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THE VALUE OF 5G CONNECTIVITY FOR MAINTENANCE IN MANUFACTURING INDUSTRY

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ABSTRACT

Digitalization is an ongoing revolution within manufacturing industry. 5G technology is expected to play an important role in ensuring connectivity. Digitalized factories set high requirements on technical availability, and therefore also on maintenance performance. However, it is difficult to get top-level decision makers to invest in maintenance, since the effects are usually deferred and difficult to verify up front. For quantifying long term effects, Discrete Event Simulation (DES) is identified as a powerful tool. In this study, DES was combined with established maintenance concepts to provide analysis of a real-world industrial 5G pilot implementation. Maintenance concepts were used to identify relevant inputs and outputs to the simulation model. The model was tested on a use case, where 5G enables support for maintenance tasks. By applying DES and maintenance concepts on more use cases, there is a potential to quantify effects of maintenance and enable digitalized production in a larger scale.

1 INTRODUCTION

The development of manufacturing industry is moving towards digitalization. Digitalization and smart manufacturing has been widely discussed, and technologies such as smart sensors, Internet of Things (IoT), and big data are highly related to smart manufacturing and digitalization. The technologies have not been discussed to a large extend in the context of whole factories, since networks have not been available to ensure high speed transferring transfer of big data sets (Kang et al. 2016). High speed transfer is expected to be enabled by 5G technology, the fifth generation of mobile radio network, and will therefore play an important role in the digitalization development in industry. 5G is also expected to be more reliable, and have therefore potential to meet the connectivity requirements in sensitive industrial processes. In automotive manufacturing, with cycle times between 40-60 sec, temporary loss of connection can generate major costs, even if the stops only last for a couple of minutes (Khaleel et al. 2015). Moreover, 5G provides the ability to transfer high volume data with low latency, enabling real time data analysis of equipment. Real time data analysis can provide information of current status of the equipment, and detect complex correlations utilizing big data analytics. This can be used for decision support in operations and maintenance, to increase flexibility, efficiency, and technical availability.

Even though maintenance plays an important role in production (Ylipää et al. 2017) it has proven difficult to quantify the value of maintenance. The major reason is that the positive effects of maintenance investments are usually deferred and difficult to verify on beforehand. There are several established methods and concepts that can be used to plan, evaluate and quantify the effects and costs of maintenance. Some examples of methods and concepts are Value Driven Maintenance (VDM) (Haarman and Delahay 2004), Reliability Centered Maintenance (RCM) (Rausand 1998), and Life Cycle Cost analysis (LCC) (Waeyenbergh and Pintelon 2002). In addition, maintenance research has been done in the context of profit, cost reduction, and performance. Alsyouf (2007) suggests maintenance as a profit generating function, based on a case study where an effective maintenance policy of a paper mill machine could, ideally, generate extra profit. By avoiding all unplanned stops and quality issues due to maintenance, extra profit corresponding to 12.5% of its yearly maintenance budget could be generated. In a survey study made by Swanson (2001), responses from plant managers and maintenance managers show a positive relationship between proactive maintenance strategies and performance. Al-Najjar and Alsyouf (2004) presents a case study where a model was developed to identify, monitor and improve economic impact of Vibration-Based Maintenance (VBM), to identify potential savings. Salonen and Deleryd (2011) proposes a concept for managing maintenance performance improvements within manufacturing industry. The concept is called Cost of Poor Maintenance (CoPM) and may help to identify justified maintenance costs and which costs relate to poorly performed maintenance. In contrast, Marais and Saleh (2009) argue that existing cost-generic models are missing the value of maintenance, and suggest a framework to quantify the value of maintenance activities.

Moreover, Discrete Event Simulation (DES) is a common tool used in industry to perform analysis to verify production capacity. It has also been used for maintenance related issues. With its ability to model complex systems, DES is a potential tool to get a view of maintenance cost depending on the dynamic behavior of the system (Alabdulkarim et al. 2013). Alabdulkarim et al. (2013) present a literature review, summarizing how simulation has been used to evaluate the ratio of preventive maintenance (PM) and corrective maintenance (CM), for scheduling PM, for staffing analysis, and for maintenance costs analysis.

Despite the knowledge provided by maintenance research, it is still difficult to prove and verify the effects and value of maintenance in industry, since the benefits (e.g. reduced failure rate and increased throughput) do not appear immediately. The difficulty related to verifying the effects makes it challenging to get top-level decision makers to invest in maintenance. This indicates a missing link between maintenance theory and industrial practice.

Therefore, this paper aims to use established maintenance concepts in combination with DES to quantify the long term effects of maintenance. By incorporating the introduction of 5G technology and increased digitalization in industry, it may be possible to approach maintenance differently. This study has been performed in connection with a digitalization project where a manufacturing company, a telecom company and researches worked together to demonstrate effects of 5G enabled manufacturing. During the project, use cases on how to utilize 5G for maintenance decisions has been specified. The use cases includes real time data analysis to predict failures. This study shows how DES can be used in combination with established maintenance concepts to evaluate these use cases. It does also provide a description of how 5G enables decision support for maintenance in this specific use case.

2 METHODOLOGY

The following methods were used in the study to: combine DES and established maintenance concepts, generate scenarios for 5G enabled maintenance, and evaluate the effects of the scenarios in a DES model.

2.1 Literature study

A literature study has been performed to see how DES has been used for maintenance issues in prior research. Established maintenance concepts were also studied to find factors considered important for further use in the simulation model. The scientific database *Scopus* has been used to search for literature from both journals and conferences. Examples of key words used in the searches are: “Value driven maintenance” and manufacturing or production; Simulation and “maintenance research”. For selecting the most relevant literature, keywords, abstract and conclusion of literature were read.

2.2 Interviews

For describing the use case and scenarios of how data analysis could be used for failure prediction, group interview were held with experts from the companies in the project. Semi-structured interviews were also conducted with process experts and maintenance experts at the case company to collect input data to the simulation model and to set up the experimental plan. Interviews were also used to identify parameters considered important for the company to evaluate in the simulation model.

2.3 Discrete event simulation

For this study, the project methodology suggested by Banks (2010) was followed. The model was built in AutoMod® and based on interviews and guided tours with observations of the manufacturing system. The model was validated by face validity (Sargent 2005) with process and maintenance experts at the company.

2.3.1 Use case and scenario description

The simulation model built for this study represents a real-world factory in discrete manufacturing. The production flow is described by Figure 1. How 5G could support maintenance decisions with data analysis and failure prediction were specified during a group interview in the project. 5G with its high bandwidth and low latency will enable more connected equipment and real-time transferring of big data sets. By having all equipment in a factory connected, analysis by specialized algorithms can be used to find complex correlations in the data. The algorithms can by the correlations further predict not only the failures, but also symptoms.

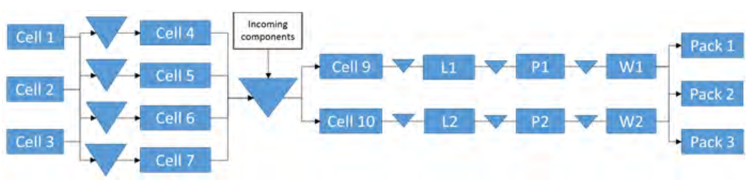

Figure 1: Description of the use case system (production flow).

A worn component can cause symptoms in the equipment, for example vibrations, resistance in movements, or increased temperature, leading to quality issues. When trying to control the development of the symptoms and their impact on quality, the speed of the machine is usually reduced, resulting in speed losses. However, speed reduction might not prevent, but only slow down the development of the symptoms, and there are no indications of when, or which component will fail. The components are expensive to hold in storage, and some are customized and manufactured by order. A failure of these components can therefore cause stops lasting for several days or even weeks. Unexpected and long failures will have an impact of the whole system, since the buffer capacity is not enough to cover up for the stop time.

With real-time data analysis, it is expected to detect deviations in the data before they appear as symptoms, and predict both symptoms that causes quality issues and failures of the components which, in turn, might cause long stops. By prediction of symptoms, the speed in the machine can be reduced before quality issues appear. By prediction of failure, an indication of remaining useful live is given, making it possible to order the spare part in time and plan the replacement to have the least possible impact of the whole system.

This use case will focus on failure prediction. To evaluate the impact of failure prediction, three critical components were chosen to focus on; components A, B, and C. The case company divides stops and failures into short, medium and long failures. In this stage of the project, the failure prediction is expected to reduce maximum duration of a long failure caused by the current component, since prediction reduces time for troubleshooting and enables preparation of repairs. For some components, time for PM is increased since more inspections is expected to be done. Five scenarios have been specified. Scenario 1, current state were no prediction is conducted; Scenario 2, failure prediction of component A; Scenario 3, failure prediction of component B; Scenario 4, failure prediction of component C; and Scenario 5, failure prediction of components A, B and C.

2.3.2 Experimental plan

The experimental plan was set up with process and maintenance experts according to the use case and the scenario descriptions in 2.3.1. Prediction of failures is expected to reduce their maximum durations. The scenarios and their effects on parameters are described in Table 1. The input parameters were changed for each resource individually, since component failure durations and probability vary independently between different machines.

Table 1: Description of the scenarios and parameters.

Scenario	Effects on input parameters
Scenario 1 – Current State	As is with current manufacturing setting
Scenario 2 – Prediction Component A	Time for PM increased Maximum duration for long failure component A decreased
Scenario 3 – Prediction Component B	Time for PM increased Maximum duration for long failure component B decreased
Scenario 4 – Prediction Component C	Maximum duration for long failure component C decreased
Scenario 5 – Prediction Component A, B & C	Time for PM increased, Maximum duration for long failure component A, B, C decreased

2.3.3 Data collection

Data related to the manufacturing processes (for example cycle times, buffer capacity etc.) were estimated by the company and based on data from the process. Data related to maintenance; number of failures, PM, and mean time to repair (MTTR) were based on interviews with maintenance experts and process experts. Further, input data for the future scenarios were estimated by the experts based on their experience of the production system and expected effects of failure prediction.

2.3.4 Delimitations

Delimitations and assumptions in the simulation model:

- Due to the novelty of the simulation model and the created scenarios, the input data is based on experts' experiences and expectations. Thus, no validation with quantitative data has been made.
- Not all identified parameters from the referred maintenance concepts (Table 2) has been used.
- Personnel not included in model – assumptions made that staff is available when needed.
- Performance and quality (in overall equipment effectiveness, OEE) were assumed not to be affected between the scenarios.

3 FRAME OF REFERENCES

The following sections will describe common concepts and methods related to maintenance, and describe how simulation has been used for maintenance related problems and questions before. It also includes a section describing 5G in industry.

3.1 Digitalization and 5G

Digitalization is an ongoing transformation in the whole society. 5G has mostly been discussed in connection to end-customer applications, such as autonomous vehicles. This is due to the direct impact on society and people's everyday life. But 5G is also expected to play an important role in the digitalization of industry, as more connected equipment and more data transferring will require higher bandwidth. Moreover, real-time remote monitoring and control of equipment require fast transferring of data with resilient and secured connectivity. 5G, with its low latency, ability to handle big data sets and reliable connectivity is therefore the potential future communication platform in factories (Arthur D. Little 2017). Another key advantage of 5G is the elimination of wiring, which enables flexible production line configuration. Some specific aims of 5G systems compared to previous generations are (5G PPP 2015): 1000 times higher data volumes, 100 times higher data rates, 10 times lower energy consumption, 5 times lower end-to-end latency, and at least 99.999% service reliability for mission critical services.

Examples of potential applications of using 5G network in manufacturing industry are remote monitoring of stationary and mobile equipment, remote control of stationary and mobile equipment, machine-to-machine communication, intra/inter-enterprise communication, and increased reality support in design, maintenance and repair.

3.2 Maintenance concepts

Established maintenance concepts were studied in order to determine relevant input and output parameters to the simulation model. Following paragraphs will provide a general description of the concepts, and the related input parameters identified can be found in section 4.1.

RCM is a planning approach of maintenance activities by focusing on the functions in a system (Rausand 1998). The functions are classified into different categories depending on how the function failures affects the system. The aim is to identify the required functions in the system, to identify the ways the system can fail, and plan the preventive maintenance tasks with objectives to prevent the most critical functions to fail. RCM can both be used to develop a maintenance program from scratch, but also to improve an existing by removing inefficient PM tasks. There are 4 principles characterizing RCM; preserve functions, identify failure modes that can disrupt the functions, prioritize the functions and select effective PM task according to it (Smith and Hinchcliffe 2004).

VDM is a maintenance management methodology with the aim to add value and profit to the company. It is a method for improving the cost effectiveness, rather than planning maintenance activities (like RCM). Haarman and Delahay (2004) describe the value drivers in maintenance as utilization, resource allocation, cost control, and safety, health, and environment (HSE). Stenström et al. (2013) presents a study where indicators from EN 15341 standards (CEN 2007) for measuring maintenance performance were used to identify indicators related to the value drivers in value driven maintenance and calculation of net present value.

Cost deployment has the objective to map the losses in a system, in order to reduce the cost of them (Yamashina and Kubo 2002). The different steps in the method is to, first investigating production losses and categorize them, then identify relationship among the losses and their costs and if there is a known way to reduce the loss. The last step is to estimate the cost reduction and prioritize the reduction of losses accordingly. Breakdown loss, short stoppage loss, and speed down loss are some losses related to maintenance.

The purchase cost does often only cover a small amount of the total cost of equipment (Waeyenbergh and Pintelon 2002). LCC analysis is an approach which considers this, by estimating the overall life cycle cost from cradle to grave. In manufacturing it plays an important part for decisions and planning related to reliability and maintainability (Reina et al. 2016). The cost of maintenance varies according to strategy and policy, and the aim of LCC is to choose the most cost effective approach to gain benefits in a long term perspective. The cost calculations are based on the cost of corrective maintenance and preventive maintenance respectively. LCC can also include to evaluate however the maintenance work should be performed internally, externally, or by contracting.

Total productive maintenance (TPM) is an approach that focuses on improving the performance-effectiveness in maintenance (Waeyenbergh and Pintelon 2002). The objectives of TPM is to maximize the equipment effectiveness and as a measure, OEE (availability, speed, and quality) is used. However, costs and profit are not taken into account, and the approach does not provide any strategy/rules regarding the use of different maintenance policies (failure based, condition based etc.).

3.3 Simulation and maintenance

Alabdulkarim et al. (2013) presents a literature review to examine how simulation has been used for mainenance research. One common application presented was maintenance policies - evaluation of PM and CM, and their impat on resource allocation, performance and cost. Planning and scheduling of PM are other common applications, and staffing are well used in simulation. Maintenance cost is major research area. Simulation has the potential to calculate maintenance operation cost depending on system dynamics and behaviour. However, studies have not focused on how to use simulation combined with established mainteancne concepts to facilitate communication of decision support for maintenance.

4 RESULTS

This chapter will present how simulation can be used to evaluate the effects of using 5G for maintenance decision support. It will present the identified possible input and output parameters based on established maintenance concepts and parameters used in the model, and the results from the simulation model.

4.1 Mapping of input and output parameters from maintenance concepts

Important model parameters to combine the benefits of DES and established maintenance concepts were identified by interpretation of the concepts presented in section 3.2 and from the project use case. Based on simulation experience of the authors, the parameters where divided into inputs and outputs (Table 2).

Table 2: Input and output identified based on the established maintenance concepts.

Concept	Input	Output
RCM	Mean time to failure (MTTF) Mean time to repair (MTTR) Failure rate function	Ratio CM and PM, Criticality (safety, environmental impact, production availability, material loss)
VDM	Number of maintenance personnel	Maintenance personnel cost, Cost of CM, Cost of PM, Production output, Production uptime, Tot. time planned maintenance, Tot. maintenance downtime, Tot. failure downtime, Tot. time to repair, Tot. waiting time, Maintenance overtime, Tot. no. of maintenance injuries, Tot. no. of failure injuries, Tot. no. of failures causing environmental damage
Cost Depl.	MTTF, MTTR, Performance Defected products per stop	Total downtime, Total defect products due to stops Total cost of stop
LCC	Operator cost, Downtime, Spare part cost, Time for PM	Cost of PM Cost of CM
TPM		Overall equipment effectiveness (OEE)
Project	Time for PM per PM-stop, MTTR Number of stops and failures	Production output, Utilization of resources, OEE, Efficiency, Flexibility, Traceability, Sustainability

Inputs and outputs to the simulation model were selected from Table 2 in order to be in line with this specific use case and the goal of the project. The selection of parameters were also limited by the accessibility of data from the company. The inputs and outputs used in the simulation model are described by Table 3. Number of failures were divided into three categories; short, medium and long failures. For these categories, different MTTR were used.

Table 3: Input and output used in the simulation model.

Input	Output
Time for PM per PM-stop, Number of failures, Failure rate function, MTTR	Production output, Utilization of resources, Total time planned maintenance, Total failure time, Total maintenance downtime, OEE (for bottleneck)

4.2 Results from simulation study

This section will present the results from the simulation model in terms of above specified output.

4.2.1 Production output

Production output from the different scenarios is described by Figure 2 and Table 4. The production output in Scenario 1 has been normalized to 100%, and all subsequent results (Scenarios 2-5) are relative to this. All future scenarios (Scenarios 2-5) shows an increased production output. The results in Table 4 indicates that predicting failures of one component (Scenario 2, 3 and 4) increases the production output by 2%. Failure prediction of all components increases the production output by 3%. Moreover, the standard deviation in Scenario 5 is lower than in all other scenarios, indicating that prediction of failures will contribute to a more robust production output.

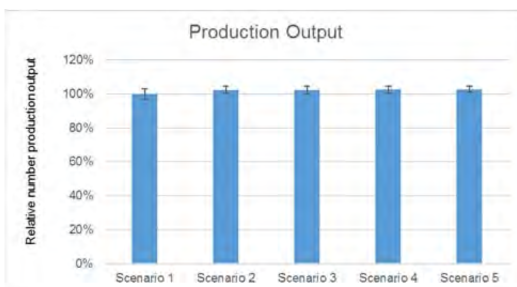

Figure 2: The figure presents relative number of production output in the five different scenarios.

Table 4: Average value and standard deviation of production output.

Scenario	Production Output	
	Average value	Standard deviation
Scenario 1	100%	3.1%
Scenario 2	102%	2.1%
Scenario 3	102%	2.3%
Scenario 4	102%	2.1%
Scenario 5	103%	1.7%

4.2.2 Utilization

Figure 3 shows the utilization of all resources in Scenario 1. From the graph it is possible to obtain the working time for each resource, as well as total time for PM, total failure time and total maintenance downtime. Total maintenance downtime is the sum of failure time and time for PM. By looking at the active period (working, failure, PM), Cell 6 is determined to be the bottleneck. The active period of Cell 6 has been normalized to 100% and the results presented in Figure 3 and Table 5 are relative to this. For example, the working time in Cell 6 in Scenario 5 is 83.8% of the active period of the cell in Scenario 1.

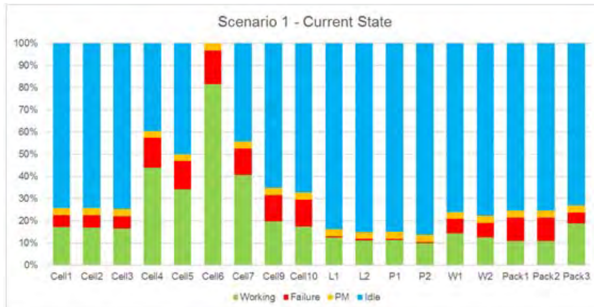

Figure 3: The figure summarize the utilization of all resources.

Table 5 describes the different states working, failure and PM, as well as total time for maintenance and increase of active period in Cell 6. By looking at the working time between Scenario 2, 3 and 4, failure prediction of component A, B and C respectively, it seems like component B have the greatest impact of improvement of working time in Cell 6. However, the results shows that failure prediction of component C is most important from a systems perspective. The active period of Cell 6 increased by 0.2% from Scenario 1 to Scenario 4. This means that the idle time, time spent on waiting for other resources due to starvation or blocking, was decreased. Scenario 5 with failure prediction of all components, enables the most efficient usage of Cell 6. Compared to Scenario 1, the working time increased from 81.7% to 83.8%. The increased working time could not only be explained by the reduction in total maintenance downtime (from 18.3% to 16.5%), but also by the increase of active period (reduced idle time). The active period increased by 0.3%.

Table 5: Utilization results of Cell 6 from the simulation model.

Scenario	Cell 6				
	Work	Failure	PM	Tot. maint	Increase of active period
Scenario 1	81.7%	15.1%	3.2%	18.3%	0.0%
Scenario 2	83.5%	13.4%	3.3%	16.6%	0.1%
Scenario 3	83.6%	13.1%	3.3%	16.4%	0.0%
Scenario 4	83.6%	13.4%	3.2%	16.6%	0.2%
Scenario 5	83.8%	13.2%	3.3%	16.5%	0.3%

The average value of working time per resource slightly increased from Scenario 1 to Scenario 5, from 22.2% to 22.8% relative the active period of Cell 6 in Scenario 1. The small increase, compared to the increase in working time of the single bottleneck, indicates that the bottleneck is highly utilized compared to the other resources, which is also shown in Figure 3. In this specific case, the improvements of the system is almost limited to the improvement of the bottleneck. However, the average value of total downtime for maintenance per resource was decreased from 10.7% to 10.0%, indicating a potential to reduce direct maintenance costs.

4.2.3 OEE

OEE of the bottleneck resource, Cell 6, can be obtained by Figure 4. The OEE in Scenario 1 has been normalized to 100%, and all subsequent results (Scenarios 2-5) are relative to this. In the figure it is possible to obtain a slightly increase of OEE, but the most clear improvement is the reduction of the standard deviation. Between Scenario 1 and Scenario 5, the average value increased from 100% to 102%, and the standard deviation decreased from 17% to 11%. This indicates a more robust OEE of Cell 6.

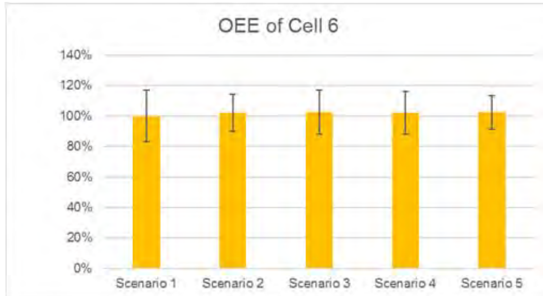

Figure 4: The figure shows how the relative OEE value was changes between the scenarios.

4.2.4 Summary results

The results indicate a potential of more efficient resource utilization and increased production output by using 5G enabled data analysis and failure prediction. The failure prediction is expected to reduce the maximum duration of long failures. This specific case shows a potential to increase production output by 3% and lower its variation from 3.1% to 1.7%. The active period of the bottleneck increased by 0.3%, which means that time spent on waiting for other resources due to starvation or blocking, was decreased.

However, the variation of production output and OEE in Scenario 1 is bigger than the potential improvement in Scenario 5, meaning that the results are not statistically significant. The results shows an uneven utilization of the resources, where improvements of the system is almost limited to the reduction of failure time of the bottleneck. But the indication of lower variation means that failure prediction can contribute to more robust production output. Moreover, the results shows a decreased average value of total maintenance downtime per resource, from 10.7% in Scenario 1 to 10.0% in Scenario 5. Reduction in total maintenance downtime means a potential to decrease direct maintenance costs.

Even though the results were not statistically significant in this specific study, simulation results can visualize the effects of maintenance. Results based on suggested maintenance concepts can be used to build business cases and justify improvements for stakeholder.

5 DISCUSSION

Maintenance organizations must take a key role in enabling industrial digitalization by securing the necessary system dependability (Ylipää et al. 2017). However, a big problem and paradox is that maintenance investments are commonly difficult to justify because the benefits (e.g. reduced failure frequency) cannot be immediately proved and verified. Given this situation, DES can be a key enabler with its ability to simulate future scenarios and provide valuable insights before the investments are decided. However, to increase the understanding and level of trust to decision makers, it is important to integrate DES to established maintenance models and current procedures around building business cases for investments. Established maintenance concepts can be used to choose relevant parameters to focus on with respect to the current question, to facilitate understanding and communication of the value of maintenance.

This study is part of a larger project targeting one of the first industrial 5G projects in the world focusing on the manufacturing industry. Understanding challenges and opportunities with digitalization in general, and 5G connectivity specifically, is important for the simulation community. In this way the community can define its role in contributing optimally to the digital transformation of manufacturing industry. Therefore, example cases as presented in this paper are necessary complements to general literature on industrial digitalization.

There are few unexpected simulation inputs and outputs identified from the established maintenance concepts selected in this study. Many of the parameters are needed in studies summarized by Alabdulkarim et al. (2013). The simulation environment as such is therefore familiar to the simulation community. However, the most important take-away from this study is the explicit combination of DES and maintenance concepts such as RCM, VDM, LCC, Cost Deployment and TPM (Rausand 1998; Haarman and Delahay 2004; Yamashina and Kubo 2002; Reina et al. 2016; Wayenbergh and Pintelon 2002). This combination creates internal validity towards maintenance decision makers.

The experimental plan was set up in order to quantify the effects of using 5G enabled decision support in this specific use case. The use case included description of failure prediction of three critical components, with expectations of reduced maximum duration of a long failure. It is not unexpected that the results indicate shorter failure time and maintenance downtime for the resources. The results are not statistical significant, but this study demonstrates how simulation can be used to evaluate the effects of maintenance.

The results shows a potentially increased, more robust production output and OEE, and decreased maintenance downtime. Moreover, failure prediction can potentially contribute to additional value which is not considered in this simulation study. Planning, customers and delivery precision were discussed by experts at the manufacturing company during the experimental planning. Increased robustness by failure prediction can reduce the uncertainty, and increase the ability to plan and deliver the products to the customers in time.

The simulation model is built to analyze a new system and possible investments in new technologies. Therefore, there has naturally been a lack of validated input data, and input data has been collected from similar equipment and assumptions made by process experts. It is worth mentioned that this study was made in an early stage of the project, and assumptions made regarding the effects of failure prediction could be considered as conservative. Real time data analysis is expected to detect deviation in the data before they appear as symptoms which causes quality issues, speed reduction, failures or other maintenance related issues. But in this specific case, failure prediction was assumed to only reduce the maximum duration of long failures, and not eliminate, or even reduce the number of them. A future vision should be to remove such failures, and only do repairs during planned stop with minimum, or no, effect of the whole system. The simulation model is built to be used in an iterative process, to be updated with new input data and features based on learnings along the project.

It should also be mentioned that this is a single case study and the authors have no intention to claim generalizability. Instead, the most important contribution of this paper is to add to interesting case descriptions inspiring further use of DES to enable industrial digitalization as well as the development and use of 5G connectivity. The bottom line is that DES can take a key role in enabling the digital transformation of manufacturing industry and facilitate investments in 5G connectivity and modern maintenance solutions. More digitalization cases are desirable to inspire further implementations. This paper proposes that that DES should be combined with established maintenance concepts to increase validity towards decision makers and thereby mitigate current problems with limited dissemination of DES.

6 CONCLUSION

This paper proposes the use of DES to be e key enabler of implementing 5G connectivity in manufacturing plants. Expected scenarios with 5G enabled manufacturing were presented based on a real-world digitalization project with manufacturing and telecom companies collaborating with researchers. This specific case focuses on the implementation of modern maintenance solutions to reach the necessary levels of productivity and availability. By combining DES with established maintenance concepts (for example VDM, RCM, LCC), a list of relevant input and output to the model was suggested. A selection of these inputs and outputs have been tested in a simulation model, based on the scenarios expected with 5G connectivity. This case-specific simulation model indicates a positive impact of implementing 5G enabled maintenance solutions with positive effects such as increased production output, improved robustness and reduced total maintenance downtime. These results can be used as decision support for investments in modern maintenance solutions. Extending the proposed approach, of combining DES with established maintenance concepts, is expected to facilitate positive investment decisions in modern maintenance solutions, and thus, enable digitalization of manufacturing industry. Finally, the results and experiences of this study will serve as inputs to the requirement specification of 5G networks and additional services offered by network providers, such as mission critical clouds and analytics services.

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