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OEE measurement at the automotive semi-automatic assembly lines

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Abstract: Manufacturing companies continuously evaluate their achieved performance based on different Key Performance Indicators (KPI). This article gives an overview about the OEE values. The study aims to provide practical OEE data of semi-automatic assembly lines used in the automotive industry. Its novelty is the revealed relationship between seat assembly lines and seat subassembly lines. Firstly, a literature review shows the scientific relevance and several cases are collected to increase OEE percentage. Secondly, the connection between chassis, tracks, recliner and mechanism assembly lines is described. Each part of OEE (availability, performance, quality) are analysed in terms of their impact.

Keywords: KPI; OEE; MES; assembly line

1. Introduction

Nowadays (when industry develops day by day), manufacturing companies are facing increasing standards and complexity regarding productivity, quality and cost efficiency [1]. Consequently, performance management has become a key issue in industry. The performance management system is important in several functional areas of management, such as operation, marketing and sales [2]. Companies, automotive enterprises, machine manufacturers and part suppliers need to measure their processes so that they can define their level of performance and can improve it [3]. Although there are many Key Performance Indicators (KPI), entrepreneurs use just six up to ten, in general. A widely-used KPI for internal efficiency is Overall Equipment Efficiency (OEE). The OEE-indicator refers to the reliability of the entire production network [4].

Production processes consist of manufacturing and assembly processes. Assembly lines are widespread in manufacturing industries such as automotive, electronics, textile or furniture industry [5]. Assembly of manufactured products accounts for over 50% of the entire production time and for 20% of total production costs [6].

In the modern assembly environment, the vast amount of shop floor data is collected and recorded in digital format using the Manufacturing Execution System (MES) to ensure that parts and production steps can be traced [7]. MES can provide an appropriate database for production control [8]. Based on the smart manufacturing concept, one of the most important elements are data [9]. In the smart factory, the cyber-physical system continuously collects data from machines and assembly lines [10]. Based on production process data, output data, machine failures data, quality records, etc., the OEE-indicator can be calculated.

2. Literature review

2.1. Overview of OEE

In a factory, the following efficiency and productivity indicators are used in production and at the assembly lines:

- Overall Equipment Efficiency (OEE)
- Overall Equipment Efficiency of a Manufacturing Line (OEEML)
- Overall Line Effectiveness (OLE)
- Overall Factory Effectiveness (OFE)
- Overall Plant Effectiveness (OPE)
- Overall Throughput Effectiveness (OTE)
- Overall Resource Effectiveness (ORE)
- Production Equipment Effectiveness (PEE)
- Overall Asset Effectiveness (OAE)
- Total Equipment Effectiveness Performance (TEEP)
- Global Process Effectiveness (GPE)

In addition, Machine Utilization (MU) and Capacity Utilization (CU) also used.

The OEE indicator was introduced by Nakajima under the Total Productive Maintenance (TPM) concept in 1988 [11]. Hedman et al pointed out that OEE is a widely-used performance indicator and companies often invest in MES where OEE measurement is the key element [12]. Steenkamp et al. works with Haldan MES which collects OEE data in the factory in order to display information on different factory levels [13].

According to Mainea et al., OEE is used as an indicator of how well equipment is used in batch production [14]. The basic formula for calculating OEE is written as:

$$OEE = a\,p\,q \;\; [\%] \tag{1}$$

where a - availability [%]; p - performance [%]; q - quality [%].

Detailed calculus example is displayed with Fig. 1 [14].

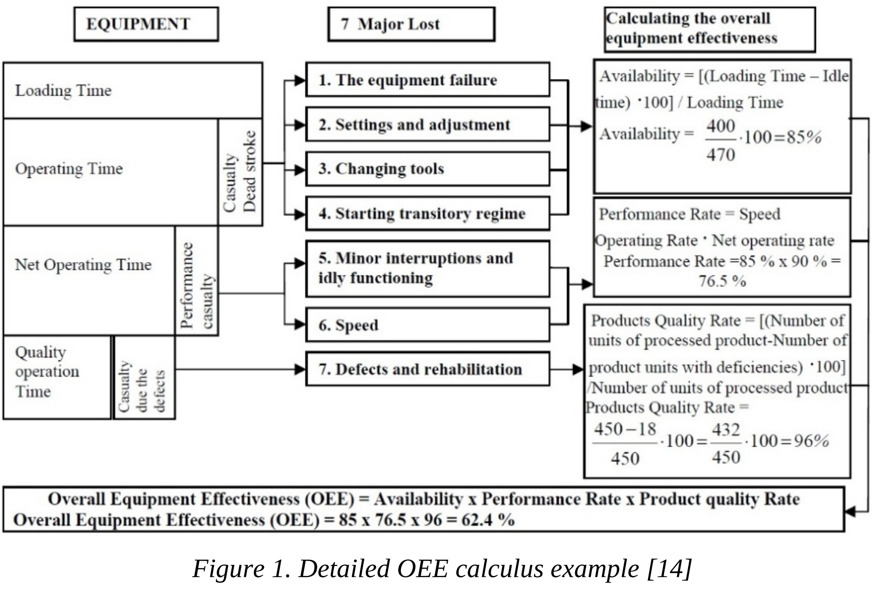

Figure 1. Detailed OEE calculus example [14]

De Grotte defined another OEE calculation method where the formula of availability, performance and quality was related to the production data [15]. From the productivity side, Saito says that productivity can be enhanced through the improvement of the method (m), improving performance (p), and utilization (u) [16].

$$productivity = m\ p\ u\ [\%] \tag{2}$$

where m - method [%]; p - performance [%]; u - utilization [%].

2.2. OEE-values in the manufacturing industry

The role of the OEE indicator is to monitor and control operational efficiency and measure the effectiveness of decisions [17]. In the manufacturing industry the OEE values are measured thus can be raised and optimized. Under ideal circumstances availability should have greater than 90%, performance greater than 95% and quality rate greater than 99%. According to this conditions OEE values are greater than 84.6% [18]. Hansen determined the excellent OEE values in the following areas:

- batch type production: OEE > 85%
- discrete process: OEE > 90%
- continuous process: OEE > 95% [19].

Subramaniyan compared 884 machines used in 23 factories in 2014. Based on his research work, the average OEE-value is 74% in food and beverage industry, 65% in mechanical workshop, 61% in plastic industry and 59% in another discrete production [18]. Almström et al. defined different levels of automation. At semi-automatic machines, the average OEE-value is 61% and 69% at the automatic machines [20].

2.3. Possibilities to increase OEE-values in the manufacturing

At companies where OEE is measured, the primary goal is to improve the OEE-value continuously. The most common methods are as follows:

- apply lean manufacturing techniques, tools and focus on Total Productive Maintenance (TPM)
- apply six sigma tools
- quality improvement methodologies
- waterfall analysis (analysis and optimization of equipment failure, setup, minor stoppage, etc.)
- line balancing for identify bottleneck
- involve operator to influence OEE

- production logistic analysis, enhancing the performance in material supply
- zero defect manufacturing
- simulation

Silva et al. presented an OEE-improvement of 16% from 70% up to 86% with the standardization of the air-conditioning system production line [21]. Mourtzis et al. described an advanced engineering educational approach where thermosiphon production line efficiency was increased by 28% [22]. Permin et al. determined a self-optimizing assembly system with model-based interpretation in three steps [23].

3. OEE-values at the automotive semi-automatic assembly lines

This chapter presents comprehensive OEE data at the seat assembly lines and reveals connection between assembly and sub-assembly lines.

3.1. Effects of OEE

The OEE-value directly impacts EBITDA, one of the most important corporal KPI-s. For this reason, it is extremely significant for industrial companies to enhance this figure. The high OEE-value contributes to the stable operation of a company (e. g. plannable scrap cost, reliable on time delivery, stable and computable headcount, less overtime, etc.). The lean manufacturing system significantly contributes to the achievement of the expected OEE-values (e.g. 5S, SMED, VSM, Kanban, etc.).

3.2. Calculation errors

When doing the follow-up of the performance, it is essential to collect and process data using a pre-defined method. It is advisable not to change the method, otherwise interpretation of data and trends can cause trouble which may result in improper measures and actions. When calculating the OEE-values, the following mistakes can occur in the industrial practice:

- change and special interpretation of the calculation method (e.g.: long-term lack of material vs planned stoppage)
- there is a change in the production process
  - negative impacts (e.g.: new control measure that increases cycle-time and decreases OEE)

  - positive impacts (e.g.: omission of an action which does not influence product function, e.g.: visual marking, the OEE-value is increasing)

- job performance is done during the expected stoppage (e.g.: break, planned maintenance)
- measurement and calculation errors (the following criterium is not fulfilled: 0% < OEE ≤ 100%)
- accidental production and assembly of products with different cycle times

3.3. OEE of semi-automatic assembly lines

Big data of manufacturing processes consist of information system data, smart equipment data, product data, user data and public data. Big data provides appropriate technical support for monitoring assembly processes [24]. The shop floor data collection was supported by MES. Due to the high-level information system, the data was reliable [25]. When using the traditional data analysis and data processing method, special attention was paid to consistency, correctness, completeness of the data [26].

The data collection was possible by a common system and a same data collection process which gathered all OEE relevant data such as scheduled time, production time, downtime, scrape rate, norm, etc. After an SQL query, the data was processed in Excel and the most important production conditions are considered (e.g. ramp-up period, reduced production based on order, etc.) Fig. 2 shows a detail of dataset. Availability, performance and quality percentages are calculated and checked thus individual OEE values become reliable.

	June 2020				July 2020			
	OEE	Availability	Performance	Quality	OEE	Availability	Performance	Quality
Assembly line 1	82.10%	91.65%	90.28%	99.22%	80.73%	90.33%	90.53%	98.72%
Assembly line 2	77.37%	87.29%	89.29%	99.28%	80.52%	88.48%	92.40%	98.48%
Assembly line 3	80.62%	89.30%	91.03%	99.18%	81.98%	88.83%	93.52%	96.68%
Assembly line 4	84.47%	94.32%	90.38%	99.09%	83.64%	99.92%	84.45%	99.12%
Assembly line 5	86.57%	99.73%	86.87%	99.92%	84.58%	99.59%	86.80%	97.85%
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮

Figure 2. Detail of values of OEE components

Analysing and comparing the OEE-values of 307 different assembly lines at 21 production facilities all over the world, the following thesis has been established. The OEE-value of semi-automatic assembly lines manufacturing the metal frame of car seats is always higher in a yearly period than the OEE-value of semi-automatic assembly lines manufacturing component equipment in the same period.

Frame construction of a seat is shown Fig. 3 together with the corresponding assembly lines where the components are made. In the production process, different component assembly actions are ahead of the assembly of the frame construction of the complete seat such as track assembly, recliner assembly, mechanism assembly (e.g. gear boxes).

Figure 3. Seat structure assembly

A The average monthly OEE-value of the semi-automatic chassis assembly lines for October 2016 and August 2020 is shown in Fig. 4 OEE values are in the range of 8% from 82% up to 90%. The only salient rise and decline can be found in the environment of appearance COVID-19 in April 2020. In this period almost all of assembly lines suddenly finished the production for weeks with higher focus and this resulted better OEE values. This was followed by a short-term economic setback. The decrease of OEE was mainly due to changes in demands and raw material supply in the form of unplanned change overs and unplanned downtimes.

Based on Fig. 5, it can be clearly seen that the OEE-value of a chassis assembly line is always higher than the OEE-value of actions performed by certain units at the assembly line in a period of 12 months.

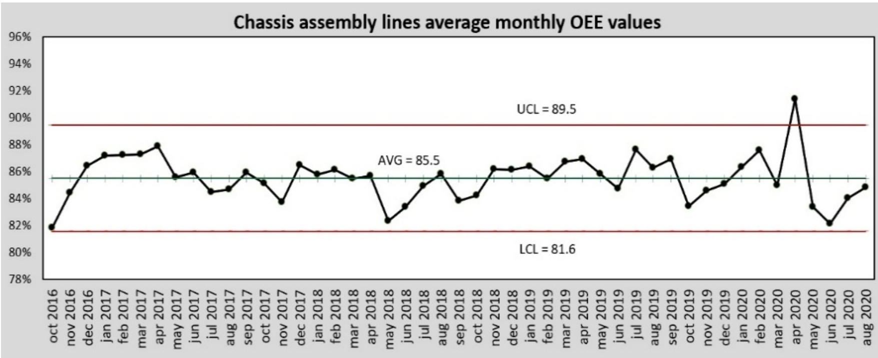

Figure 4. Chassis assembly lines average monthly OEE values

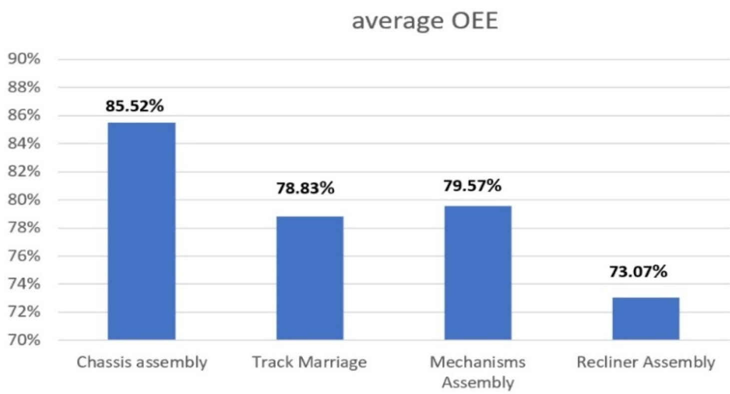

Figure 5. Average OEE values of different semiautomatic assembly lines

It can be identified, that the OEE-value of semi-automatic assembly lines manufacturing the metal frame of car seats depends on the number of workers. Final assembly lines with a staff of more than 10 employees have a higher OEE-value than semi-automatic assembly lines with less employees. The difference is at least 3% a year. The main reason for this difference is that more attention, control, technological and engineering support are allocated to the assembly lines requiring more people because profit has to be maximized.

Based on the review of OEE-components (availability, performance, quality), the analysis has shown that the most focus is placed on quality resulting in the highest achievement. This component reaches the highest percentile rate in each semi-automatic assembly line. Performance ranks second and availability ranks in the last place. Figures of the OEE-components are shown in Table 1.

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Table 1. OEE components values

	OEE	Availability	Performance	Quality	number of assembly lines	number of average person
Chassis assembly	85.52%	93.47% (3.)	94.01% (2.)	98.93% (1.)	127	10 - 40
Track Marriage	78.83%	85.89% (3.)	93.58% (2.)	98.93% (1.)	67	4 - 8
Mechanisms Assembly	79.57%	89.99% (3.)	90.62% (2.)	98.32% (1.)	61	3 - 6
Recliner Assembly	73.07%	84.30% (3.)	88.59% (2.)	97.70% (1.)	52	3 - 10

4. Conclusion

Considering a yearly period, the OEE-value of semi-automatic assembly lines manufacturing the metal frame of car seats is always higher than the OEE-value of semi-automatic assembly lines manufacturing component equipment in the same period of time. The average value of seat chassis assembly lines is 85.5%, the average value of sub-assembly lines is between 73% and 79.5%. In addition, the OEE-value depends on the size of the staff working at the assembly line. Final assembly lines with a staff of more than 10 employees have a higher OEE-value than semi-automatic assembly lines with less employees. The difference is at least 3% a year. It could be the subject of further analysis to compare other seat manufacturing technologies (e.g. welding, stamping, etc.) to assembly lines and big data research after pattern in the data for preactive measures.

References

[1] R. Glawar, F. Ansari, Cs. Kardos, K. Matyas, W. Sihn, Conceptual design of an integrated autonomous production control model in association with

a prescriptive maintenance model (PriMa), *Procedia CIRP* 80 (2019) pp. 482–487.
doi: *https://doi.org/10.1016/j.procir.2019.01.047*

[2] F. Antreter, The Possibilities of the Performance Measurement to the Estimating of the to Logistic Processes Joining Supplementary Work Hour Demand at the Automobile Manufacturer Factory, *Acta Technica Jaurinensis* 3 (3) (2010) pp. 267-283.

[3] M. Sokovic, D. Pavletic, K. K. Pipan, Quality improvement methodologies – PDCA Cycle, RADAR Matrix, DMAIC and DFSS, *Journal of Achievements in Materials and Manufacturing Engineering* 43 (2010) pp. 476-483.

[4] J. Oliveira, J.C. Sa, A. Fernandes, Continuous Improvement through 'Lean Tools': An Application in a Mechanical Company, *Procedia Manufacturing* 13 (2017) pp. 1082–1089.
doi: *https://doi.org/10.1016/j.promfg.2017.09.139*

[5] T. L. Nguyen, M. T. Le, T. T T.Vu, N. H. Do, Lean line balancing for an electronics assembly line, *Procedia CIRP* 40 (2016) pp. 437–442.
doi: *https://doi.org/10.1016/j.procir.2016.01.089*

[6] H. ElMaraghy, W. ElMaraghy, Smart Adaptable Assembly Systems, *Procedia CIRP* 44 (2016) pp. 4–13.
doi*: https://doi.org/10.1016/j.procir.2016.04.107*

[7] M. Subramaniyan, A. Skoogh, H. Salomonsson, P. Bangalore, J. Bokrantz, A data-driven algorithm to predict throughput bottlenecks in a production system based on active periods of the machines, *Computers & Industrial Engineering* 125 (2018) pp. 533–544.
doi*: https://doi.org/10.1016/j.cie.2018.04.024*

[8] B. Denkena, M.A. Dittrich, S. Wilmsmeier, Automated production data feedback for adaptive work planning and production control, *Procedia Manufacturing* 28 (2019) pp. 18–23.
doi: *https://doi.org/10.1016/j.promfg.2018.12.004*

[9] A. Kusiak, Smart manufacturing, *International Journal of Production Research* 56 1–2 (2018) pp. 508–517.

doi: *https://doi.org/10.1080/00207543.2017.1351644*

[10] C. L. Constantinescu, E. Francalanza, D. Matarazzo, O. Balkan, Information Support and Interactive Planning in the Digital Factory: Approach and Industry-Driven Evaluation, *Procedia CIRP* 25 (2014) pp. 269–275.
doi: *https://doi.org/10.1016/j.procir.2014.10.038*

[11] S. Nakajima, Introduction to TPM: Total Productive Maintenance, Productivity Press Cambridge, 1988.

[12] R. Hedman, M. Subramaniyan, P. Almström, Analysis of critical factors for automatic measurement of OEE, *Procedia CIRP* 57 (2016) pp. 128–133.
doi: *https://doi.org/10.1016/j.procir.2016.11.023*

[13] LP Steenkamp, D. Hagedorn-Hansen, G.A. Oosthuizen, Visual Management System to Manage Manufacturing Resources, *Procedia Manufacturing* 8 (2017) pp. 455–462.
doi: *https://doi.org/10.1016/j.promfg.2017.02.058*

[14] M. Mainea, L. Duta, Patic C., I. Caciula , A method to optimize the Overall Equipment Effectiveness, IFAC Proceedings (2010) pp. 237–241.
doi: *https://doi.org/10.3182/20100908-3-PT-3007.00046*

[15] P. De Grotte, Maintenance performance analysis: A practical approach, *Journal of Quality in Maintenance Engineering* 1 (2) (1995) pp. 4-24.

[16] S. Saito, Reducing labour costs using industrial engineering techniques, Maynard’s Industrial Engineering Handbook, McGraw-Hill, New York, 2001.

[17] K. Mahmood, M. Lanz, V. Toivonen, T. Otto, A Performance Evaluation Concept for Production Systems in an SME Network, *Procedia CIRP* 72 (2018) pp.603–608.
doi: *https://doi.org/10.1016/j.procir.2018.03.182*

[18] M. Subramaniyan, Production Data Analytics – To identify productivity potentials, Chalmers University of Technology, Gothenburg, Sweden, 2015.

[19] R.C. Hansen, Overall Equipment Effectivness: A powerful production / maintenance tool for increased profits, New York Industrial Press, 2001.

[20] P. Almström, A. Kinnander, Productivity Potential Assessment of the Swedish Manufacturing Industry, Swedish Production Seminar, (2007)

[21] I. Antoniolli, P. Guariente, T. Pereira, L. P. Ferreira, F.J.G. Silva, Standardization and optimization of an automotive components production line, *Procedia Manufacturing* 13 (2017) pp. 1120–1127. doi: `https://doi.org/10.1016/j.promfg.2017.09.173`

[22] D. Mourtzis, D. Tsakalos, F. Xanthi, V. Zogopoulos, Optimization of highly automated production line: An advanced engineering educational approach, *Procedia Manufacturing* 31 (2019) pp. 45–51. doi: `https://doi.org/10.1016/j.promfg.2019.03.008`

[23] E. Permin, F. Bertelsmeier, M. Blum, J. Bützler, S. Haag, S. Kuz, D. Özdemir, Self-Optimizing Production Systems, *Procedia CIRP* 41 (2016) pp. 417–422. doi: `https://doi.org/10.1016/j.procir.2015.12.114`

[24] F. Tao, Q. Qi, A. Liu, A. Kusiak, Data-Driven Smart Manufacturing, *Journal of Manufacturing Systems* 48 (2018) pp. 157–169. doi: `https://doi.org/10.1016/j.jmsy.2018.01.006`

[25] G. Schuh, T. Potente, C. Thomas, F. Brambring, Improving data integrity in production control, *Procedia CIRP* 9 (2013) pp. 44–48. doi: `https://doi.org/10.1016/j.procir.2013.06.166`

[26] C. Reuter, F. Brambring, Improving data consistency in production control, *Procedia CIRP* 41 (2016) pp. 51–56. doi: `https://doi.org/10.1016/j.procir.2015.12.116`