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Data-Based Assembly Patterns for Overall Equipment Effectiveness at Semi-Automatic Assembly Lines

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Abstract

In industrial practice, production planning is a key factor for manufacturers and suppliers. The entire planning process spans from the appearance of the customer demand to the fulfillment of the demand. Operational execution is based on pre-planned production processes and operations using properly allocated resources. The accurate planning of assembly operations within production is an extremely complex process in terms of efficiency. Predicting stochastically variable efficiencies is difficult due to the ever-changing manufacturing conditions. This paper defines typical assembly process situations for a semi-automatic assembly line and examines their consequence for the Overall Equipment Effectiveness (OEE). Firstly, a literature review demonstrates the scientific relevance. Secondly, the classification of patterns based on assembly process description parameters is described taking into account the positive and negative effects on the OEE. In addition, the assembly patterns and their characteristics are illustrated through a real automotive example.

Keywords

OEE, assembly pattern, assembly line, cycle time

1 Introduction

In industrial practice, the efficiency of assembly processes is fundamentally determined by the feasibility of the production plan and the availability of the allocated resources. Continuous increase in efficiency, among others, is supported by the environment of Industry 4.0 [1, 2], Smart Manufacturing [3, 4], Big Data [5, 6], and Artificial Intelligence (AI). Using different data mining techniques reveals the hidden production patterns in manufacturing-related data [7].

Nowadays, much more data is generated in the field of production and assembly than can be processed since the production lines are equipped with sensors and modern camera systems [8]. In addition, the products have barcodes and unique identifiers, which further increases the amount of data. Data collection, recording, and storage can be automated and integrated with various systems, e.g., Manufacturing Execution System (MES) [9, 10]. MES can provide information and a database for work planning and production control [11, 12]. From digital shop floor data [13], the value of Overall Equipment Efficiency (OEE) is available in real-time and in case of performance deterioration immediate operational countermeasures can be taken [14, 15].

The aim of this paper is to reveal and identify different pattern categories at the semi-automatic assembly lines as a function of OEE.

The paper is organized as follows. Section 2 focuses on the relevant scientific work regarding OEE and manufacturing patterns. Following, Section 3 describes the assembly pattern categories with positive and negative effects on OEE. Section 4 displays the revealed assembly patterns in industrial practice. Section 5 concludes the paper.

2 Literature review

In the scientific literature, the concept of Overall Equipment Effectiveness and data mining are extensive. In terms of OEE, more than 850 papers were published between 1996 and 2020 [16].

Some of them present in detail the concept of OEE [17], its different calculation methods [18], and the derived additional efficiency measures, such as Overall Equipment Effectiveness of a Manufacturing Line (OEEML) [19], Overall Throughput Effectiveness (OTE) [20], and GPE (Global Process Effectiveness) [21]. Numerous case studies describe efficiency improvements in different ways

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in various areas. Involving diverse Lean manufacturing methods, OEE was also analyzed through its components (availability, performance, and quality). Typical values of OEE as a standard and best practice Key Performance Indicator (KPI) for batch type production, discrete process, and continuous process were defined by Hansen [22].

Regarding data mining, monitoring of production data began in the late 1980s, but current data mining methods were developed in the 2000s. According to Frawley and Piateski, data mining is "the non-trivial extraction of implicit, previously unknown, and potentially useful information from data" [23].

In the manufacturing and assembly domain, data mining is applied for predictive maintenance, failure detection, quality control, production planning and scheduling, and decision support systems [24]. Several data mining methods are used, including classification, regression, clustering, dimensionality reduction, dependency modeling, association discovery, change and deviation detection, and pattern discovery [25, 26]. According to Laxman and Sastry, the pattern is a local structure that makes a specific statement about a few variables or data points [27]. There are several applications of machine learning in pattern recognition [28]; these can be supervised learning (e.g., classification), unsupervised learning (e.g., k-means clustering), and reinforcement learning [29].

Tao et al. analyzed production abnormalities and found that before the occurrence of specific disturbances, certain patterns can be captured in the time series of data (e.g., energy consumption, torque, etc.) in time series [30].

Muchiri and Pintelon describe the chronic and sporadic losses as a pattern in manufacturing. Chronic disturbances are small and hidden, while sporadic losses occur quickly and have large deviations from the normal state [31].

Gröger et al. stored the manufacturing optimization patterns in a Manufacturing Pattern Catalogue. These patterns were presented as typical optimization processes such as best practices [7].

Niedermann et al., in the field of deep business optimization, defined several patterns, including parallelization, elimination, decomposition, resource allocation, and automated approval pattern. More than twenty optimization patterns were collected in a pattern catalog [32]. Niedermann and Schwarz applied different data mining techniques such as clustering for triage patterns, a decision tree for automated decisions, and multiple regression for resource selection [33].

After reviewing the relevant literature, it can be stated that the manufacturing patterns and manufacturing pattern catalogs are mentioned in several places; however, assembly patterns and OEE patterns detailed in industrial practice were not found.

3 Classification of assembly patterns

In the field of assembly, characteristic patterns are sets of data that are closely related, occur regularly, are predictable, and identify assembly efficiency.

This article focuses on semi-automatic assembly lines or hybrid assembly lines where automatic devices are combined with manual work in one system.

At semi-automatic assembly lines, assembly patterns are based on the cycle time measured at each workstation. The cycle time data of each workstation and each product type is provided by the Manufacturing Execution System (MES). To reveal patterns that affect the OEE, the start and end times of assembly operations at each workstation must be known, resulting in cycle time or other momentary disturbances that affect the assembly process. Special attention should be paid to the bottleneck station that determines the output as well as the OEE value of the assembly line.

This article discusses the patterns that are present on assembly lines on a daily and weekly basis. Patterns that occur infrequently are not currently examined (e.g., certain cases of quality error).

Assembly patterns can be classified into the following categories depending on their time of appearance:

- time-dependent (e.g., shift start, type change);
- time-independent (e.g., machine failure).

Another grouping can be formulated according to the effect on the elements of OEE:

- effect on availability (e.g., machine failure);
- effect on performance (e.g., longer test time);
- effect on quality (e.g., dimensions and tolerances).

Moreover, disturbances in patterns can be planned (e.g., regular quality checks) and unplanned (e.g., material shortage).

The deviations can be related, among others, to:

- machine, workstation, tool, etc.;
- human (operator, setter, etc.);
- process;
- material;
- production plan;
- a combination of these, etc.

In the following, based on the recorded start and end points of the cycle time, the assembly patterns are explained by describing each category.

3.1 Assembly patterns with positive effects on OEE

Patterns that can be revealed at semi-automatic assembly lines with a positive effect on OEE, i.e., increased efficiency, are shown in Table 1.

The assembly process is continuous if the cycle time of each workstation is realized within the planned time frame. It is interrupted if another none productive time occurs between operating times. It is plannable if the exact time and duration of the pattern can be determined in advance and resources can be assigned to it. Unplanned patterns, which usually require immediate intervention, decrease the OEE value the most.

Patterns that increase the OEE can be characterized as follows:

1. Normal assembly:
   - the right type and quality of products are assembled with the expected cycle time;
   - there is no disturbance in the system;
   - most characteristics of assembly processes;
   - basis of production planning and scheduling.
2. Capacity extended assembly:
   - allocated added resources (e.g., added staff, added equipment, tool, etc.) with systematic production planning;
   - typical short term in a crisis situation (e.g., urgent delivery);
   - disadvantages also occur (e.g., faster tool wear, higher maintenance cost, extra costs).
3. Human experience:
   - higher performance, faster setup, products are assembled within the expected cycle time;
   - constantly broadening , valuable knowledges.
4. Specific event performance:
   - carefully planned assembly period (e.g., audit session, speed day);
   - not a long period;
   - it does not occur frequently.

Table 1 Assembly patterns with positive effects on OEE

Type of pattern category	Effect on OEE	Assembly process	Plannable
Normal assembly	+	continuous	yes
Capacity extended assembly	+	continuous	yes
Human experience	+	continuous	yes
Specific event performance	+	continuous	yes

For each pattern, the assembly process is continuous. In addition, it is predictable and plannable. The goal of operation management is to keep most of the production going according to the normal assembly process.

3.2 Assembly patterns with negative effects on OEE

Patterns that can be revealed at semi-automatic assembly lines that negatively affect OEE, i.e., reduce efficiency, are shown in Table 2.

Patterns that decrease the OEE can be characterized as follows:

1. Type change:
   - occurs when changing the product type;
   - some products or parts are scrap or should be repaired;
   - fast start after the type change;
   - regular activity, can be classified based on duration and difficulty.
2. Workstation failure with downtime:
   - downtime occurs;
   - unexpected, not planned;
   - immediate intervention is required;
   - it also includes material shortages.
3. Process parameter change:
   - change of one or more process parameters (e.g., workstation cycle time increases);
   - more critical if it occurs at the bottleneck station;
   - in some cases, it is not visible (human perception is not possible);
   - raw material effect (e.g., plastic parts with different cavities).
4. Assembly scrap:
   - individual or serial occurrence;
   - controllable by machine (e.g., if it occurs five times, then stop the machine);

Table 2 Assembly patterns with negative effects on OEE

Type of pattern category	Effect on OEE	Assembly process	Plannable
type change	–	interrupted	yes
workstation failure	–	interrupted	no
process parameter change	–	continuous	no
assembly scrap	–	continuous	yes
trial run, test series	–	interrupted	yes
human effect and behavior	–	interrupted	no
shift change	–	interrupted	yes
shut down	–	interrupted	yes
poka-yoke check	–	interrupted	yes

- tolerance effect (parts are on the tolerance limit);
- at semi-automatic line depends on the human experience.

5. Trial run, test series, and upgrade:
   - experiment or introduction of a new part, component, subassembly, or assembled product;
   - workstation, equipment upgrade;
   - software update;
   - MES, network correction.
6. Human effect and behavior:
   - compliance with factory regulations (e.g., longer brake time, assembly operations started later, ended earlier);
   - support and assistance to the other workstation (to a slower operation in general);
   - training period;
   - job rotation (planned operator change between workstations);
   - human factor (e.g., fatigue);
   - build of excess buffer between workstations.
7. Shift change:
   - start and stop assembly operations;
   - dedicated time (e.g., every workday 14.00);
   - active information flow;
   - more setup and checking operations within a short time (mandatory operations based on automotive standards).
8. Shut down:
   - workstations are shut down for a longer time (e.g., weekends, holidays, etc.);
   - affects all workstations.
9. Poka-yoke check or verification:
   - short-term, planned downtime (at a specified time, e.g., after shift change, after type change);
   - control according to standards;
   - predetermined duration, supported by based on Single Minute of Exchange of Die (SMED) principle.

Negative patterns can interrupt the continuity of the assembly process but, in some cases, can be planned in advance.

4 Identification of assembly pattern categories in industrial practice

At an automotive company, data patterns were analyzed on a seat structure semi-automatic assembly line. Using production data sources, pattern categories were discovered and then defined. The determined categories were taken into account during the production planning, thus making the line output more accurate. Fig. 1 shows the applied process.

Over a longer period of time (e.g., half a year, in a three-shift production), assembly patterns can be explored using a variety of data mining programs. However, it is necessary to know the functional operation process and logistical circumstances of a given assembly line to reveal real and correct patterns. Fig. 2 shows a real industrial example of the area of a semi-automatic line for planned pattern categories for an afternoon shift.

Based on these data, the time and duration of the shift change, poka-yoke check, event performance, type change, and shut down can be planned and taken into account to predict the OEE value.

The effect on OEE under real assembly conditions is shown in Fig. 3. In this case, the OEE value is reduced by different percentages due to workstation failure, process parameter change, type change, poka-yoke check, shift change, and assembly scrap.

However, the capacity extended assembly increased the OEE value. Generally, a one-minute assembly loss results in a 0.208% OEE reduction regarding an eight-hour shift.

The revealed patterns and their effects support production planning and resource management, which results in production cost reduction. Based on real industrial example, one percent efficiency improvement in a semi-automatic assembly line saves 15,000 € with 15 shifts of operation per week.

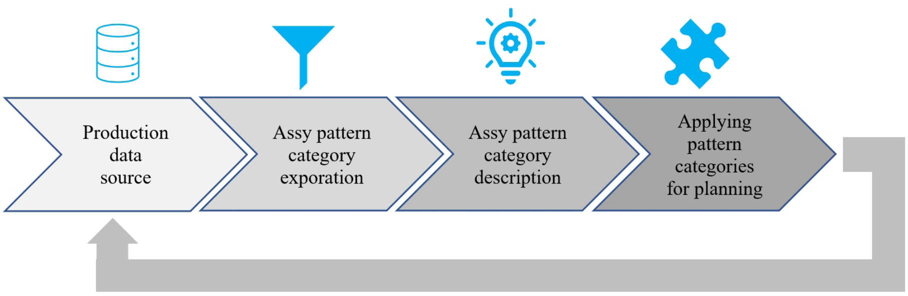

Fig. 1 From data to applied pattern categories

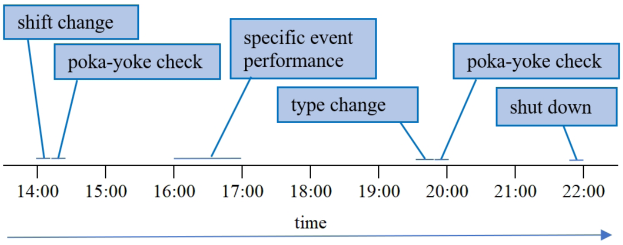

Fig. 2 Example of plannable pattern categories at an assembly line

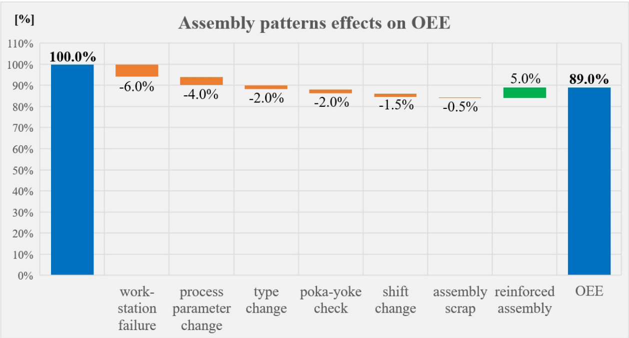

Fig. 3 Real example: pattern category effects on OEE

Assembly patterns may be interrelated; for example, due to a shortage of raw materials, product changes may occur to ensure continuous assembly and better use of resources, which requires poka-yoke control. In this case, at least three pattern categories are connected, which can even be a best practice. Another example, type change is followed by a process parameter pattern, which again results in a type change. A portion of the combination of possible correlations is shown in Table 3. It is important to assign the rows to the columns in Table 3 so that the direction of consequence can be interpreted.

Factory practice and the applied quality assurance system used must be taken into account when interpreting the possible combinations. For example: during the assembly operation, the type change should always be

Table 3 Possible interconnections of pattern categories (a portion of the full table)

Pattern categories	Normal assembly	Type change	Work station failure	Shift change	Poka-yoke check
Normal assembly	–	yes	yes	yes	yes
Type change	no	–	yes	yes	yes
Workstation failure	yes	yes	–	yes	yes
Shift change	no	yes	yes	–	yes
Poka-yoke check	yes	yes	yes	yes	–

followed by a poka-yoke check, then normal assembly can be/is expected.

5 Conclusion

In this article, typical assembly process situations for the semi-automatic assembly line as a function of OEE have been presented. Based on the cycle time of each workstation, assembly pattern categories were identified, such as the time of occurrence, effect on the elements of OEE, and the aspects of production planning. Assembly pattern categories were revealed at hybrid automatic assembly lines that positively and negatively affect the OEE. During a case study at an automotive company, patterns were analyzed on a seat structure semi-automatic assembly line. The effect on OEE under real assembly conditions was detailed. The revealed pattern categories and their effects support production planning and resource management, which reduces production costs. Possible interconnections of pattern categories were also presented. A future research goal could be to predict the OEE based on the assembly pattern categories, which can also help predict assembly costs and manpower parameter values.

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