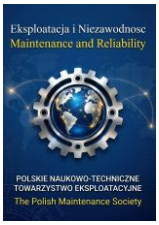

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Towards ensuring sustainable production - experimental study of the assembly process in the automotive industry

Sławomir Kłos[1], Justyna Patalas-Maliszewska[1,*]

[1] Institute of Mechanical Engineering, University of Zielona Góra, Poland
* Corresponding Author: j.patalas-maliszewska@iim.uz.zgora.pl

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Abstract

Enhancing sustainable production (SP) requires monitoring of industrial activities, particularly in relation to the Sustainable Development Goals (SDGs). In the automotive industry, implementing actions to enhance SP in line with the SDGs remains a key challenge. This study fills a research gap and develops a tool leveraging Industry 4.0 technologies for monitoring and reporting selected indicators characterizing SP, while maintaining high efficiency in core manufacturing operations. Experimental work is conducted based on the surface-mount assembly process for the production of electronic components used in a measuring device in the automotive industry. In the analysed case study the research results demonstrate the main relationships between assembly line efficiency and selected SP factor, namely energy consumption. Next, it proposes AI-based model for predicting energy consumption in assembly process towards ensuring SP. The results are generic for automotive industry due to a novel approach to integrate assembly efficiency parameters and SP indicators using IoT and ERP.

Keywords: *assembly process efficiency, sustainable production, monitoring, predictive analytics, Internet of Things,*

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Highlights

- Approach to monitoring assembly process towards sustainable production (SP).
- Real-time monitoring of assembly efficiency and SP indicators using IoT and ERP data.
- Verification of the novel approach in a real-life automotive case study.
- Proposal for predicting energy consumption in assembly process towards ensuring SP.

1. Introduction

The assembly process can significantly improve the efficiency of the overall manufacturing system [1]. Surface Mount Technology (SMT) is the subject of many studies and analyses due to the size of the industry and the number of employees [2–3]. Research on SMT includes analyses of process efficiency and improvement strategies [4], inspection and classification of electronic circuit connections [5], as well as studies on component allocation problems and component placement sequencing in SMT assembly [6].

Sustainable production (SP) is understood as the creation of goods and services that are: non-polluting, energy- and resource-efficient, economically viable, safe and healthy for employees, communities, and consumers, as well as socially and creatively satisfying for all working people [7]. SP currently requires the development of solutions and tools that enable production according to the Sustainable Development Goals (SDGs). The advanced technologies can provide support in implementing the assumptions of the SP concept, including areas such as energy consumption reduction and predictive modelling [8]. The integration of information systems supporting production management, such as Enterprise Resource Planning (ERP), with Industry 4.0 and even Industry 5.0 (I4.0/I5.0) technologies enables real-time data monitoring, processing, and analysis for the implementation of proactive actions. Implementing the principles of SP has become crucial for production managers. I4.0/I5.0 technologies, particularly Internet of Things (IoT) and Artificial Intelligence (AI), offer

opportunities to improve efficiency, flexibility, and sustainability in manufacturing [9]. Data acquisition through IoT technology and continuous real-time data streaming allows the development of models that support controlling the level of SP. AI enables building systems that support real-time decision-making, facilitating the achievement of SDGs targets. In the context of improving SP, monitoring industrial activities is particularly important regarding SDGs, namely SDG 9: Industry, Innovation and Infrastructure and SDG 12: Ensure sustainable consumption and production patterns. To achieve SDG 9, manufacturing enterprises should invest in resilient infrastructure and increase digitalization [10]. The goals to be achieved in implementing SP in accordance with SDG 12 are: to achieve the sustainable management and efficient use of natural resources (SDG 12.2); reduce food losses along production and supply chains, including post-harvest losses (SDG 12.3); achieve the environmentally sound management of chemicals (SDG 12.4), substantially reduce waste generation through prevention, reduction, recycling and reuse (SDG 12.5); Encourage companies, especially large and transnational companies, to adopt sustainable practices and to integrate sustainability information into their reporting cycle (SDG 12.6) [11]. A crucial aspect of building SP is raising awareness of the need to implement environmentally friendly practices [12], also within the enterprise. Our work focuses on the integration of information acquired from the assembly process, as well as on the monitoring and reporting of the values of the environmental subset of SP indicators.

Currently, a key challenge and research gap is the development of tools leveraging Industry 4.0 (I4.0) technologies for monitoring and reporting SP levels, while maintaining high efficiency in core manufacturing operations [13]. So, firstly to identify the research niche the literature analysis (Table 1) is provided in order to define existing solutions for monitoring processes in manufacturing companies and SP measures in the automotive industry.

Table 1. The theoretical contribution.

Theoretical/Experimental study	Analysed process in manufacturing in the context SP	Contribution	References
Experimental study	Plastics injection industry, manufacturing and assembly process of components for the automotive industry	An approach to recover old equipment towards increasing the sustainability of the processes.	[14]
Empirical study	Automotive manufacturer producing commercial vehicles	A framework for value-oriented digital services to monitor the performance of data-drive production logistics, which consists of data collection, data analysis, and information delivery, integrating nine key factors.	[15]
Experimental study	Automotive industry/ injection molding processes	An autonomous sensor system for monitoring stamping, which consists of data acquisition (pressure, mold temperature and closing force, ambient conditions and time and location of the tool utilization),	[16]
Case Study	Automotive industry/ Tire production	The best-case scenario for improving the efficiency of the motorcycle tire production process.	[17]
Experimental study	Additive manufacturing/ Fused deposition modeling (FDM) process	Analysis of parameters such: print layer height, number of layers, material fill percentage, infill type, and build orientation to improve sustainability by reducing energy and material consumption.	[18]
Experimental study	Automotive industry/ Cylindrical plunge-cut grinding process	AI-Driven Approach to Monitoring Grinding Wheel Conditions based on the sensor data.	[19]
Experimental study	Automotive industry/ ipolymer over-injection moulding	A framework for balancing the save energy and an increase in production rate. It introduces the benefits of automation for sustainability and productivity.	[20]
Experimental study	Automotive industry/ Surface Mount Technology (SMT)	Real-time monitoring of assembly efficiency and the selected SP indicators (energy consumption, ambient temperature of the assembly line, relative humidity, CO2 concentration) using IoT and ERP data.	Our paper

Table 1 highlights the theoretical contribution of our research compared with the literature results. To the best of our

knowledge and based on the current literature analysis (Table 1), no studied research works have identified how can data and information regarding assembly process efficiency and SP can be integrated to enable the real-time monitoring and how the implementation of the emerging technologies according to I4.0 impacts SP. Therefore, in this paper the following research questions are examined:

- RQ1: How can Industry 4.0/5.0 technologies support the real-time monitoring of assembly line efficiency and environmental SP indicators?
- RQ2: How the linkage between assembly process efficiency with selected SP indicators can influence future research trends in SP research for the automotive industry?

Although large automotive industry enterprises implement initiatives aimed at continuous process improvement, enhancing efficiency, and waste elimination [21], they do not always adequately adapt to regulatory or societal expectations regarding their environmental and social performance [22].

The main contributions of the work can be summarized as follows:

- It develops a novel approach to monitoring assembly process efficiency and sustainable production (SP).
- It applies over 1,000,000 records of real-life IoT-based data collected from environmental parameter sensors and over 750,000 records from ERP systems, gathered between September 2021 and November 2023, using a case study of the surface-mount assembly process in the production of electronic systems for an automotive measuring device.
- It analyzes the values of indicators describing assembly process efficiency and a environmental subset of SP indicators, using the real-life data.
- This study explores the potential for achieving SDG 12 enhancing SP while maintaining assembly line efficiency through the use of information communication systems, IoT, and AI within production enterprises.

Chapter two describes the research methodology and describes the assumptions for the experimental works. The total real-life data obtained: work time of SMT line, rearming time, conservation time, fault time (line failure), downtime (lack of material) and number of projects as efficiency of assembly line and energy consumption, CO_2 concentration, temperature and humidity as the selected SP parameters. Chapter three provides the correlation analysis and next develops the AI-based model for predicting energy consumption in assembly process towards ensuring SP. This research proposed the approach which uses data from IoT and ERP system for monitoring assembly process efficiency and SP indicators (chapter four). Chapter five indicates insights for production managers and concludes the work.

2. Material and methods

2.1. The research methodology

The research methodology aligns with Design Science Research (DSR) [23,24]. Our approach includes the following stages according to DSR: develop, test, and validate the proposed framework in a testbed environment.

Theoretical work (develop):

- Stage 1: Developing an approach to study the relationship between assembly line efficiency and the need to enhance the level of sustainable production (SP).
- Stage 2: Defining indicators for studying assembly line efficiency and monitoring the level of SP in the context of the assembly process.

Experimental work (test and validate):

- Stage 3: Developing a research unit.
- Stage 4: Data collection for analyzing the relationship between assembly line efficiency and the need to enhance the level of SP under real conditions.
- Stage 5: Application of correlation analysis methods andto analyze the relationship between assembly line efficiency and the need to improve the level of SP.
- Stage 6: Validation the AI-based model's effectiveness on real-world data.

Figure 1 illustrates the proposed approach to monitoring assembly process towards sustainable production (SP), (Stage 1 of the research methodology).

The proposed approach (Fig. 1) is illustrated using the example of a surface-mount assembly line (SMT). The design and assembly of electronic systems constitute one of the key industrial sectors and represent a crucial area of innovation enabling the development of virtually all branches of the

automotive industry. Electronic modules installed in vehicles, aircraft, and industrial machinery require high performance and reliability. The efficiency of the assembly line is determined based on the analysis of operating times: SMT line working time, setup (rearming) time, maintenance time, failure time, downtime (material-related), and other unreported times (Stage 2 of the research methodology). Next, considering that energy is an almost fundamental resource—similar to drinking water [12]—and incorporating expert opinion from the analyzed automotive case study, the following SP indicators were selected for further analysis (Stage 2 of the research methodology): monthly energy consumption [kWh], ambient temperature of the assembly line (°C), relative humidity (RH), and CO_2 concentration (ppm). Moreover, the temperature and the humidity influence soldering quality; CO_2 may affect operator comfort and safety. Subsequently, the values of these indicators (related to PE and SP) are acquired in real time from IoT sensors and the ERP system during process execution. Statistical analysis enables the identification of the most significant relationships between the indicators describing assembly line efficiency and the selected SP indicators. The application of an AI model allows for the development of a predictive model for the SP factor that shows the strongest correlation with the efficiency of the analyzed assembly line.

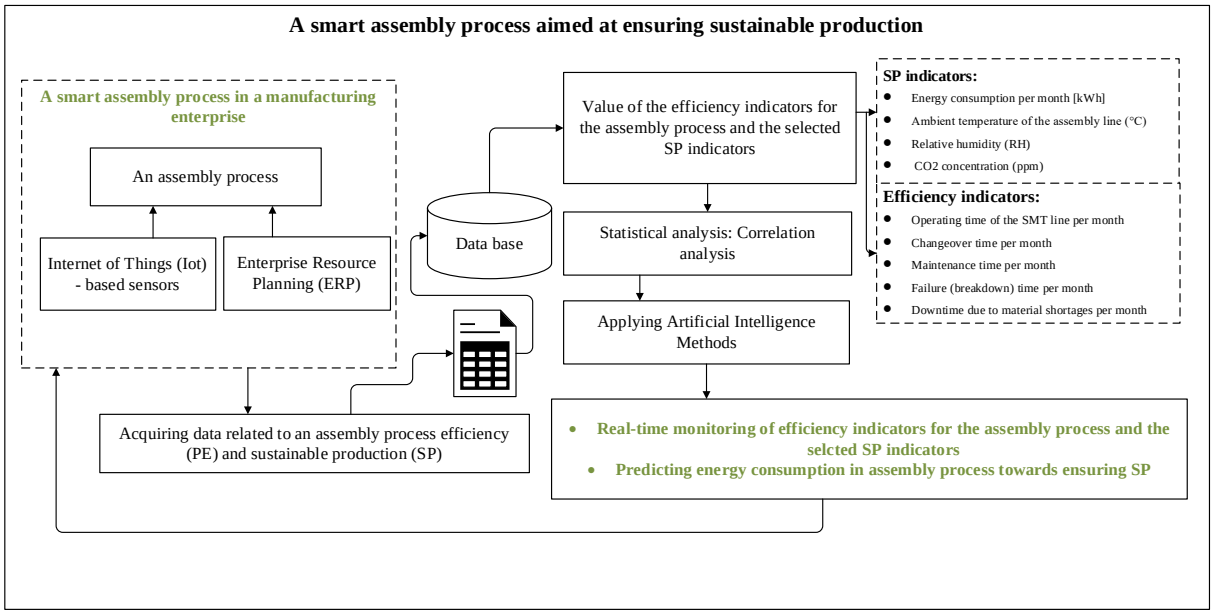


Figure 1. An approach to monitoring assembly process efficiency and SP.

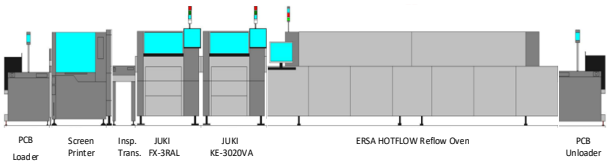
2.2. Research unit

The experimental research was carried out on research unit developed at the analyzed case study from the automotive industry. The analysed SMT line consists of :

- ERSA VERSAPRINT S1-3D screen printer with the ability to control 3D paste deposition;
- JUKI FX-3RA "chip shooter" pick-and-place machine with a theoretical output of 66,000 CPH (chips per hour) according to IPC9850 standard;
- JUKI KE-3020VA "flexible machine" pick-and-place machine with a theoretical output of 17,100 CPH according to IPC9850 standard, equipped with two cameras for precise assembly of microprocessor systems, BGAs, connectors, etc.;
- ERSA HOTFLOW 3/14e reflow oven with seven heating zones;
- The entire system is integrated with transport by ASYS.

The surface mounting process is described based on the production of electronic circuits for the ND30 electrical network parameters analyzer. Manufacturing one of the ND30 involves making 3 PCBs. One PCB (designated as Ethernet board 103) includes the assembly of approximately 40 electronic components. The line operator has a list of orders covering the planning period for 3 consecutive days. The list is also available to warehouse employees. Every day, a warehouse employee verifies the list of needed elements and prepares reels that will ensure the line's operation throughout the day. Another employee checks the component rolls and places them in the appropriate SMT line feeders. When starting each subsequent

project, the operator verifies the list of material needs and places the appropriate reels with components in the feeders. For this purpose, the operator removes the spool in the feeder and replaces it with a new one. The feeder location is pre-determined and saved in the Pick and Place machine program, but the operator can change it if necessary. The correct operation of the feeders is checked by means of a trial run, during which the machine "learns" the position and orientation of the components in the feeder. Then the operator goes to the printer settings and removes the template from the old project. Aluminium sheet templates are cleaned with propylene to remove any remaining solder paste using a high-pressure air gun. The operator places the old template in the designated place and takes a new template (up to ND30), fits it to the frame and cleans it with a compressed air gun. In the next step, the required number of PCBs is loaded into the printer feeder and at the same time, the program in the ERSA HOTFLOW machine is set, determining the required soldering temperature profile of the ND30 product components. The ERSA HOTFLOW device is waiting to reach the set temperature. In the next step, the line starts printing (the process of applying solder paste to the solder pads of the boards). The conveyor starts and printing starts, once printing is completed the machine checks if the solder paste has been applied correctly and printing is completed within 12 seconds according to the machine's specifications. The conveyor moves the PCB to an open visual inspection point where the operator identifies any defects in the solder paste application. The PCB is then transferred to the FX-3RAL device, which checks the correct orientation of the PCB and starts placing the electronics components (6 components are taken from the feeder and placed on the PCB on the front and back sides of the PCB). The PCB is then moved to the KE-3020VAL device. The same process is repeated as in FX-3RAL, but the number of nozzles is 24. Only 12 nozzles can work at a time. Then, the PCB is visually inspected for the arrangement of components. If they are not in the correct orientation, the operator either corrects it manually or directly checks the machine to relearn the correct positioning. The procedure depends on the number and types of failures. The PCB then goes to a reflow soldering machine, which heats the paste to create a permanent solder joint. The research unit consists of the assembly line in the automotive industry and installed sensors that collect data related to SP indicators using IoT. Figure 2 presents the research units. For the energy consumption measurement study, the ND30IoT network parameter meter from Lumel S.A. and for SD parameters registration the HT 22IoT were used.



(a)

(b)

Figure 2. Research unit – (a) SMT line diagram for surface-mount assembly of electronic systems, (b) ND30IoT and HT22IoT sensors installed in the control cabinet of the SMT line.

The product mix manufactured on the PCB line includes over 1,000 different products, including: energy meters, power network meters and analysers, digital meters, transducers and separators, power factor controllers, temperature controllers, power controllers converters, data loggers, analogy meters, current transformers, shunts, temperature sensors, power supplies, etc. The production of products is not seasonal and, due to market requirements, is highly fragmented and adapted to customer needs. Within a month, 50 - 120 different product series (projects) are completed on the PCB assembly line, and production series can range from hundreds to thousands of products. In 2024-2025, monthly production line utilization ranged from 61% to 86%, primarily dependent on the number of projects, which directly impacts the number and total changeover time. The share of monthly changeover times during this period ranged from 15% to 38%.

The Table 2 presents an example of the efficiency indicator for the assembly line measurement.

Data on the assembly line efficiency were recorded by operators on specially prepared touch terminals integrated with the ERP system (stage 4 of the research methodology, Figure 3). Data was recorded at intervals of one minute on the line and subsequently consolidated into monthly periods, as this timeframe was deemed appropriate in the studied enterprise for

analysing SMT line efficiency.

Table 2. The example of efficiency of the assembly line in February 2024.

Time available [h]	510.0	100.00%
Time work SMT line [h]	425.2	83.37%
Time rearming [h]	76.6	15.02%
Time conservation [h]	4.9	0.96%
Time fault [h]	1.6	0.31%
Downtime (material) [h]	1.51	0.30%
Other - not reported time [h]	0.19	0.04%
Total number of projects	90	

Energy consumption was measured using the ND30IoT measuring device. The ND30IoT used in the study has a current declaration of conformity with the relevant harmonized standards: BS EN IEC 61000-6-4:2019, BS EN IEC 61000-6-2:2019, BS EN 61010-1:2020. The ND30IoT is a programmable digital instrument designed to measure, among other things, the parameters of three-phase 3-wire and 4-wire networks in both symmetrical and asymmetrical systems. It allows the measurement of: the effective values of voltage and current, active, reactive, and apparent power, active, reactive, and apparent energy, power factors, frequency, harmonics of current and voltage, as well as averaged active and apparent power. The value of each measured quantity is saved in CSV format files and then transmitted to the master system via an Ethernet interface.

HT20IoT data logger has been designed to measure, monitor and record temperature and humidity. The device HT20IoT used in the study has a current declaration of conformity with the relevant harmonized standards: EN 61000–6–4:2007, EN 61000–6–2:2005 EN 61010–1:2010 EN 50581:2012. It is implemented in facilities where monitoring and recording of temperature, humidity and CO_2 concentration are important for the accuracy of the whole process e.g.: in server rooms, drug and food warehouses, laboratories, etc.

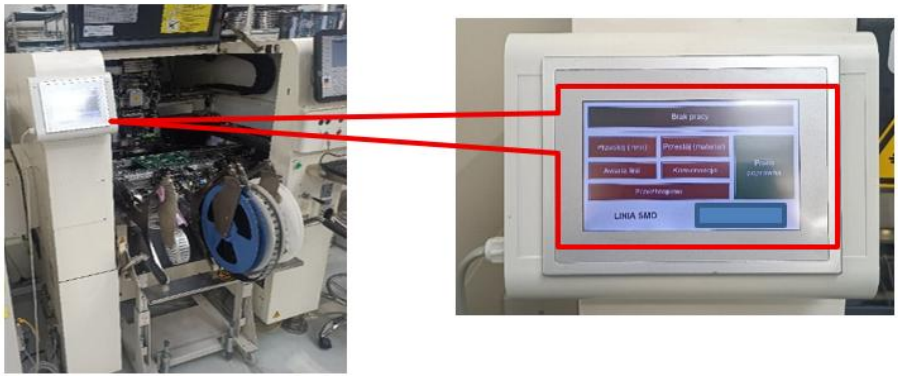


Figure 3. Station for recording performance parameters of the SMT line.

3. Results

3.1. Data acquiring

Searching the answer to research question RQ1, experimental studies were conducted in the real assembly process at a manufacturing company in the automotive industry on the research unit (Figure 2).

To better understand the analysed assembly process, the entire production process for the class of orders under study is also described. The production manager assigns the production order to the SMT machine operator according to the schedule. The operator starts production. All components must be ready according to the list in order to place the feeder directly into the machine. The operator checks the list of components and if all are available, production begins. After soldering the components onto the PCB (Printed Circuit Board), a visual inspection (AOI Automated Optical & Vision Inspection Systems) of all PCBs is performed to identify any visual defects. After passing the visual inspection, the PCB can proceed to through-hole assembly (THT - Through-Hole Technology), where all through-hole elements are soldered onto the board. After THT, the device undergoes calibration, during which the required software is installed and all elements are connected to obtain the final product - the counter. Then the meters are calibrated and labels and serial numbers are attached to them. Finally, their proper operation is checked and the quality is checked for compliance with IEC standards.

Next, data regarding the values of indicators describing assembly line efficiency and the selected SP factors was collected using IoT-based data and data from ERP systems from

September 2021 to November 2023, based on the example of the surface-mount assembly process for the production of electronic systems for a measuring device in the automotive industry. To measure energy consumption, an ND30IoT network parameter meter was used, which records the amount of energy drawn by the SMT line at a sampling interval of 1 minute. For further analysis, the monthly average values of the obtained data were used (Figure 4 and Figure 5). Compared to daily or weekly aggregation, monthly data ensure the representative illustration of energy usage trends while minimizing the impact of short-term disruptions. For energy consumption the data was compiled for individual monthly periods in tabular form and then numerically integrated using the trapezoidal method.

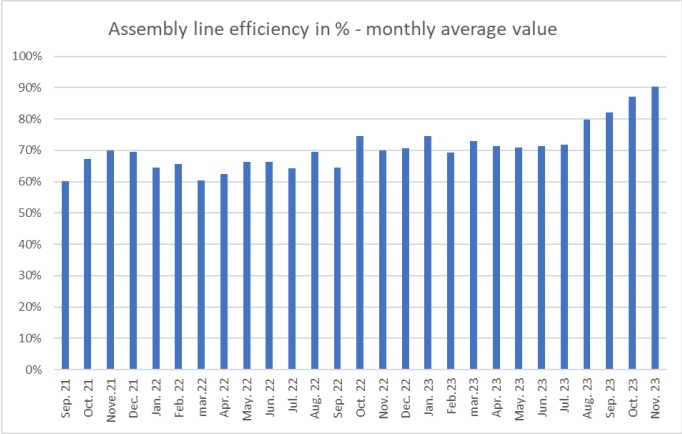
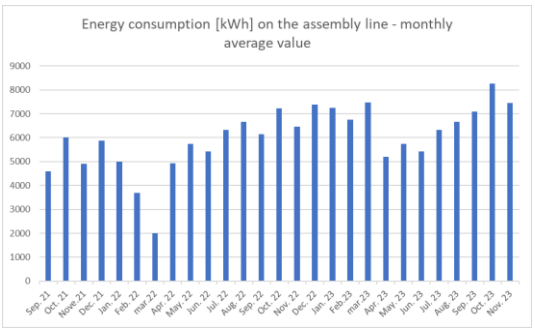


Figure 4. Assembly line efficiency – real – life data from the surface-mount assembly process based on the production of electronic systems for a measuring device in the automotive industry.

Over 1,000,000 records of real-life IoT-based data from environmental parameter sensors (with a sampling rate of approximately every 2 seconds) and over 750,000 records from ERP systems was collected. The inconsistent timestamps between the IoT and ERP data streams were aligned through synchronization to a common timeline, namely into monthly periods.

The experimental research results confirm that the integration of data and information from the ERP system and those obtained from I4.0 technology, such as IoT, supports the real-time monitoring of assembly line efficiency and environmental SP indicators (RQ1).



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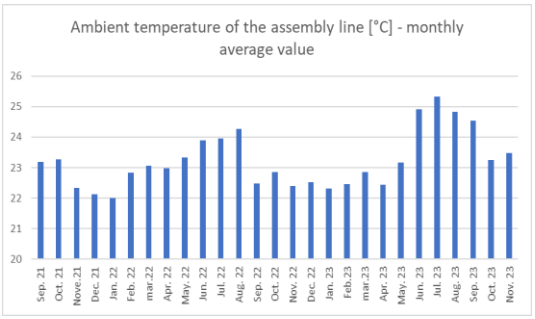

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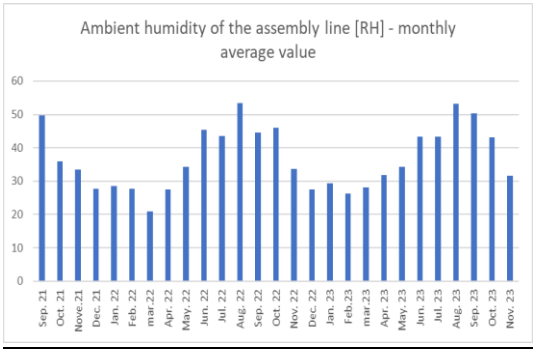

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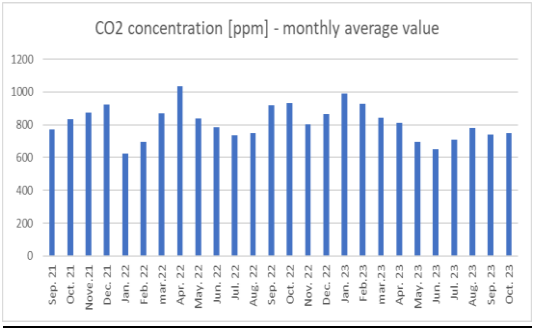

(d)

Figure 5. Indicators related to SP implementation on the assembly line: a) Energy consumption on the assembly line per month [kWh], b) Ambient temperature of the assembly line (°C), c) Relative humidity (RH), d) CO2 concentration (ppm) – real – life data from the surface-mount assembly process based on the production of electronic systems for a measuring device in the automotive industry.

3.2. Statistical analysis and AI applying

Next, statistical analysis was conducted to establish the linkage between assembly process efficiency with selected SP indicators in order to find an answer to RQ2. Therefore, according to the fifth stage of the research methodology, the correlation analysis is provided. It is a statistical method that describes the strength of the linear relationship between two variables. The value that characterizes the relationship is the sample correlation coefficient (r). It takes values in the closed interval <-1; 1>. A value of -1 indicates a perfect negative correlation, while a value of 1 indicates a perfect positive correlation. A value of 0 indicates no linear correlation [25]. The correlation coefficients (1):

$$r = \frac{\Sigma(x_i-\overline{x})(y_i-\overline{y})}{\sqrt{\Sigma(x_i-\overline{x})^2\Sigma(y_i-\overline{y})^2}} \quad (1)$$

where x_i and y_i are variables respectively x and y, and $\overline{x}$ oraz $\overline{y}$ - the average value of these variables.

During statistical analysis, the correlation between assembly line efficiency and parameters defining the SP level was examined. The data were tested for linearity, equality of variances, and normality. The analysis was conducted using the software package Statistica ver. 14.1.0.4 (StatSoft Polska Sp. z o.o., Kraków, Poland).

Table 3 presents the results of the study, where: r^2 — coefficient of determination; t — t-statistic value testing the significance of the correlation coefficient; p — probability value.

Table 3. Correlation.

Relationships	Correlation	r^2	t	p
Energy consumption per month [kWh]/ assembly line efficiency	0.7189	0.5168	5.0672	0.0000
Ambient temperature of the assembly line (°C) /assembly line efficiency	0.2731	0.0746	1.3910	0.1769
Relative humidity (RH)/assembly line efficiency	0.3422	0.1171	1.7842	0.0870
CO2 concentration(ppm)/assembly line efficiency	-0.1176	0.0138	-0.5806	0.5669

Next, a scatterplot (a 95% confidence interval) was added to the statistical correlation analysis (Fig. 6). The energy parameter was selected due to the most significant relationship between the parameters.

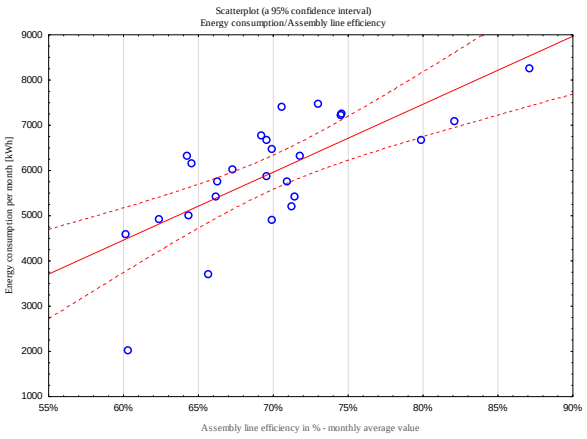

Figure 6. A scatterplot for energy consumption and assembly line efficiency.

Statistical analysis enables the identification of the most significant relationships between the indicators describing assembly line efficiency and the selected SP indicators. However, the correlation does not imply causality, even though the relationship is strong.

The application of an AI model allows for the development of a predictive model for the SP factor that shows the strongest correlation with the efficiency of the analyzed assembly line. Therefore, for further analysis, based on the correlation results (Table 3), the relationship between assembly line efficiency and SP indicators was adopted: energy consumption on the assembly line per month. A neural network, namely MLP (Multi-Layer Perceptron). The MLP was selected because it is a relatively simple and fast AI method. To build the models, a neural network with a logistic activation function was used. The activation function was applied for this purpose, due to the form of the data obtained from the sensors and is particularly useful in artificial neural networks with backpropagation. The function maps the range $(-\infty, \infty)$ na $(0, 1)$ [26,27] with a logistic activation function

The weight factors were determined during the neuron training process using supervised learning. To generate the neural network, Statistica 14.1.0.4 was used. The neural network models used in the study are presented in Figure 7.

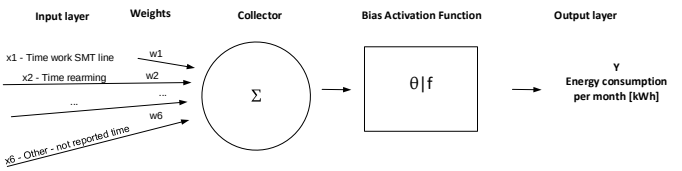

Figure 7. MLP network structure for prediction of a) energy consumption on the assembly line, where: w1…w6 - the weight factors, Y – measurement value.

Table 4 illustrates the MLP networks, with the activation logistics function, in terms of the network quality achieved, for training, testing and validation, respectively and the error function. The best model was the MLP network with the structure 6–5–1, where 6-5-1 refers to the number of inputs (6), the number of neurons in the hidden layer (5) and the number of output networks (1).

Table 4. MLP network structure for prediction of energy consumption on the assembly line per month.

Network name	Quality (learning)	Quality (testing)	Quality (validation)	Error (learning)	Error (testing)	Error (validation)	Learning algorithm	Error function
MLP 6-7-1	0.510224	0.933877	0.560869	1050614	416880.5	342270.3	BFGS 4	SOS
MLP 6-5-1	0.584278	0.998964	0.816914	1108697	673735.1	652598.0	BFGS 2	SOS
MLP 6-3-1	0.798223	0.919324	0.919121	447458	315050.5	229576.4	BFGS 27	SOS
MLP 6-11-1	0.503494	0.910411	0.539855	1027310	437136.8	336864.9	BFGS 3	SOS
MLP 6-5-1	0.538702	0.907815	0.623698	1099670	651791.0	620826.5	BFGS 2	SOS

The obtained monthly energy consumption values were compared with the forecast for energy consumption on the assembly line per month (Table 5).

Table 5. Comparison of actual values with the values forecast for energy consumption on the assembly line per month.

Month	Energy consumption per month [kWh]/– a real value	Energy consumption per month [kWh]/– a predictive value	Error
December 2023	7193	5579	22%
January 2024	7052	5574	21%
February 2024	6312	5578	12%
Marz 2024	6843	5576	19%
April 2024	7021	5573	21%
May 2024	6792	5572	18%

To validate the AI-based model, additional metrics such as MSE, RMSE, and MAE are often used, Therefore, studies were conducted in Matlab with daily input data for the year 2023: the line's operating times: time work SMT line, time rearming, time conservation, time fault, downtime (material) and other - not reported time, energy consumption. Totally, 272 x 9 = 2448 was data as the input data. Figure 8 presents an example of energy consumption measurement by the SMT line on December 2023 in kWh. The daily power measurement was obtained and then the monthly value was calculated by integrating the determined mileages.

In the first step, data normalization was performed, which brings all numbers into a common range [0, 1], preventing the model from getting lost in large values and allowing it to learn faster. Next, the data was divided into training, validation and test sets in the proportion of 70:15:15 and next was trained the MLP network using the Bayesian Regularization algorithm, which protects against outlier errors. The following calculates errors were received: MSE: 6.34, RMSE: 2.52, MAE: 1.09, MAPE: 0.41%.

The presented results indicate that the AI-based model may be useful for predicting energy consumption and assembly line efficiency. Given the variability of SMT processes and energy-load characteristics, a 12–22% prediction error is acceptable at this stage and can be improved with additional input variables in future work. At the same time, this constitutes a significant challenge aimed at identifying a strong linkage between assembly process efficiency with selected SP indicators for the automotive industry.

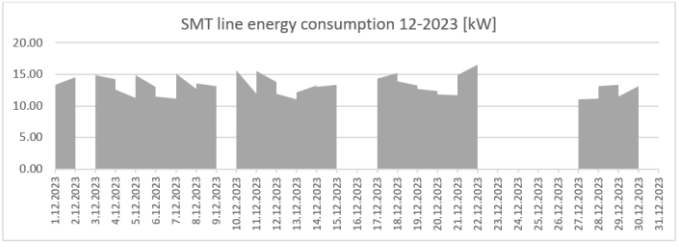

Figure 8. Example of monthly energy consumption by the SMT line recorded using the ND30IoT - numerical integration of the area under the graph (7 193 kWh).

4. Discussion

The sustainable development of electronics assembly lines is driven by European Union regulatory requirements, particularly

due to the high energy consumption associated with reflow soldering ovens, ventilation systems, and environmental control systems. The experimental research results and the proposal for predicting energy consumption in assembly process towards ensuring SP constitute a viable framework for the automotive industry.

The theoretical contributions of this paper involve two aspects. Firstly, it introduces a new perspective on real-time monitoring of the assembly process towards SP, based on IoT and ERP data collected from a real-life assembly line. Previous literature has primarily treated sensors as the main tools for data acquisition; in contrast, this study examines the integration of data and information from IoT-based systems and ERP systems as input for monitoring. Secondly, our research expands the literature on exploring the relationship between improving process efficiency and simultaneously enhancing the level of sustainable production. The findings suggest that the application of statistical analysis and artificial intelligence serves mainly as a tool for delivering results and can be involved in organizational decision-making. This constitutes the answer to the RQ1.

However, this study has certain limitations. It was conducted for a specific class of orders, and similar analyses should be performed for other order types. Another limitation is the restricted set of data used to determine process efficiency. In future work, data collection should be expanded to include additional parameters, such as feeder speed, placement speed, template cleaning frequency, placement accuracy, vacuum level, and others. Nevertheless, the universality and practical applicability of our approach are evident. The presented framework can be considered a universal solution applicable in enterprises within the automotive industry, similar to the study [28], which developed guidelines for productivity improvement in the machining of components for stamping dies. Both in the subject literature and in our study, an important aspect is the collection of data specific to a given enterprise. The approaches presented in the literature, as well as in our work, highlight the difficulty of implementing such solutions due to the need for manufacturing knowledge that is closely tied to a particular enterprise. But, the application of such solutions enables the development of a knowledge base within the organization and its effective management through the collection, formalization, and sharing of acquired knowledge. The use of AI makes it possible to build decision-support systems based on accumulated manufacturing knowledge. As a result, each subsequent order/project can be executed more efficiently by leveraging the enterprise's accumulated knowledge.

In seeking to answer the RQ2: How can the linkage between assembly process efficiency and selected SP indicators influence future research trends in SP research for the automotive industry? a new and interesting area for further research is the analysis of occupational safety factors for operators working on assembly lines. According to the study [29], smart manufacturing has significantly increased the implementation of real-time equipment health monitoring systems. In our approach, we selected SP indicators that have an impact on the health of the employees. The subject literature emphasizes that production processes are characterized by a high level of interaction between the operator and the machine, which significantly increases the complexity of the work environment and the potential sources of hazards [30]. Particulate matter (PM) is a European indicator used to assess air quality and health impacts. Air Pollution Associated with Total Suspended Particulate and Particulate Matter According to the International Organization for Standardization (ISO), particulate matter is small particulate matter with a diameter of less than 75 μm that settles under its own weight but can remain in the air for some time [31]. PM particulate matter is divided into PM10 (<10 μm) and PM2.5 (<2.5 μm), with finer PM2.5 penetrating deeper into the respiratory system, showing greater toxic potential and impact on cardiovascular and respiratory diseases. Building a safe work environment is an important goal, but many organizations still face significant challenges. Production environment expose workers to air pollution, and other hazards, while also new I4.0 technologies may introduce safety risks that require new actions in a manufacturing. This is a new aspect of further research in the context SP for the automotive enterprise.

5. Conclusions

The proposed approach, which integrates real-time data acquisition related to assembly process efficiency and SP using IoT technologies and ERP systems, combined with the application of AI demonstrates promising research outcomes. At this stage of the research it is possible - through real-time

monitoring of selected SP parameters: the energy consumption, ambient temperature of the assembly line, relative humidity, CO2 concentration and line efficiency by using IoT-based sensors and data obtained from an ERP information system. The main issues are the integration of data from ERP systems and IoT sensors often with missing values or different time resolutions and next the development the most effective AI-based model. This represents significant research potential, as future work will focus on identifying an appropriate artificial neural network architecture and conducting in-depth analyses. Subsequently, research efforts will be directed toward the analysis of occupational safety factors for operators working on assembly lines and net integrating the AI-based model with the ERP system currently implemented within the company. Finally, this approach can be considered a practical tool for supporting production managers in data-driven decision-making. It can also be integrated with existing internal company information systems, such as Business Intelligence.

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