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Procedia CIRP 57 (2016) 128 – 133

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49th CIRP Conference on Manufacturing Systems (CIRP-CMS 2016)

Analysis of critical factors for automatic measurement of OEE

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Abstract

The increasing digitalization of industry provides means to automatically acquire and analyze manufacturing data. As a consequence, companies are investing in Manufacturing Execution Systems (MES) where the measurement of Overall Equipment Effectiveness (OEE) often is a central part and important reason for the investment. The purpose of this study is to identify critical factors and potential pitfalls when operating automatic measurement of OEE. It is accomplished by analyzing raw data used for OEE calculation acquired from a large data set; 23 different companies and 884 machines. The average OEE was calculated to 65%. Almost half of the recorded OEE losses could not be classified since the loss categories were either lacking or had poor descriptions. In addition, 90% of the stop time that was classified could be directly related to supporting activities performed by operators and not the automatic process itself. The findings and recommendations of this study can be incorporated to fully utilize the potential of automatic data acquisition systems and to derive accurate OEE measures that can be used to improve manufacturing performance.

Peer-review under responsibility of the scientific committee of the 49th CIRP Conference on Manufacturing Systems

Keywords: Overall equipment efficiency; operator influence; loss classification; performance measurement

1. Introduction

Overall Equipment Effectiveness (OEE) is a widely used performance indicator in manufacturing industries around the world. It was initiated when Nakajima [1] introduced the Total Productive Maintenance Concept (TPM) where the main goal is to improve and sustain equipment efficiency. Most of the research involving the OEE measure is, thus, related to maintenance [2, 3], but also to areas such as performance measurement [4-6] and productivity improvements [7-9].

The increasing digitalization of industry provides means to automatically acquire and analyze manufacturing data. As a consequence, companies are investing in Manufacturing Execution Systems (MES) where the OEE measurement often is a central part and important reason for the investment. However, the validity and usefulness of OEE measures are highly dependent on the data collection and, as stated by Saenz de Ugarte, Artiba [10], technology can assure the availability of data but not guarantee that the data is accurate.

The purpose of this paper is to identify critical factors and potential pitfalls when operating automatic measurement of OEE. It has been accomplished by analyzing a large set of raw data used for OEE calculation, provided by an industrial software company specialized in real-time production follow-up and disturbance handling. The paper is initiated with a literature review on the OEE measure. It is followed by modelling and analysis of the empirical data set. Conclusions are drawn with implications for both theory and practice as well as for future research.

2. Overall Equipment Effectiveness

The OEE measure is considered most suitable for semi-automatic and automatic manufacturing processes [11] and it originates from the highly automated semiconductor industry [12]. It is defined as the ratio between the time spent on

Peer-review under responsibility of the scientific committee of the 49th CIRP Conference on Manufacturing Systems
doi:10.1016/j.procir.2016.11.023

producing goods of approved quality to the scheduled production time (loading time) [1]. One of the main reasons for the widespread application of OEE, among both researchers and practitioners, is that it is a simple, yet comprehensive, measure of internal efficiency [5]. In particular, the measure is incorporated as an important driver for improvement initiatives [4, 7]. The basic formula for calculating OEE is written as:

$$OEE = Availability \times Performance\ efficiency \times Quality\ rate \quad (1)$$

where availability is defined as a ratio of planned production time minus downtime (breakdowns and changeovers) over planned production time. Performance efficiency is the ideal cycle time times the number of products produced over actual runtime. The quality rate is the ratio between accepted products over number of products produced. These three factors aim to capture what Nakajima [1] defines as the six big losses in production.

Downtime losses:

1) Equipment failures are categorized as time losses when productivity is reduced, and quantity losses caused by defective products.
2) Setup and adjustment time losses result from downtime and defective products that occur when production of one item ends and the equipment is adjusted to meet the requirements of another item.

Speed losses:

3) Idling and minor stop losses occur when the production is interrupted by a temporary malfunction or when a machine is idling.
4) Reduced speed losses refer to the difference between equipment design speed and actual operating speed.

Quality losses:

5) Reduced yield occurs during the early stages of production from machine start up to until stabilization.
6) Quality defects and rework are losses in quality caused by malfunctioning production equipment.

Consequently, the downtime losses are used to calculate the availability factor, the speed losses determine the performance efficiency of the equipment, and the quality losses are incorporated to calculate the quality rate.

Previous research has shown that even though OEE is well defined in the literature, the interpretation of its underlying loss factors is a common reason for variations between companies [7]. An accurate OEE measure is, as stated, determined by companies' data collection ability and the level of accuracy needed [4, 5]. However, since the equipment efficiency is affected by the surrounding environment the OEE measure also depend on the actions of operators as well as the production planning and control polices of the company [12, 13]. The reminder of this paper presents an analysis of how these issues are of relevance in the context of automatic measurement of OEE. Besides identifying critical factors and potential pitfalls, it is also investigated how much of the total loss time that is operator influenced and how this, in turn, affects the OEE measure.

3. Data description

The empirical data set includes production follow-up data from 23 manufacturing companies and 884 machines. It covers a period of six months of production, starting from October 2013 to March 2014. All participating companies are situated in Sweden and operate the same system for automatic measurement of OEE. The data have been sorted into four industrial groups based on the nature of the companies' production system and the products they manufacture (Table 1). There were no company specific information provided other than industry type and number of machines.

Table 1. Number of companies and machines in each industry group.

Industry group	Food and Beverage	Mechanical Workshop	Other Automated Discrete Production	Polymeric (Rubber and Plastics)
Count companies	7	9	4	3
Count machines	244	364	119	157

The data was acquired as a single MS Excel file with loss descriptions and corresponding loss time durations for each machine. In total, there were 499 individual descriptions of loss times, which were grouped into eight categories:

- Planned downtime
- Setup time
- Measurement and adjustment
- Equipment failure
- Idling and minor stoppages
- Other down time losses
- Scrap/Rework
- Unclassified losses

The proportion of planned downtime constitutes non-scheduled time (e.g., weekends and shutdown due to lack of orders), scheduled maintenance, R&D usage, engineering time, breaks, meetings, and operator training. Since OEE is defined based on planned production time, these planned downtime losses were excluded in the calculation. The category unclassified losses include loss causes that were described as unclassified (i.e., "uncategorized", "no reason code", "other") and losses that could not be grouped into any of the other categories since they either lacked or had a poor description that could not be interpreted.

4. Results

4.1. OEE calculation

The calculated OEE measures represent the aggregated performance of the various machines. Bottleneck machines could not be identified since there were no available description of the companies' production flows. Figure 1 depicts the distribution of performance in OEE across all industrial groups at a 95% confidence level. As can be seen, the distribution is not symmetrical and using average values will therefore not reflect the true average as it is significantly influenced by the outliers. The overall median OEE of all 23 companies is 70% whereas the average OEE is 65%, indicating a positively skewed performance with more spread in the lower quartile region. The highest performance found in the Food and Beverage industry group with a median and average OEE of 74% while the Other Automated Discrete Production industry group has the lowest median and average OEE of 59%.

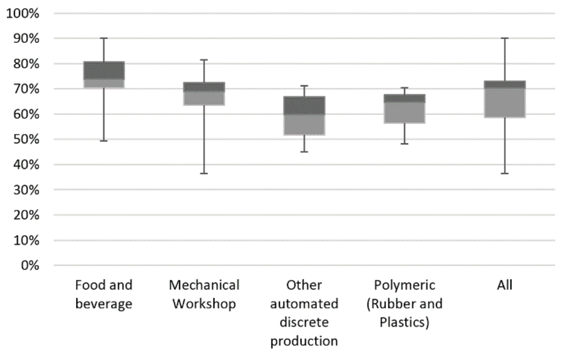

Figure 1. OEE comparison between the different industry groups.

The companies had not logged information concerning equipment design speed or actual operating speed for any of the machines. Therefore, it was not possible to calculate performance efficiency as ideal cycle time times the number of products produced over actual runtime. However, for the companies it was possible to define a performance rate for each machine. During the analysis it was found that the recorded performance rate for 702 out of 884 machines had the value 100%, implying that almost 80% of the machines were operating at 100% performance efficiency.

In addition, the quality rate could not be calculated as the ratio between accepted products over number of products produced since this information was not available. Instead, companies could define quality efficiency values for each machine. It was found that 796 out of 884 machines had a recorded value of 100%, implying that 90% of the machines were operating with a quality rate of 100%.

4.2. Distribution of losses

The recorded loss times were in the form of elapsed times and not event times. As can be seen in Figure 2, unclassified losses represents about 19% of the scheduled production time for all machines. This corresponds to more than half of the entire proportion of recorded loss time. The two second major losses are equipment failures (5%) and other downtime losses (5%), closely followed by setup losses (4%). The low presence of remaining losses is consistent with the high efficiency rates of the performance and quality factors.

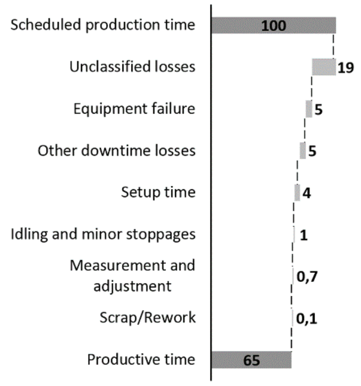

Figure 2. Distribution of losses for all industry groups [%].

4.3. Operator influenced loss time

The amount of operator influenced loss time was determined by systematically classifying each of the loss categories, based on their description in the data file, as either 'operator influenced loss time', 'may be operator influenced loss time', or 'not operator influenced loss time. Naturally, the proportion of unclassified losses, which lacked proper descriptions, had to be excluded. It is important to note that operator influence on loss times does not state that the losses are caused by operators, but refers to the fact that the operators are crucial factors in influencing the duration of the loss time [14, 15]. The three levels of operator influence were defined as follows:

- ***Operator influenced loss time***; losses where the duration of downtime, from when a failure occurs until the point at which the equipment returns to operations, is dependent on the activities carried out by operators (i.e., detection and repair). This also includes manual activities performed during equipment idle time, such as changeovers, measurements and adjustments.
- ***May be operator influenced loss time;*** losses where the duration of downtime may be dependent on the activities performed by operators. It primarily concern categories related to material shortage and waiting time. In those cases, it is not possible to determine if the equipment idle waiting for an operator to attend (i.e., refill material or attend the blocking/starvation of the machine) or if the idle time is more influenced by other factors than the operator. For instance, caused by an *overall lack of material in the inventory or balancing losses due to production system design.*
- ***Not operator influenced loss time;*** *losses where the duration of downtime is independent from the activities performed* by operators. For instance, lack of material from supplier, external deliveries etc.

The classification of loss time into levels of operator influence resulted in the distribution shown in Figure 3. There it can be seen that about 90% of the downtime recorded (excluding unclassified losses) can be directly related to supporting activities performed by operators and not the automatic process itself. As seen in Figure 4, setup time constituted the largest proportion of operator influenced downtime for the 'Mechanical workshop' and 'Other automated discrete production' industry groups. Whereas the 'Food and beverage' and 'Polymeric (rubber and plastics)' industry groups had equipment failures as the largest proportion of operator influenced downtime.

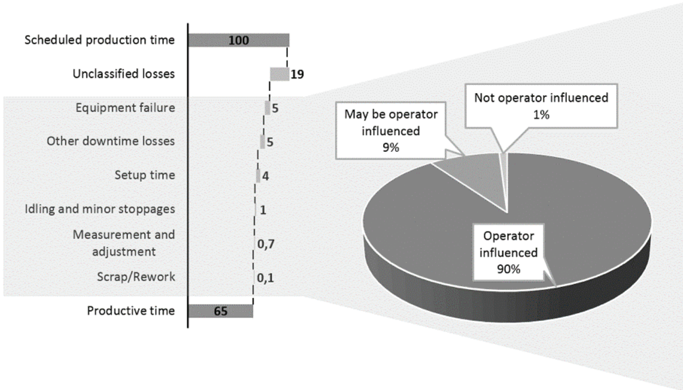

Figure 3. . Classification of loss time into levels of operator influence.

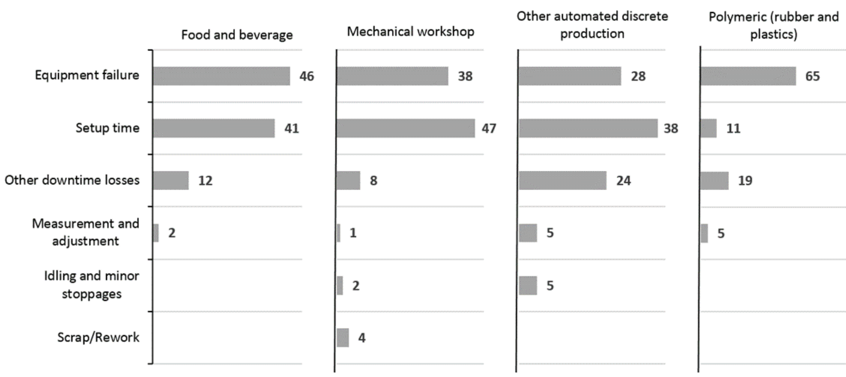

Figure 4. Distribution of 'Operator influenced loss time' across industry groups [%].

5. Discussion

Our results show that even though automatic OEE measurement facilitates acquisition of large amounts of detailed data, the degree of which the resulting OEE measures actually reflect that the equipment is doing what it is supposed to do is directly dependent on how well companies are able to interpret and define the underlying factors of OEE. This refers to the three main factors of availability performance efficiency and quality rate in general, and their underlying loss causes in particular.

It was found that over 80% of the machines, reportedly, had 100% performance efficiency. This means that they either are operating at equipment design speed or that the companies do not measure cycle times. Analogously, about 90% of the machines had a reported quality rate of 100%, which suggests that either there is no scrap or that companies do not measure the amount of accepted products per machine. In our view, it is not likely that such a large proportion of machines are operating at full efficiency rates. This can be strengthened by the fact that '100%' constitute the default value for these factors in the measurement system. Even under ideal conditions is a quality rate of

100% is not realistic in practice [1, 5]. Also, concerning the speed efficiency, previous research can confirm that many companies refrain from operating time data related functions and, consequently, do not measure cycle times or have sufficient knowledge about the theoretical maximum performance [16, 17].

The aggregated OEE measures revealed performance differences between the industry groups. However, as stated by Andersson and Bellgran [7], it is not the actual OEE figure that is most important, but how it can be used for improvements. Since the causes for over half of the measured loss time could not be classified, it will have a negative influence on how valuable the data is for directing improvement initiatives. It is of course possible that operators and production technicians that spend time on the shop floors know and can interpret what the unclassifiable losses are for their machines. Though, for decision makers higher up in the organization, who are responsible for prioritizing and investing in improvement initiatives, much of the improvement potential will remain hidden when the causes of losses are not communicated.

Furthermore, our findings are aligned with previous research who state that despite that OEE is supposed to measure individual equipment efficiency, it is affected by the surrounding environment [5, 12, 13]. This often refers to materials handling, buffers and ques. With the analysis of operator influence, we have shown that in order to improve equipment efficiency, it is also required to focus attention and efforts primarily on how supporting activities performed by operators are planned and executed. The OEE measure, consequently, captures the results of supporting activities, but is limited when it comes to representing the areas of improvement for these manual work tasks. The identified differences in the distribution of operator influenced time among industry groups is reflected by the characteristics of the different production systems.

To summarize, when the factors of performance efficiency and quality rate are left at default values and a large amount of losses remain unclassified, it can be questioned if companies really are measuring the *overall* equipment efficiency or just the availability. This also raises the question on how suitable the OEE measure is for benchmarking equipment efficiency when it is not obvious how individual companies interpret and define the OEE factors. It is difficult to determine speed efficiency [5] and companies might consider recording the quality rate per machine as too detailed. Nevertheless, the technical system for automatic measurement indeed has the capability and capacity of handling these issues. Though, in order to fully utilize the potential of these types of automatic data acquisition systems it is required that companies invest both time and efforts on accurately defining the core data.

6. Conclusion

The research presented in this paper has identified critical factors that directly affect the accuracy and applicability of OEE measures when operating systems for automatic measurement of manufacturing data. It has been found that when the measurement is automated, it is even more important that companies do not distance themselves from managing the detailed characteristics of their manufacturing processes.

Practitioners can incorporate the results to fully utilize the potential of automatic data acquisition systems and to derive accurate OEE measures that can be used to improve manufacturing performance. The findings is also of relevance for academics when using large sets of manufacturing data, derived from automatic measurement systems, for modelling and analysis.

Suggested future research efforts include investigating the level of awareness among decisions makers concerning the measurement of OEE and how it affects their policy decisions.

Acknowledgements

This research is carried out within the Sustainable Production Initiative and the Production Area of Advance at Chalmers University of Technology. The support is gratefully acknowledged by the authors. We would also like to thank Mikael Persson, CEO of Good Solutions AB, who provided the dataset and who was most helpful in answering questions and providing expert knowledge.

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