, consequently the *OEE*.

Therefore, Fig. 1. illustrates the proposed framework that combines data analytics with discrete event simulation for *OEE* optimisation. Next, each step of the framework is described.

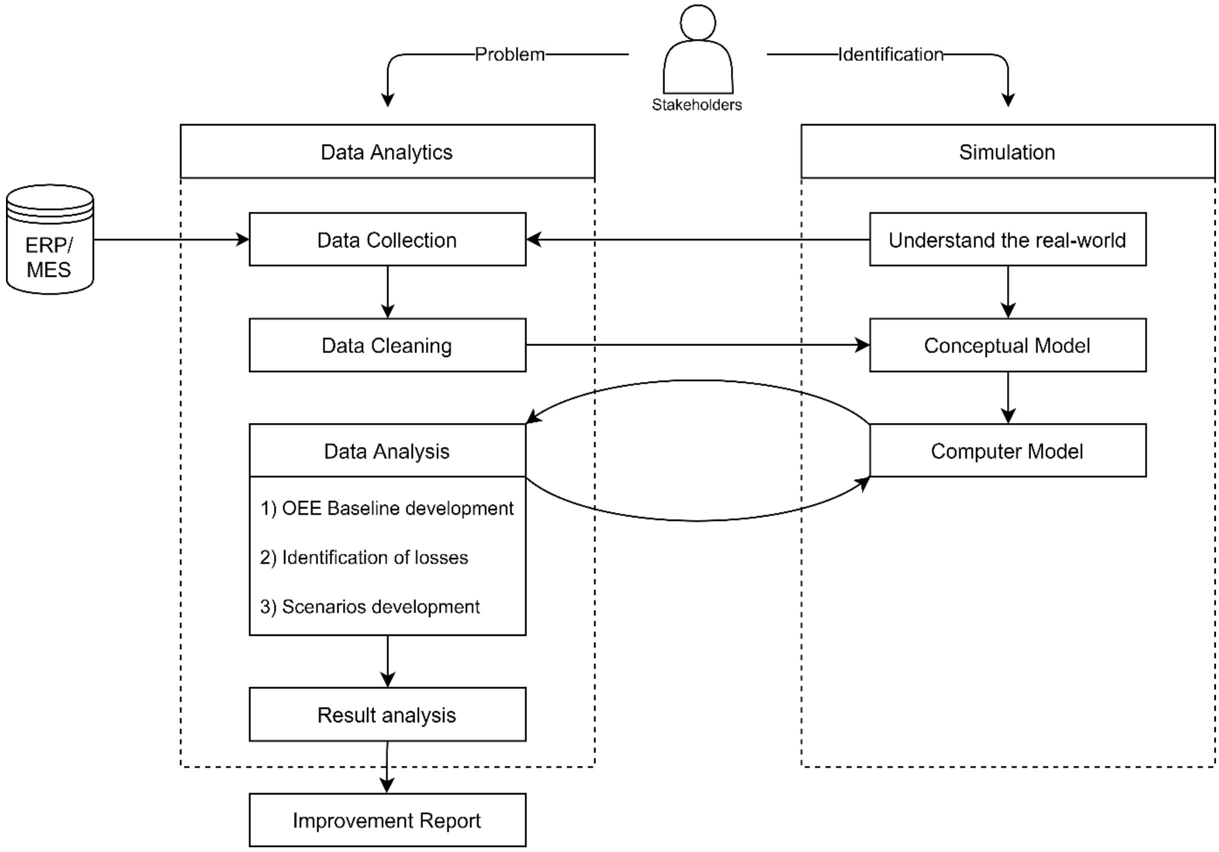

Figure 1: Data-driven approach for *OEE* improvement based on simulation and data analytics.

3.1 Problem identification, data collection, and data cleaning

The data-driven model highly depends on the information and knowledge gathered in collaboration with the relevant stakeholders. The data for the case study included 16 SKU's, undergoing the same process but with different setup and processing times, gathered over a two-month period. It was collected from the ERP/MES of the company, and process descriptions were analysed to provide an understanding of the production processes. Meaning, developing a basis for understanding the current production, including information such as flowcharts describing the processes and decisions within the production, an overview of the production floor and machinery placement. Additionally, information about what regulatory restrictions the stakeholder must adhere to, as well as historical production data, including processing times and a log of registered failures occurring in the production, was required.

Furthermore, information about planned production (shifts) and planned downtime (setup and/or cleaning time), ideal cycle time, as well as potential required storage time, are needed to establish the necessary foundation for *OEE* calculations. In addition to these, data detailing First Pass Yield (*FPY*) and rejected parts are required, together with specifications about different product numbers, which may be included to create a more comprehensive simulation.

In section 4, a case study is presented to exemplify the approach and show the opportunities and results of using the framework presented in Fig. 1. The production line in which the approach was tested consists of three types of processes, one of which includes two similar machines working in parallel. The data collected regarding this line were cleaned by removing outliers and corrupted data, and knowledge gained in the problem identification step was the basis for establishing flowcharts to develop the conceptual model.

3.2 Conceptual and computer model

he first two steps of the simulation modelling process are essential for the further development and quality of the end results. Based on the knowledge and data gathered from the stakeholder, the boundaries and limitations (e.g., aggregation of failure types) for the simulation are formulated and inserted into a conceptual model. This includes flowcharts of all the included processes and how they may need changes or rearrangements to provide a more accurate computer model. Note that clarifying the rigidity of a simulation and how the conceptual model may differ from the real world supports producing more accurate simulations.

During the computer model development, an iterative approach must be taken, focusing on continuous model validation. Throughout this process, the individual process/machinery is constructed, tested, and validated concerning the conceptual model and the real world. Throughout the implementation of processing times, failure codes, returned products, etc., data analytics tools become handy while treating historical data into the necessary format for the simulation tool to use. The iterative approach of adjustments and validations ensures the validity and accuracy of the final model.

Verification and validation are an integrated part of developing simulation models and appears, alone or together, in each stage of the modelling process. Verification means checking the model's internal logic, examining whether all necessary details are displayer for proper running of simulated process while validation focus on checking the conformity of the simulation model with the real process [21]. They are performed in a series of white- and black-box validations. Data analytics become helpful, as the results of the simulated processing and failure times can be visualised and compared to the real-world data gathered from the ERP/MES system. As mentioned, these validation processes are performed continuously throughout the model development, and therefore should not only be used once the simulation model is completed.

A computer simulation model highly depends on the quality of available data [22]. The various forms of validations often require a comparison of some part of the model with the real-world data. Therefore, it is important to ensure an accurate basis of data from the real world, as the data may be inaccurate or differ due to, e.g. small sample sizes. Examples of validation criteria used in the case study include comparing simulated required time per batch and throughput per period with real-world historical data, using line and bar charts for visual representation.

3.3 Data analysis

With the computer model validated, the implementation of *OEE* monitoring becomes the next step. To create a basis for improvement, an *OEE* baseline based on all parameters influencing *OEE* is derived from the simulation (e.g. downtime, *FPY*, etc.). Making the relevant measures for the *OEE* calculations and implementing data transfer enables data from the simulation software to be extracted, analysed and visualised as gauge and line charts in the data analytics software. Also, the software combination creates an overview of the failures registered in the production and makes it possible to identify the occurrences of each failure in proportion to each other.

The *OEE* baseline comprises data from all the stations in the production line. Due to the setup of the simulation software, the software tracks and monitor each process, making it possible to derive the individual factors for availability, performance, and quality by use of simple programming as the simulation runs. The *OEE* measures for each machine can be combined into a single overall measure of how effectively the planned production time is utilised to make a quality product. This is done by weighing the different factors according to each other. The weighted *OEE* represents the total time required to make a quality product, divided by the total net available time [23].

A deeper analysis and understanding of the score is thereby possible. However, with the benefits of using simulation comes downsides due to the rigidity of the software. The *OEE* data will show signs of a warm-up period before stabilising [24, 25], which affects the overall *OEE* score. Yet, data analytics allows identification of the warm-up period, through line charts and thereafter removing the data before a stable chart is reached. Additionally, the simulation program allows for tracking data as often as desired, making it possible to extract large datasets to form the basis for decision-making and actions. Also, it allows for further analysis and visualisation of the individual *OEE* scores for each machine used (e.g., column charts showing performance or availability). Thereby, identifying places for improvement, enabling the stakeholders to compare the current state with the results of an improvement, and validating the observations done on-site.

The next step is to identify the losses and areas of improvement. To increase *OEE*, the baseline developed above helps identify the time losses by categorising them according to the Six Big Losses [26], allowing to find countermeasures to increase productivity [14]. Identifying the biggest losses within the production is eased using Pareto diagrams created in the analytics software. Hence, it facilitates to find the reason(s) for loss and thereby decide on the relevant countermeasures. Furthermore, visualising the weighted *OEE* score provides a clear view of the stabilised score and thereby show if it is a world-class performing production line. Moreover, the fact that each individual score, which the weighted *OEE* is based on, can be visualised is beneficial for finding bottlenecks and hidden causes for a low *OEE*.

Taking the example of increasing productivity by lowering losses affecting availability. The reasons for availability loss can be due to unplanned and planned stops, which are divided into losses caused by equipment failures or time spent on setup and adjustments. With data analytics, it is possible to create an overview of registered failures by representing them in a Pareto diagram. Hence, it is possible to point out which failure is the reason for the most lost time, which can result in the best outcome if improved upon. On the other hand, graphs and an *OEE* timeline creates an overview of the planned stops and how they affect the process and overall *OEE*.

The factors of availability, performance and quality are mutually dependent, and therefore, it can be hard to determine where an, e.g., the bottleneck is causing trouble. However, with the possibility to check every measurement made, the factors for each machine can be monitored to uncover trends or patterns. By using column charts for showing the results, it eases the process of interpreting how the changes may affect the *OEE* score. Thus, it facilitates finding the critical points to focus on and evaluating how the production line performs under certain circumstances.

Next, scenario development and analysis takes place. Based on Pareto charts, critical points of improvement are found and combined with knowledge about countermeasures from the Six Big Losses. Hence, it is possible to define scenarios deemed promising for increasing *OEE*. Also, the different scenarios can shed light on potential mutual dependencies, which requires scenarios with several measures taken. The improvements depend on stakeholders who understand the production line process in detail. Therefore, the managers can decide feasible degrees of improvements for each process (e.g., percentage of failure reduction, setup time reduction, capacity increase, etc.).

If the aim is to increase availability, which is known to be dependent on planned and unplanned stops, a scenario could be to decrease the occurrences or Mean Time To Repair (*MTTR*) of a failure happening. Even though data analytics can point out the most occurring failures, the company might opt to improve another failure if they are more confident with its potential implementation, given their experience.

Furthermore, despite the expectations, the results might not be showing a linear increase in *OEE* performance. Specific percentage-wise optimisations might lead to a high gain and therefore be more suitable as less effort is required to increase *OEE*. Hence it can be beneficial to compare the results of each scenario to each other with different extents of improvement. By analysing the scenarios, using column charts, and business insight it is possible to identify the most suitable approach, leading to additional experiments. Moreover, with the many possibilities of treating the data in analytics software, the function of creating reports and dashboards is the basis for decision-making. Thus, it could be that several improvements should be implemented due to an interdependence causing a higher increase in *OEE*. However, the possibility of testing several scenarios allows for finding the scenario with the best potential for a high *ROI*.

3.4 Report development

For sharing and informing the stakeholders about the results, data analytics tools offer dynamic dashboards which can be converted into static reports. With the software, it is possible to create charts that provide an overview of the gain in *OEE* according to different measures implemented. Furthermore, it enables creating charts that provide the function to investigate more thoroughly, providing more insights into the knock-on effects of the actions taken. Additionally, the report visualises the results and eases the process of selecting the most promising action plan and comparing results in a visual way. Moreover, the visible data representation makes it less challenging for simulation model developers to explain and communicate the findings for people unaware of the production or simulation.

3.5 Summary

The steps of combining simulation modelling process with data analytics approach includes dealing with large datasets, validating the data to achieve high confidence in the results and visually presenting the outcome by use of the software. It requires the right software, which can be costly. However, it is possible to perform risk-free tests of different improvement ideas without compromising production time and money. Furthermore, it avoids misinterpretations and misleading conclusions by providing a clear overview of tendencies.

4. DISCUSSION

To exemplify the approach, the framework has been applied in a case study. In the following paragraphs, the results obtained are presented and discussed.

Performing both white and black box validations using the data analytics tool Power BI made it possible to perform data cleaning, visualise data from the real world and compare the historical data with the data extracted from the simulation. Furthermore, the software combination created an overview of the failures registered in the production and made it possible to identify the occurrences of each failure in proportion to each other.

The *OEE* baseline, seen in Fig. 2 showed a relatively low *OEE* score for availability compared to performance and quality, classified as world-class. Therefore, a more thorough analysis of the factors affecting availability is performed by use of Power BI. Thus, looking at the planned and unplanned stop time, both elements are cause for lost time, and the focus is therefore directed towards finding possible improvement measures which can reduce the lost time spend on stops. As the stops can be due to failures, setup and adjustments, a closer look at these factors are necessary to point out the most promising approaches. Using Power BI, the registered failures are organised and displayed in Pareto charts to help identify the most common failures resulting in the biggest losses.

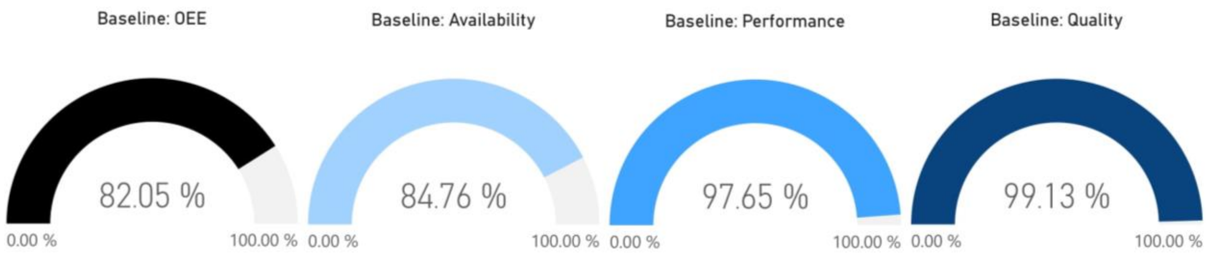

Figure 2: Analysis of availability, performance and quality for the *OEE* Baseline.

4.1 Scenario development and analysis

Based on the expressed desire from the stakeholders to improve upon availability alongside observations from the visualised data, the case study will test the impact of enhancing this factor. Based on the extracted data from the simulation of the current scenario, the following scenarios are constructed to alleviate bottlenecks and improve upon the weighted *OEE* score.

First, lower the planned downtime within process A by 1, 2, 3, 4, and 5 hours and process B by 1, 2, 3, 4, 5, and 6 hours. Secondly, improving upon the top 3 failures within process A and process B, taking the following two different approaches:

- Improving upon the occurrences of the problem. In other words, making sure the failures do not happen as often.
- Improving upon the Mean Time To Repair. Advance the speed of solving the individual failure and thereby limit downtime.

The current simulated scenario and the improved scenarios are based on two months of production to mitigate the warm-up period. The *OEE* score for the entire simulated period is represented as an average and will thereby show the greatest tendencies for improvements. Additionally, a point of consideration is the amount of data produced, as for this example, two months of production, including three processes, generates 19 columns with approximately 60,000 rows, which takes significant processing time.

Based on the data extracted from the tests bringing down planned downtime on process B, it can be observed in Fig. 3 that the largest *ROI* is achieved by a reduction of one hour and next two hours. Whereafter the *ROI* diminishes as a new bottleneck is formed elsewhere in the production.

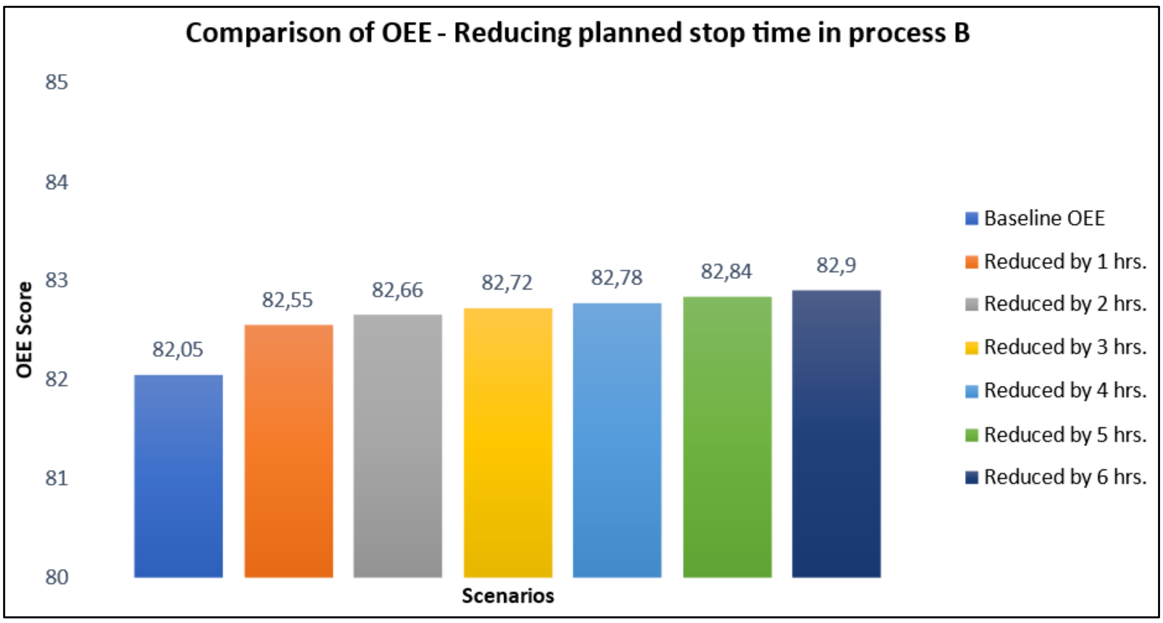

Figure 3: Comparison of *OEE* scores when optimising on planned stop time for process B.

The same comparison of lowered planned downtime for process A was carried out using the same procedure. Thus, similar results were reached. Hence, the most significant gain was reducing planned downtime from 0 to 1 hour and next from 1 to 2 hours.

Through the process of multiple tests on the improvement upon failures in process A, the comparison of optimising failure, named here as X, in relation to *MTTR* and occurrences by 5 %, 10 % and 15 % can be seen in Fig. 4. The largest improvement is achieved through a 5 % decrease in *MTTR*. Hereafter, further improvement is resulting in a decrease in *OEE* due to new occurring bottlenecks. On the other hand, optimising within occurrences, a smaller achievement is seen while performing a 5 % improvement. However, a larger increase in *OEE* is seen from 10 % improvement within occurrences.

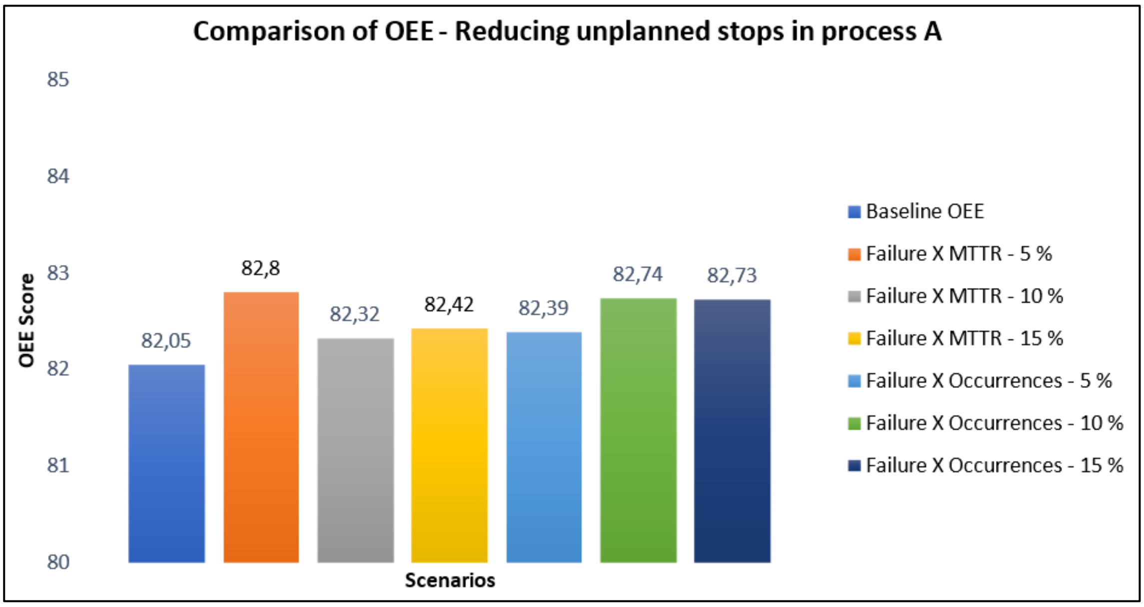

Figure 4: Comparison of *OEE* scores when decreasing unplanned stop time for process A.

Based on the best performing scenarios from the improved planned downtime tests, a set of combinations are constructed to identify correlating factors and suggest an improvement strategy.

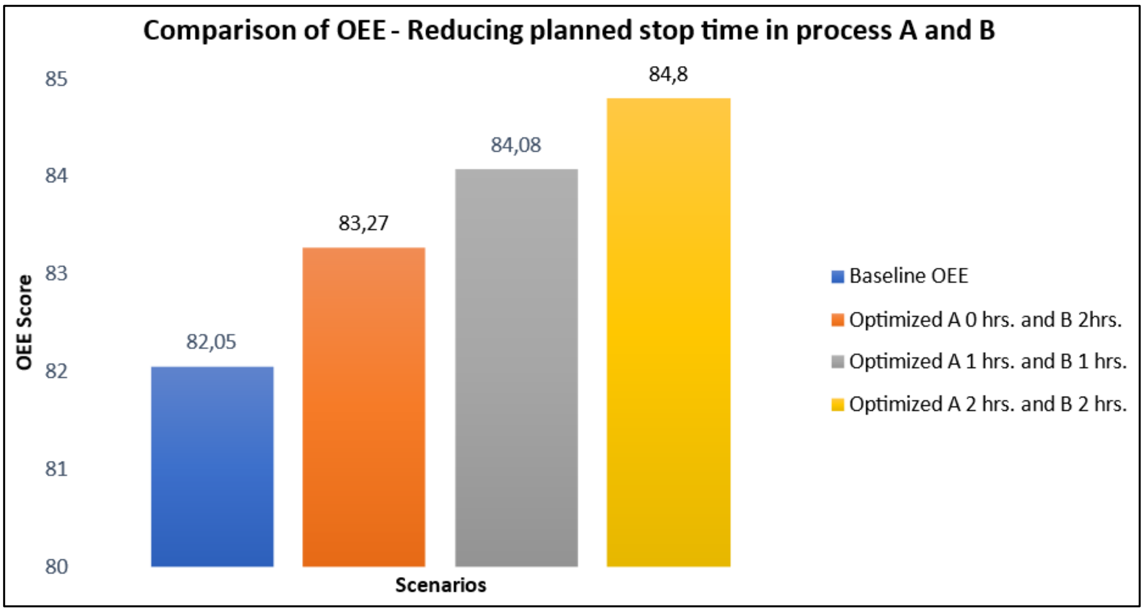

Figure 5: Comparison of *OEE* scores when optimising planned stop time for both processes A and B.

As seen in Fig. 5, bringing down planned downtime for process B in two hours does not increase the *OEE* score as much as if process A and B are improved simultaneously, which indicates a correlating factor that may support the decision-making on where and how to enhance. Also, showing the gain in *OEE* for reducing planned downtime by two hours for each process is not twice the size of one hour's improvement for both processes.

Although the reduction of downtime or other improvements leads to a predictable conclusion of enhanced productivity, the changes in the input do not necessarily change in direct proportion to the outputs since interdependencies in the manufacturing process usually lead to nonlinear results, as demonstrated in this case study. Therefore, our data-driven approach provides managers and practitioners with a quantitative way to analyse whether the efforts to achieve a certain improvement are worthwhile before redesigning a process.

5. CONCLUSIONS AND FURTHER DIRECTIONS

Summing up the approach suggested in this paper, the framework consisting of understanding the real world, converting it into a conceptual model and using simulation to make a computer model and analyse it to find the basis for *OEE* measurements by use of data analytics software. Combining the strengths of two different tools used in the Industry 4.0 is new in the field and increases the value of improving manufacturing processes by use of simulation and data analytics. Hence the benefits of using the proposed framework for increasing *OEE* is to risk-freely test different approaches, see the outcome of the tests, spot tendencies and interdependencies without risking the production, staff, and invest in less effective measures.

The use of data analytics, both tools and methods, for analysing the data created by the simulation software solves the issue often seen when the producers of the simulation models want to present the results and data gained in the model. Here, the lack of visuality limits the communication between the developers and the stakeholders. Hence the aspect of being able to visualise production flows and KPI's like *OEE* is considered. Thus, making it easier to convey progress and data in interdisciplinary cooperation. This can also add value in businesses when presenting suggestions for improvement to decision-makers who can visually understand and make data-driven decisions. Furthermore, the fact that the entire production line is mapped and monitored in simulation also makes it possible to see the knock-on effect both upstream and downstream from any measures implemented. Thereby, it is possible to ensure that any investments do not negatively affect other parts of the line.

The limitation of this approach includes the investments in software to fully utilise the power of the tools. Furthermore, the amount of data and the current setup of the software is not fully capable of transferring the big data sets, which causes the transferring process to be long and time-consuming. Therefore, it requires additional development of the programs to fit this new combination of tools.

To achieve a better decision-making process for managers, further development within interactive dashboards/reports that combine historical data, simulated data, and changes/effects should strengthen the ties to a data-driven management structure.

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