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# Case Study: Testing the Overall Efficiency of Equipment in the Production Process in TX Plant Simulation Software

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**Abstract**
The article deals with a widely used method of measuring the overall efficiency of equipment (OEE), which in combination with technologies and software tools is gaining in importance. The overall efficiency of OEE equipment is a key performance metric for machines and equipment to identify hidden capacities and increase production productivity. The intensification of Industry 4.0 in traditional manufacturing companies supports and creates the conditions for their transformation into a smart factory. The integration of intelligent machines and devices with complex human-machine communication network systems requires a new direction in measuring and increasing OEE. Mass customization, resp. personalization of production raises a high need to monitor, improve and further maintain productivity. The aim of the article is to create a simulation model of the production process and test the energy consumption of selected equipment using TX Plant Simulation software with a proposal of measures to increase the OEE of the company.

**Keywords**
Process, Simulation, Efficiency, TX Plant Simulation, OEE, Energy consumption.

## Introduction

Increasing productivity is currently the biggest challenge for companies in terms of competitiveness in the global market. Productivity in industry itself is efficiency. Efficiency refers to the resources needed to achieve the desired results. These basic sources include the time during which the production process of the facility takes place, as well as the amount of funds and energy expended. In terms of efficiency, the effect itself is a value that is primarily related to meeting societal needs, including the share of economic activity of staff.

Efficiency can be applied to several areas of the production process. They create an interaction between an industrial enterprise and workers who perform important tasks. The more correct and consistent employees perform their tasks, the more effective they are. Of these tasks, it is necessary to mention in particular the correct use of technology, communication and organization. In the following analysis of the literature, it is possible to see just the scope of interest that needs to be considered in the context of efficiency. The above analysis is with an emphasis on the goal on which the presented article is focused, i.e. to the overall equipment effectiveness (OEE).

The changes facing factories and production in the global market are unpredictable due to the increasing personalization of products. Approaches to such a trend are elaborated in the authors' works (Vavrik et al., 2020; Saderova et al., 2020; (Rosova et al., 2020; (Stefanik et al., 2003, Grznar et al., 2021), these are new factory concepts based on the concept of reconfigurable production lines. The methodology combines classical mathematical operations for production layout design with approaches such as simulation, cluster analysis and LCS algorithm. This combined method with the LCS algorithm and a completely different approach to production line design has not yet been used.

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The case study (Ondov et al., 2022) carried out in a medium-sized company aimed to take the first step towards sustainable production development, eliminate bottlenecks in production and shorten the production process. They have proven that even the simplest Industry 4.0 solution brings the desired improvement. The means to verify and evaluate the proposed solution was a simulation in the ExtendSim program. With the help of the simulation, the company avoided wasting resources and saved the time needed for verification in the classic and usual ways. The model has evolved to evaluate the implemented innovation is a tool that the company can use in the future (Krajcovic & Plinta, 2012; Buckova et al., 2019; Straka et al., 2020a).

The study of the authors (Lindegren et al., 2022) shows that the reduction of downtime resp. other improvements lead to a predictable conclusion about increased productivity, but changes in inputs do not necessarily change in direct proportion to outputs. This is due to interdependencies in the production process, which usually lead to non-linear results.

In the study (El Ahmai & El Abbadi, 2022; Straka et al., 2019), the authors focus on improving the flow time of asynchronous automotive assembly lines and on using simulation instruments to identifying bottlenecks and to reducing the buffer time. The results of the experiments show that the presented algorithm significantly exceeds the existing results, especially for large-scale problems. It also points to further research in this area regarding the adaptation of the algorithm in case all workstations are already organized according to cycle time in descending order, so in this case more work can be done to generalize and improve the proposed algorithm.

In addition to the above, high efficiency of the production process can also be achieved by eliminating selected physical factors of the working environment such as noise, dust, lighting, etc., which must be measured, analysed, simulated and evaluated in this context. Before implementing measures, is appropriate to model and simulate these measures and to assess their effectiveness on a preliminary basis, and making possible corrections if necessary (Moravec et al., 2021; Fusko et al., 2019).

The authors (Agárdi & Nehéz, 2021) deal with the Unrelated Parallel Machines Scheduling Problem (U-PMSP) in connection with the solution of discrete optimization problems in which different production tasks are assigned to identical parallel machines at specific times. The authors conclude that the proposed genetic algorithm can be used effectively in solving very complex problems of parallel machines. This study is also beneficial in the context of increasing OEE.

The implementation of Industry 4.0 technologies has raised concerns among governments and companies about the dehumanization of the industry in the future. in this context, the issue of sustainable industrial development has arisen. Concerns about the implementation of the technology of the fourth industrial revolution became the basis for building the assumptions of Industry 5.0. (Saniuk et al., 2022; Straka et al., 2020b; Fedorko et al., 2019).

The authors (Saniuk et al., 2022) address the issue of identifying the social and economic expectations of the development of the fourth industrial revolution in the context of the development of sustainability, humanization and resilience of Industry 4.0. with the potential in developing an investment strategy and government policy to support the development of an industry based on human-centric digitization of the economy.

## Importance of OEE influenced by Industry 4.0

OEE is so far one of the most effective metrics for monitoring the status of the production process. The aim is to identify the productivity losses that arise during production. The main role of OEE is to save energy and human resources.

The beginnings of the introduction of OEE in companies can be dated to the 1950s. The question is what the significance is; resp. will have OEE in the implementation of Industry 4.0 technologies. The high acceleration of technological progress shifts the potential of the methods and techniques used so far by the Toyota production system. OEE will thus gain momentum in connection with technology. As there is an increased need to monitor, improve and increase productivity, real-time OEE solutions can help increase the effectiveness of this metric.

With real-time information flow, it is possible to quickly analyse production data and identify the source of the problem – such as equipment failure, reduced speed, idle time, tool delays, etc. The system can be programmed to monitor selected KPIs and related actions, messages, notes and warnings to perform root cause analysis. OEE is still relevant, but its importance has been exacerbated by the opportunities and challenges posed by Industry 4.0 technologies and processes (Clarke, 2022).

When it comes to real-time information, the data source for OEE is the MES/Manufacturing Execution

System. The data is processed for analysis of downtime, several outputs, discrepancies, waste and more. It is also possible to generate KPI-based reports in real-time, allowing operators to visualize production line performance. It's a way to identify low-performing equipment and take the necessary steps to fix, reps. increasing efficiency.

Three key OEE factors include availability, performance and quality. By analysing OEE losses Table 1, including machine failure, machine deceleration, and scrap disposal, the company can optimize the OEE of its existing equipment. OEE is a key performance metric for identifying hidden capacities and increasing production productivity (SIMTech, 2022).

According to the (LeanProduction, 2022) is considered a reference score, what is considered a "good" OEE score (Fig. 1):

- OEE score of 100% is perfect production: production of only good parts, as fast as possible, without stopping time.

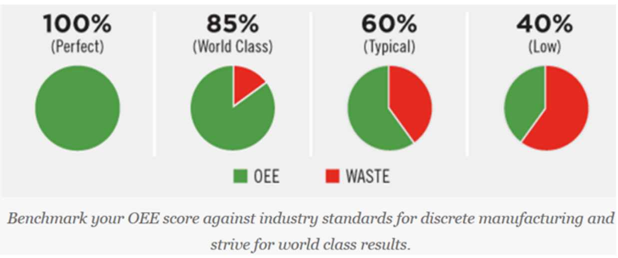


Fig. 1. OEE score for discrete manufacturing (LeanProduction, 2022)

Table 1
6 Big Losses affecting OEE

| Availability | Performance Rate | Quality Rate |
|---|---|---|
| • Breakdown losses<br>• Setup and adjustment losses | • Idling and minor stoppage losses<br>• Reduced speed losses | • Quality defect and rework losses<br>• Start-up (yield) losses |

- OEE score of 85% is considered world-class for discreet manufacturers. This is a suitable long-term goal for many companies.
- The OEE score of 60% is relatively typical for discrete manufacturers but suggests that there is considerable room for improvement.
- An OEE score of 40% is not at all unusual for manufacturing companies, which are just beginning to monitor and improve their production performance. It is a low score and in most cases can be easily improved by direct measures (eg. by monitoring the reasons for the downtime and addressing the biggest sources of the outage – one by one).

The formula to calculate Overall Equipment Effectiveness is as follows:

$$\textbf{OEE} = \textbf{Availability} \times \textbf{Performance} \times \textbf{Quality}$$

At present, an OEE score of 85% is considered exceptional. The reality is that many production facilities do not reach this level, which allows for significant improvements.

OEE Model (Focke & Steinbeck, 2018) is in Fig. 2.

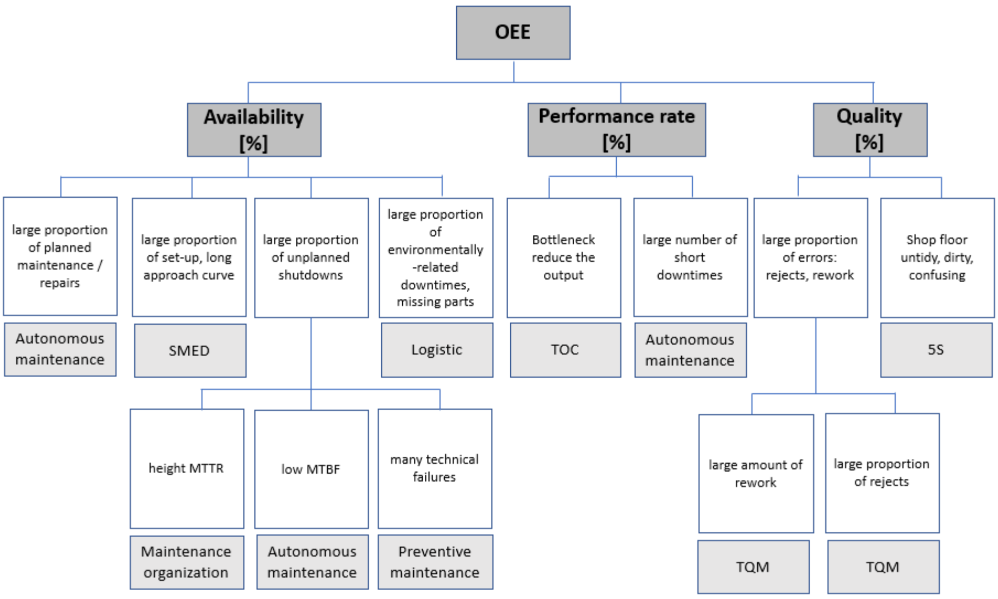


Fig. 2. Model OEE with the optimization methods

## Energy simulation module in TX Plant Simulation software

The researched company is focused on custom production of assembly groups and components according to individual customer requirements. The company's production program portfolio is focused on the processing of grey and ductile iron and steel castings, production of cylinders and rotating bodies, design, supply and service of industrial automation systems, committee and assembly of automatic packaging machines, repair, production and assembly of electrical equipment and metrology and calibration activities.

The case study was created in version. 16. The Energy simulation module can be used in dimensioning the capacities of production resources as well as in the decision-making process on the use of the potential of the equipment, resp. to reduce the overall energy consumption of equipment. It is possible to monitor and test energy consumption and operating states for selected modelled objects on the simulation model, i.e. productivity, process times, operating times, failures, machine reconfiguration, erroneous outputs, etc. The software belongs to the Siemens PLM PLM software community group.

Energy consumption varies from machine to machine. It depends on the type of operating condition. To perform the simulation, it is necessary to define the input information, Fig. 3.

The Energy Analyzer was inserted into the simulation model and individual objects or machines. The object assignment check is located after opening Energy in the Objects, Fig. 4.

The table contains the number and name of the machines, actual energy, current input and other parts of energy consumption. The table will open before by starting and after running the simulation, basic data are collected.

The machining centres are displayed on the X-axis and the kWh of the machine is displayed on the Y-axis. The green colour indicates how much time the material is spent on the operation and how much energy is consumed. The orange colour represents the time required to set up the machine, set the jig or tool program. The yellow colour represents the time when the machine is idling, that is, the engine is running, but the machine is empty. It also indicates which machine has a high potential for energy savings without setting the standby mode.

Red specializes in disorders. Gray is the standby mode and black is the lowest power state. Figure 5 shows the ratio of Kwh consumption to the operating time of the production activity. It talks about kW consumption during the entire duty cycle of the change. Records the number of kW per certain working hours.

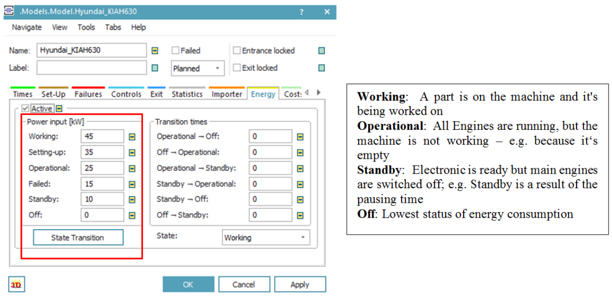


Fig. 3. Setting the values regarding the energy consumption of the centres

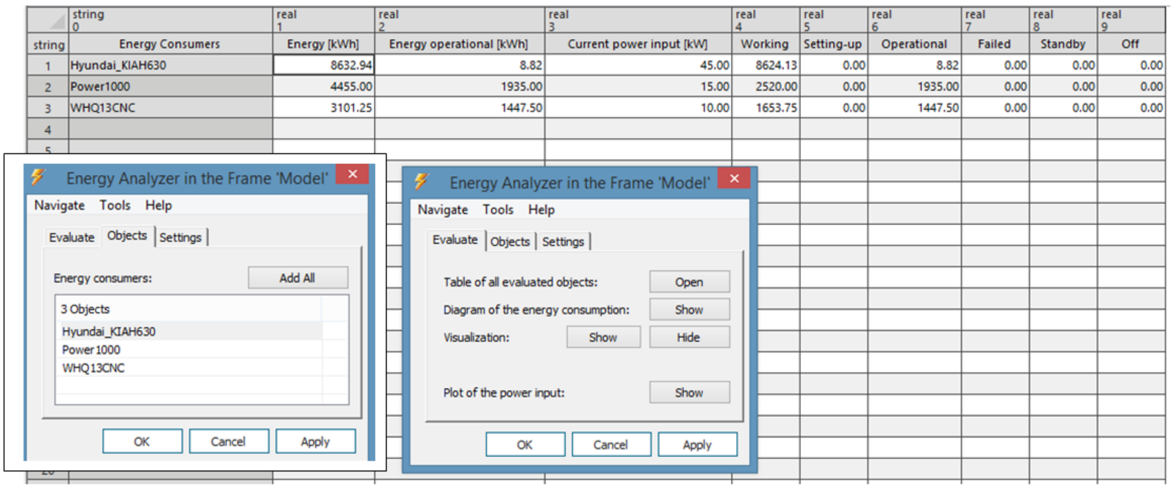


Fig. 4. Assigning objects via the Energy Analyzer

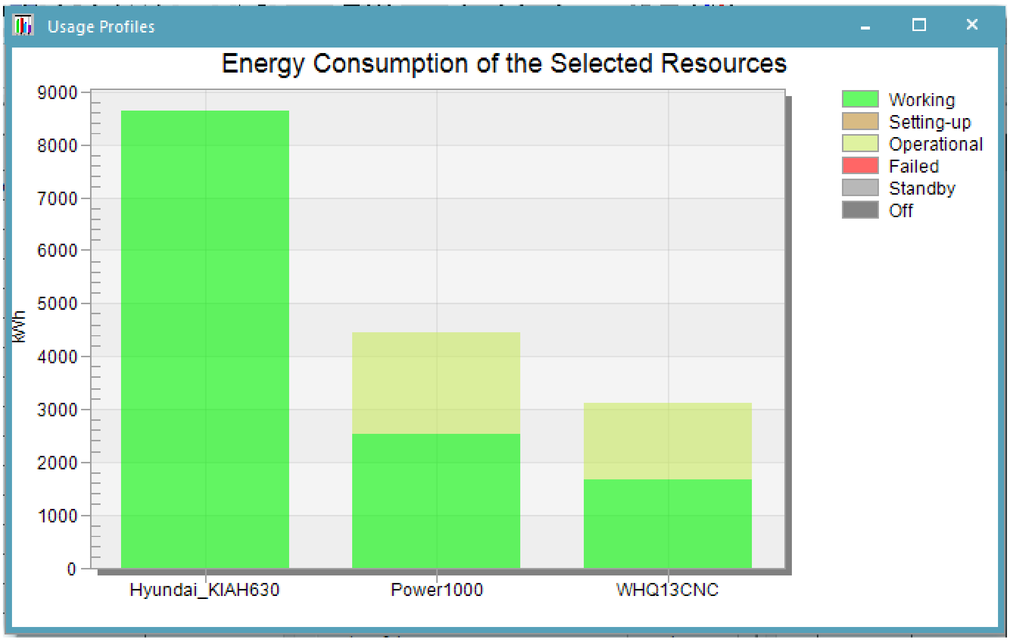


Fig. 5. Resulting graph of energy consumption

Figure 6 represents the output in the form of power consumption of the machines. Energy consumption Hyundai_KIAH63 was found at 8632.94 kWh, where its input was 45 kWh. Power1000 and its consumption is 4455.0 kWh and input data.

The Energy Analyzer enabled the display of the display and its basic data. Figure 7 shows the total consumption of the measured devices. The total energy consumption is 16 189.2 kWh. Of this, the time for the operation, i.e. the time when the machine waits for the next operation, is 3 391.3 kWh, Fig. 8.

The Energy Analyzer module provided testing of the machines based on the input data. It enabled the visualization of selected measured machines. Power consumption during the simulation run can be visualized in two ways, in 2D and 3D views. Fig. 8 show an

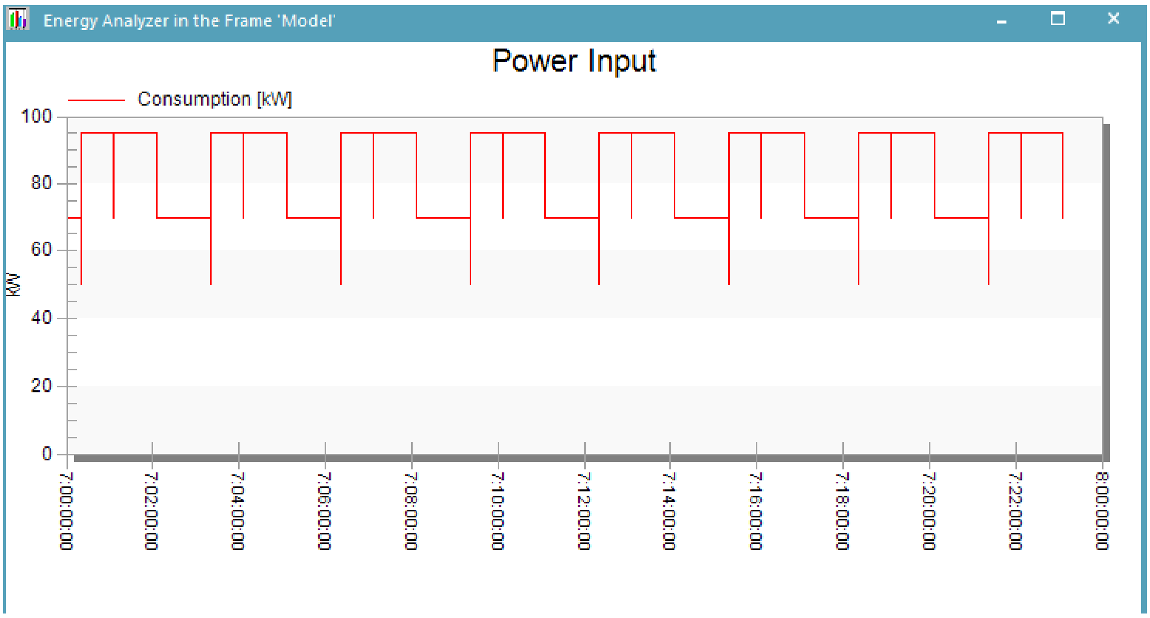


Fig. 6. Power consumption graph

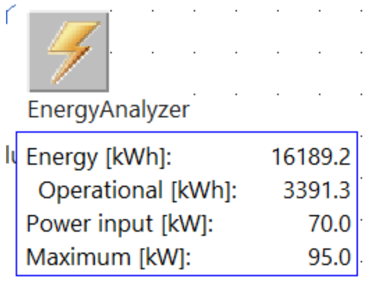


Fig. 7. Modul Energy Analyzer

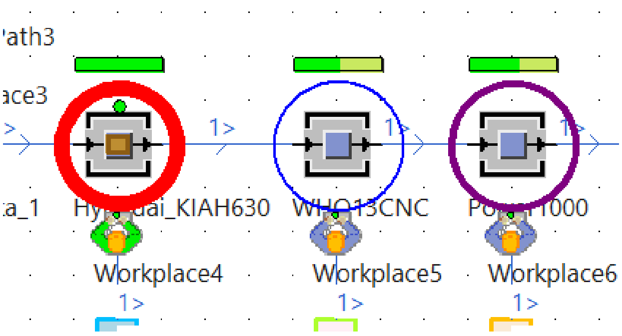


Fig. 8. Energy consumption

example of a 2D view from a measurement simulation. Each machine is marked with circles:

1. red wide circle indicates the highest energy consumption,
2. the average energy consumption is indicated by a purple circle,
3. thin blue circle indicates the lowest power consumption.

2D and 3D view of the final simulation is shown in Fig. 9 and Fig. 10.

The 3D view shows bar graphs that show the power consumption of selected devices during simulation run. Measurement of individual machines using software showed statistics on machine utilization.

Specifically, the following pictures show how energetic they were consumption and how many% of the total energy consumed. Fig. 11 points to the Hyundai_KIAH630, which had a consumption of 8,632,944 kWh. Of the total energy consumption, 99.90% of the energy used is the actual operation of the machine. From Fig. 12 it can be seen that the first machine Hyndai_KIAH630 is the busiest and its energy consumption is the highest.

The so-called module The energy analyzer made it possible to determine the energy consumption of selected machines, which were created in a simulation model. TX Plant simulation software made it possible to find new ways to work with data on energy consumption and also showed the speed of output processing. He was able to analyze the data and create new experiments. Energy consumption and the reason for its loss depend on the performance of machines and their parts such as motors, bearings and lighting that have a high impact on energy consumption.

One way to use energy more efficiently during production is to reduce the machine's energy consumption. It depends on the load and the number of hours it is in circulation. In the previous chapters, we have listed the times the machine performs. We also included the time when the engine is running resp. waiting for the next operation. This process consumes energy. All components that the machine contains show energy. Energy is also consumed in phases when the machine is not productive. The solution is to shut down the machine during the non-production phases, and also to ensure a carbon-based lubricant change and a friction-reduced bearing change. Replacing the lighting with LED lighting can also be a solution, which will help reduce energy consumption.

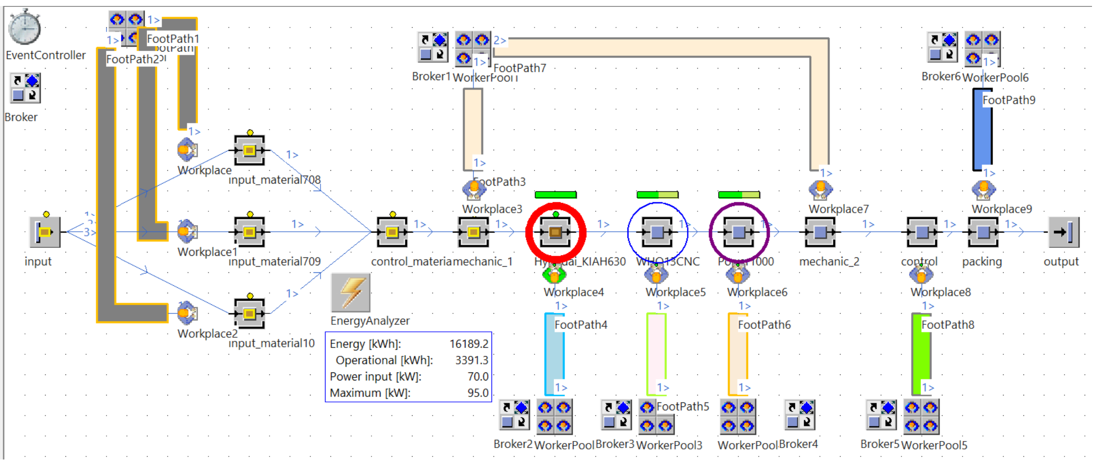


Fig. 9. 2D view of the final simulation

 

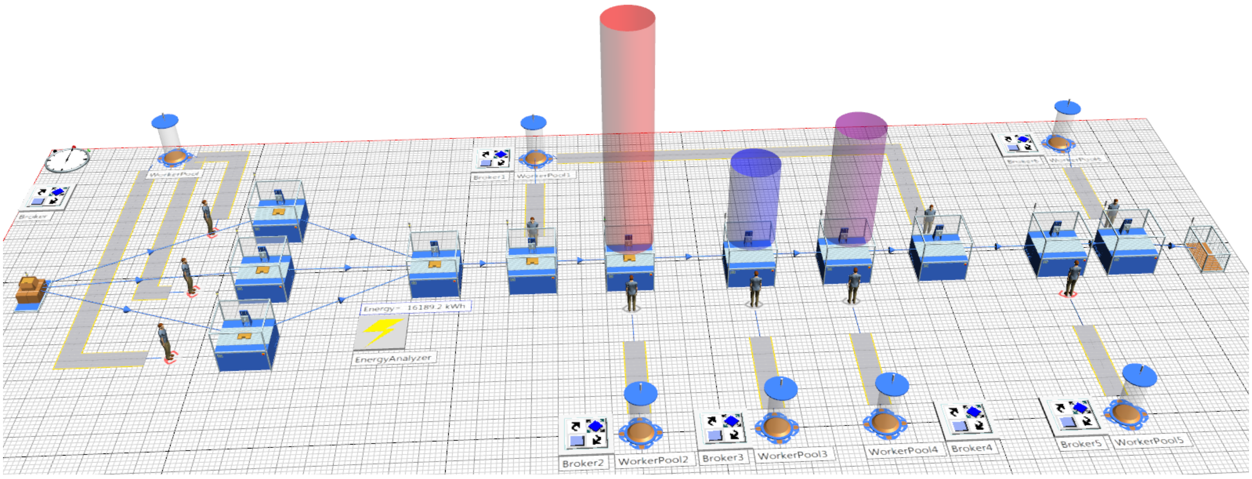


Fig. 10. 3D view of the final simulation

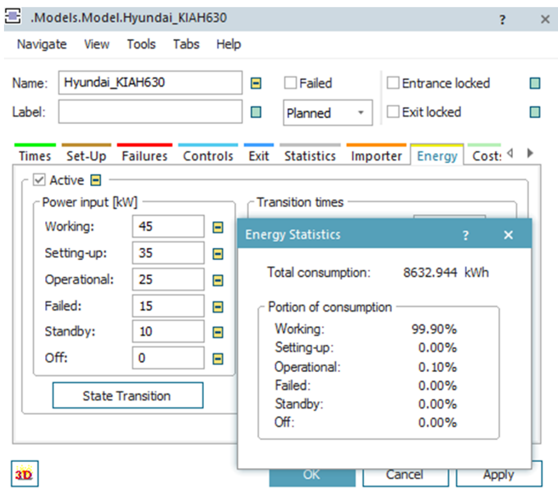


Fig. 11. Total consumption of Hyundai_KiaH630

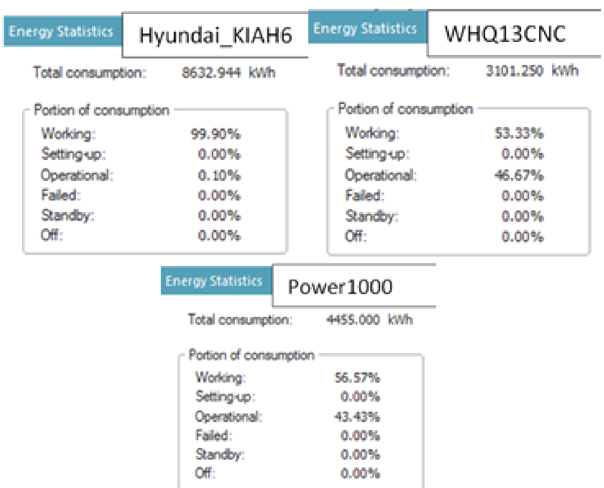


Fig. 12. Resulting statistics from the simulation run

## Conclusions

Important element of Industry 4.0 is proactivity, which makes it possible to streamline the OEE metric compared to the reactionary approach used in practice. This pushes OEE calculations beyond real-time data monitoring into predictive modeling of various scenarios. Technologies that support this approach include digital twin technology and simulation in conjunction with virtual reps. augmented reality.

Using these technologies, it is possible to model and simulate scenarios and analyze their impact on selected factors, e.g. and OEE without interrupting the production line. The outputs from the simulation runs can then be implemented directly into the production line. From the output of the analysis, the authors (Barosz et al., 2022) processed the main human and robotic factors that most influence the production process, Table 2. The authors propose a theoretical framework for measuring the efficiency of intelligent factories as a function of the combined efficiency of the human cognitive system, intelligent machines and their shared communication systems. From the above it follows that there is a need to focus on human cooperation vs. robot, which also initializes Industry 5.0.

The future connected with Industry 4.0 technologies will be in a high level of automation, robotics, implementation of artificial intelligence elements and tools for collecting, storing and processing big data, such as cloud computing, sensors, and big data. Perfect informatization and digitization will be the basis for intelligent factories, which combine all production and logistics processes, making production smarter, more efficient and more sustainable.

Table 2
Human and robot factors in the production process (Barosz et al., 2022)

| | Human Factor | Robot Factor |
|---|---|---|
| Work parameters | Unstable, slow work, fatigue | Stable, fast work |
| Adaptation for new task | Fast adaptation | Slow programming |
| Flexibility, working area | Large flexibility, large operating range | Lower flexibility, limited range |
| Errors and failures | High human errors rate | Low failures rate |
| Replacement and repair | Can be replaced | Require repairing |
| Labour cost | High | Low |
| Investment cost for human/robot workstation | Low | High |

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## References

Agárdi A. and Nehéz, K. (2021), The Unrelated Parallel Machines Scheduling Problem with Machine and Job Dependent Setup Times, Availability Constraints, Time Windows and Maintenance Time, *Management and Production Engineering Review*, Vol. 12, No. 3, pp. 15–24. DOI: 10.24425/mper.2021.138527.

Bangsow S. (2015), *Tecnomatix Plant Simulation. Modeling and Programming by means of examples*, Springer, Switzerland.

Barosz P., Gołda G. and Kampa A. (2020), Efficiency Analysis of Manufacturing Line with Industrial Robots and Human Operators, *Applied Science*, Vol. 10. DOI: 10.3390/app10082862.

Bucková M., Skokan R., Fusko M. and Hodon R. (2019), Designing of logistics systems with using of computer simulation and emulation, *Transportation Research Procedia*, Vol. 40, pp. 978–985. DOI: 10.1016/j.trpro.2019.07.137.

Clarke P. (2022), The Relevance of OEE in the Industry 4.0 and Smart Factory Era, online: https://slcontrols.com/the-relevance-of-oee-in-the-industry-4-0-and-smart-factory-era/ [date of Access February, 2022].

Clarke P. (2022), The Relevance of OEE in the Industry 4.0 and Smart Factory Era, online: https://slcontrols.com/the-relevance-of-oee-in-the-industry-4-0-and-smart-factory-era/ [date of Access February, 2022].

El Ahmadi SEA. and El Abbadi L. (2022), Reducing Flow Time in an Automotive Asynchronous Assembly Line – An application from an automotive factory, *Management and Production Engineering Review*, Vol. 13, No. 1, pp. 99–106. DOI: 10.24425/mper.2022.140880.

Fedorko G., Vasil M.and Bartosova M. (2019), Use of simulation model for measurement of MilkRun system performance, *Open Engineering*, Vol. 9, No. 1, pp. 600–605. DOI: 10.1515/eng-2019-0067.

Focke M. and Steinbeck J. (2018), Steigerung der Anlagenproduktivität durch OEE-Management Definitionen, Vorgehen und Methoden – von manuell bis Industrie 4.0, Springer Gabler, Wiesbaden, Germany, ISSN 2197-6708.

Fusko M., Buckova M, Gaso M., Krajcovic M., Dulina L. and Skokan R. (2019), Concept of Long-Term Sustainable Intralogistics in Plastic Recycling Factory, *Sustainability*, Vol. 11, No. 23. DOI: 10.3390/su11236750.

Grznar P., Krajcovic M., Gola A., Dulina L., Furmannova B., Mozol S., Plinta D., Burganova N., Danilczuk W. and Svitek R. (2021), The Use of a Genetic Algorithm for Sorting Warehouse Optimisation, *Processes*, Vol. 9, No. 7. DOI: 10.3390/pr9071197.

Krajcovic M. and Plinta D. (2012), Comprehensive approach to the inventory control system improvement, *Management and Production Engineering Review*, Vol. 3, No. 3, pp. 34–44. DOI: 10.2478/v10270-012-0022-0.

Lindegren M.L., Lunau M.R. and da Silva E.R. (2022), Combining simulation and data analytics for OEE improvement, *International Journal of Simulation Modelling*, 2022, Vol. 21, No. 1, pp. 29–40. DOI: 10.2507/IJSIMM21-1-584.

LeanProduction. OEE (Overall Equipment Effectiveness), https://www.leanproduction.com/oee/ [date of Access February, 2022]

Moravec M., Badida M., Mikusova N., Sobotova L., Svajlenka J. and Dzuro T. (2021), Proposed Options for Noise Reduction from a Wastewater Treatment Plant: Case Study. *Sustainability*, Vol. 13, pp. 2409. DOI: 10.3390/su13042409.

Ondov M., Andrea R., Sofranko M., Feher J., Cambal J. and Feckova Skrabulakova E. (2022), Redesigning the Production Process Using Simulation for Sustainable Development of the Enterprise, *Sustainability*, Vol. 14, No. 3, pp. 1514. DOI: 10.3390/su14031514.

Rosova A., Behun M., Khouri S., Cehlar M., Ferencz V. and Sofranko M. (2020), Case study: The simulation modeling to improve the efficiency and performance of production process, *Wirel. Netw.*, Vol. 28, pp. 863–872. DOI: 10.1007/s11276-020-02341-z.

Saderova J., Rosova A., Kacmary P., Sofranko M., Bindzar P. and Malkus T. (2020), Modelling as a Tool for the Planning of the Transport System Performance in the Conditions of a Raw Material Mining, *Sustainability*, Vol. 12, p. 8051. DOI: 10.3390/su12198051.

Saniuk S., Grabowska S. and Straka M. (2022), Identification of Social and Economic Expectations: Contextual Reasons for the Transformation Process of Industry 4.0 into the Industry 5.0 Concept, *Sustainability*, Vol. 14, No. 3. DOI: 10.3390/su14031391.

Stefanik A., Grznar P. and Micieta B. (2003), *Tools for continual process improvement – Simulation and benchmarking*, Intelligent Manufacturing and Automation, 14th International Symposium of the Danube-Adria-Association for Automation and Manufacturing, pp.443–444

Straka M., Hurna S., Bozogan M. and Spirkova D. (2019), Using continuous simulaton for identifying bottlenecks in specific operation, *International Journal of Simulation Modelling*, Vol. 18, No. 3, pp. 408–419. DOI: 10.2507/IJSIMM18(3)477.

Straka M., Khouri S., Lenort R. and Besta P. (2020a), Improvement of logistics in manufacturing system by the use of simulation modelling: A real industrial case study, *Advances in Production Engineering and Mangement*, Vol. 15, No. 1, ppl 18–30. DOI: 10.14743/apem2020.1.346.

Straka M., Tausova M., Rosova A., Cehlar M., Kacmary P., Sisol M., Ignacz P. and Farkas C. (2020b), Big Data Analytics of a Waste Recycling Simulation Logistics System, *Polish Journal of Envirnmental Studies*, Vol. 29, No. 3, pp. 2355–2364. DOI: 10.15244/pjoes/108684.

Vavrik V, Gregor M., Greznar P., Mozol S., Schickerle M., Durica L., Marschal M. and Bielik T. (2020), Design of Manufacturing Lines Using the Reconfigurability Principle. *Mathematics*, Vol. 8, No. 8. DOI: 10.3390/math8081227.

SIMTech (2022), REAL-TIME OEE FOR INDUSTRY 4.0, https://www.a-star.edu.sg/simtech/kto/advanced-manufacturing/real-time-oee [date of Access February, 2022]