Journal of Electrical Engineering, Electronics, Control and Computer Science – JEEECCS, Volume 9, Issue 31, pages 43-48, 2023

A Case Study Of Predictive Maintenance Using Data Analysis For A Flexible Manufacturing Line

Carmen Stan, Mihaela Oprea, Alexandru-Calin Stan
Department of Automatic Control, Computers and Electronics
Petroleum-Gas University of Ploiesti
Ploiesti, Romania
carmen.nica1991@yahoo.ro, mihaela@upg-ploiesti.ro, alex_stan2010@yahoo.com

***Abstract* – In the last decades, the manufacturing industry has been in continuous development with technological breakthrough and enhancements. The purpose of enhancing production efficiency it is directly linked with the trend in costumers' requirements, needs, product competition and availability on the market. This paper presents a predictive maintenance strategy based on data analytics for a flexible production line using the historical warning errors of the equipment of the line to achieve a condition-based maintenance plan.**

Keywords-Flexible production line; Predictive maintenance; Data analytics; Condition based maintenance;

I. INTRODUCTION

In the last few years, the trend of developing, implementing, and optimizing the manufacturing systems can be identified in all industrial countries. This is a result of a saturated market demand that requires products availability at any time, in various shapes and types, with the highest quality and the lowest price.

Therefore, in the manufacturing industry, the ability to timely respond to market change becomes the highest advantage. This is translated into the need of having the best business vision and strategy and the latest technological enhancements. But nevertheless, having the objectives of maximizing the profit by reducing the production costs, waste of material as a direct cause of non-conform production. On the other hand, using valuable manufacturing knowledge, under the form of ontologies or knowledge-based systems can improve the decision-making and thus, can increase production quality and productivity. Several research work reported recently in the manufacturing domain related literature present either ontologies (see e.g. (Polenghi et al., 2022), (Ramírez-Durán et al., 2020), (Roldán-Molina et al., 2021)) or knowledge-based systems (see e.g. (Cao et al., 2022), (Hartmann et al., 2022)) in which knowledge is derived from databases (e.g. (Kang et al., 2022)), mainly via machine learning or data mining (see e.g. rule mining in maintenance (Grabot, 2020)). Thus, we have developed an ontology that conceptualizes the main knowledge that was used in our research work.

The paper presents a data analytics-based strategy for predictive maintenance of a flexible production line by using historical warning errors of equipment in order to achieve a condition-based maintenance plan. A case study is described for a filling production line.

The paper is organized as follows. Section II presents the general concepts and the main business indicator for a manufacturing system. An example of a filling production line layout is represented, from which we will use data that will be analyzed in the following sections. Also, a preliminary form of an OWL ontology that conceptualize the subdomain of our research work is briefly described at the end of the section. Section III is dedicated to data acquisition and database, where the syntax and the objectives are detailed for each equipment of our production line. Section IV focuses on data analysis and the decision making for the condition-based maintenance plan. The final section concludes the paper.

II. FLEXIBLE PRODUCTION LINE

A flexible production system is defined as a system that receives as input information (data regarding the raw material, human resources, data required by the system to perform the task, the status of the equipment, utilities) and as a result of the process, this data is transformed in output data (Morosan, 2013) as it is shown in Fig. 1.

From quality assurance point of view the finished goods / services must comply with the quality standards required both by manufacturing but also the legal ones.

Figure 1: Block scheme of a manufacturing system.

There are a multitude of definitions for a flexible manufacturing system, from which two of them best describe the main advantages and benefits:

1. A flexible manufacturing system is defined as a number of equipment, connected to each other by an automatic transport system that is centrally controlled and monitored by a programmable logic controller (Tao, 2018).

2. The main purpose is to provide the necessary flexibility to complete the technological process in the parameters set in order to obtain the schedule production. Different modules of the manufacturing process can produce a part of the final product/ piece. For possible changes of product, the system is able to adapt to the new configurations of the required model (Morosan, 2013).

A manufacturing system is flexible if it has the ability to make a number of different parts. At the end of the operation, the machine tools are automatically prepared for the next part. Changes to equipment or parts to be produced are made without manual intervention.

A. Key business indicators

A flexible manufacturing system is controlled and monitored to ensure compliance with the quality standards of the finished product, timely detection of any defects that may occur in the technological process, efficiency and increase productivity, cost optimization. (Mehrabi, 2002).

The use of data collected in the production process allows the transition from a manufacturing process consisting of primary processes to a manufacturing industry based on intelligent processes, thus improving the productivity and efficiency of the process (Dalota, 1996).

The key business indicator for a flexible production line is represented by the productivity of the manufacturing process.

OEE (Overall Equipment Effectiveness) is the indicator regarding the way in which the process and results are carried out. In order to calculate OEE (see equation (1)), the availability of the process, the efficiency of the process and the quality of the process outputs are taken into account (Peter, 2019).

$$\text{OEE}=\text{Availability} \times \text{Performance} \times \text{Quality} \qquad (1)$$

Availability is defined as the period in which the equipment is available for production (see equation (2)).

$$\text{Availability}=\frac{\text{work time}}{\text{operating time}}\times 100 \qquad (2)$$

Performance is defined as the number of units produced in a given period of time compared to the specification given by the supplier (see equation (3)).

$$\text{Performance} = \frac{\text{Actual speed}}{\text{Nominal speed}}\times 100 \qquad (3)$$

Quality is defined as percentage good products-total products count (see equation (4)).

$$\text{Quality} = \frac{\text{Good product count}}{\text{Total product count}}\times 100 \qquad (4)$$

An OEE of 100% represents perfect production manufacturing only good parts, at the maximum speed and without any downtimes.

By measuring the OEE for a manufacturing system, offers information regarding how the system can be optimize and to assess the success of an improvement implementation

To increase the OEE, 6 major categories are considered to improvement initiatives:

- Equipment failure: breakdowns.
- Start-up after change over: operational adjustments.
- Minor stoppages during production.
- Actual operating speed.
- Losses during start-up.
- Material losses during production.

The benefits of improving the Overall Equipment Effectiveness are:

- Reduce costs of production.
- Reduce costs of equipment maintenance and repairs.
- Reduce the probability of quality failures and losses of material by having a better insight into the production process.
- Production runs at maximum capacity reduces the need of further investments.
- Timely response to market demand.

Further, we will define the main concepts of maintenance strategies that will be approached in this paper:

- corrective maintenance
- preventive maintenance
- predictive maintenance

B. Schematic representation of a Filling production line

Improvement initiatives are continuous implemented in ordered to improve the OEE. Operational losses of efficiency can be significant improved by having strict operational standards and procedures, train and retrain the operators.

In the paper below it will be tackled one of the main causes of loss of efficiency on the manufacturing line that it is considered to have the highest negative impact into the line functionality: equipment breakdown. If the operational part is acknowledged and known to take place (production plan set in accordance) if the procedures are missing or the operators are not trained, the breakdown of an equipment is unpredictable. An equipment breakdown can cause a production line to stop production if the affected workstation is critical or in best scenario to restart production if a backup station is available (even if the backup is available, the timeframe between stop and resume production is considered downtime) (Eversheim,1982).

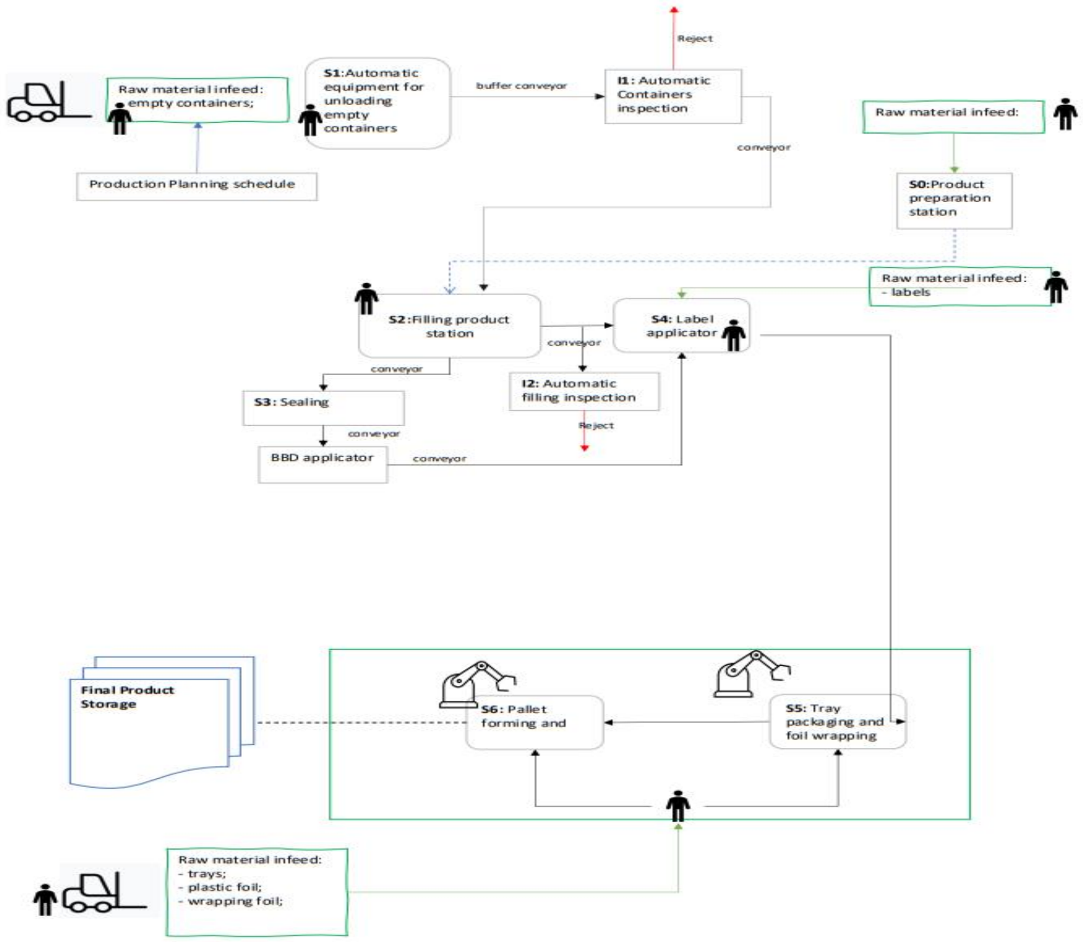

Figure 2. Filling production line

In Fig. 2, it is schematically represented a filling production line.

Furthermore, a case study of a line that consists of seven working automated stations, marked with S0 (Product preparation station), S1 (Automatic equipment for unloading empty containers), S2 (Filling product station), S3 (Sealing), S4 (Label applicator), S5 (Tray packaging and foil wrapping), S6 (Pallet forming and wrapping) that are operated, supervised and supplies with raw materials by an employee.

Any issue that appears on the line, the employee has the task to verify, intervene (if the level of intervention is in accordance with the level of qualification) or to notify the maintenance department.

C. The ontology

In order to provide a conceptualization of our research work subdomain, we have designed and implemented in Protégé 4.3 a preliminary form of an OWL ontology, OntoFlexibleManufact that includes general concepts from the manufacturing domain (e.g. production line, resource) and specific concepts from the equipment maintenance in flexible production lines subdomain (predictive maintenance, product quality, overall equipment effectiveness), as well as relations between concepts (e.g. hasResource, hasEquipment).

Fig. 3 shows a screenshot with a selection from the ontology concept hierarchy.

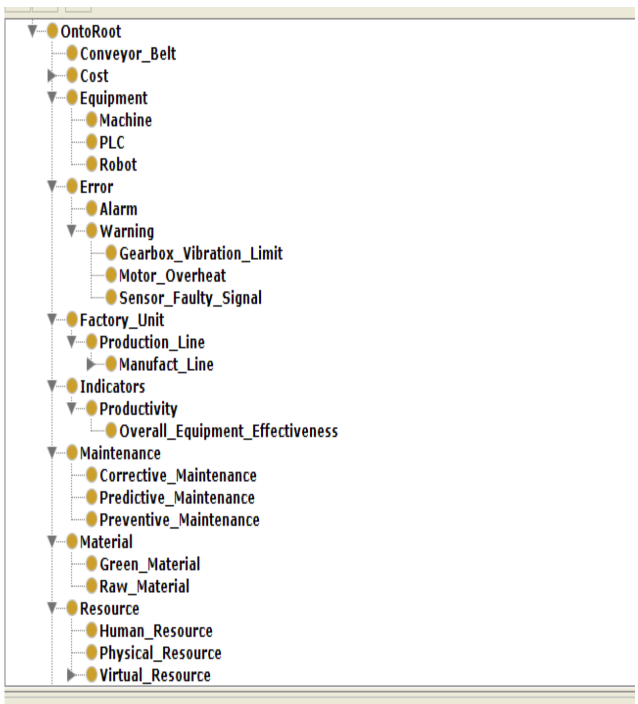

Figure 3. The ontology concept hierarchy - selection (in Protégé 4.3).

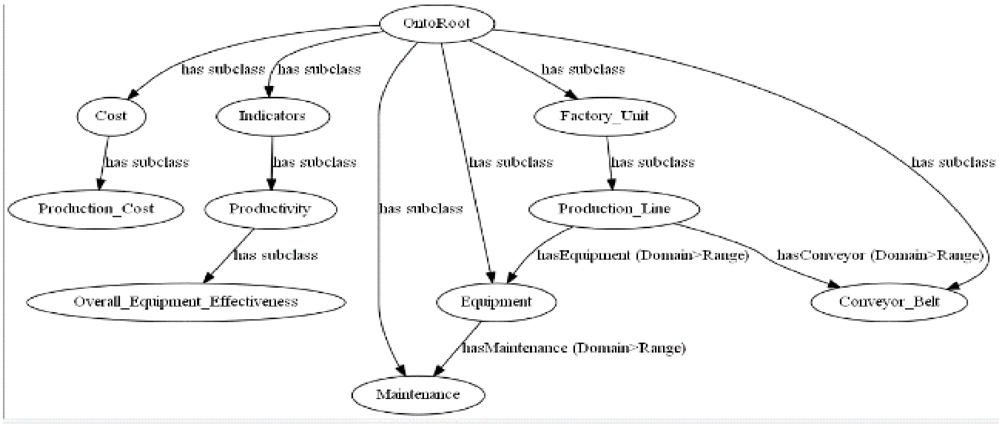

Figure 4. A knowledge graph from the developed ontology (in GraphViz).

Fig. 4 presents a knowledge graph which shows the taxonomic relations (isa), as well as other types of relations (e.g. compositional relations has Equipment, has Conveyor). Two examples of taxonomies included in the ontology are presented in Fig. 5.

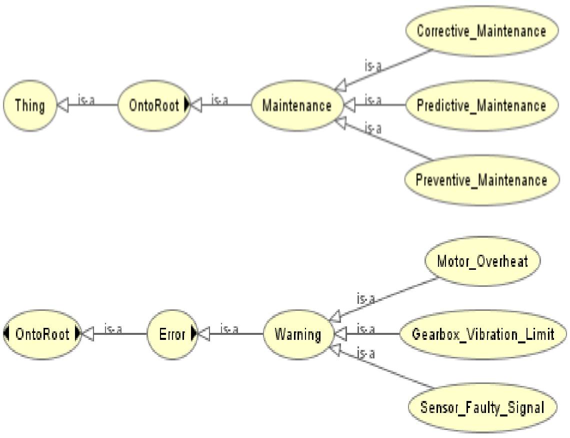

Figure 5. Selection of taxonomies included in the ontology hierarchy (in OWL Viz).

III. DATA ACQUISITION AND DATABASE

From operational point of view, there are multiple types of errors that are notified on the operator panel during production:

- Warnings- notifies the operator regarding the issue that appeared on the line but without stopping the production.
- Alarms- notifies the operator regarding the issue that appeared on the line and stops the production. An alarm on the line determines a downtime. The alarms are reporting issues of different parts of the equipment that can only be solved by corrective maintenance (replacement/ refurbishment).

Any alarms will stop the line and will affect either the performance of the line (due to the faulty equipment, the workstation will not be able to run at nominal speed) or the availability (can be minor stoppages or can lead to breakdowns). For predictive point of view an ideal case will be to avoid the alarms that implies equipment stops and to have a planned response for any warning.

In this paper will focus on analysing the historical warnings on each equipment to predict a future breakdown and to plan maintenance intervention based on it. Each equipment has a well define purpose in the functionality of the production line and has a greater or lesser importance. For example, the S0 and S1 are critical for line functionality (the entire will stop if one of this equipment will have an alarm) but for S6 there is the option (backup equipment) to switch to a different format (packs) or not to apply the stretch.

In this scope we will analyse the data from 3 categories of warnings:

- Motor_overheat – each electrical motor is equipped with a temperature sensor that measure the temperature inside the coils of the motor. Based on this temperature we can determine if the motor is running normally or has an abnormal working condition.
- Sensor_faulty_signal we define as faulty signal a sensor signal that is not in the normal working range of the process that can be caused by an internal fault of the sensor or external factors such as dirt, dust, drops of water.
- Gearbox-vibration_limit- each gearbox is equipped with a vibration sensor that measure the vibration on three axes and for each we had set a limit warning threshold for vibration. Vibration that helps us to determine the working condition of the gearbox.

Each message will be sent as a warning message to the operator panel and to our database. This warning message will only notify the operator but will not stop the equipment. In Fig. 6 is represented the process of data acquisition from each equipment and the structure of the database. For every equipment we run a script (s0.sh, s1.sh, s2.sh, s3.sh, s4.sh, s5.sh. s6.sh) that transfer the warnings and alarms to a database in which we store the data for every workstation of the production line.

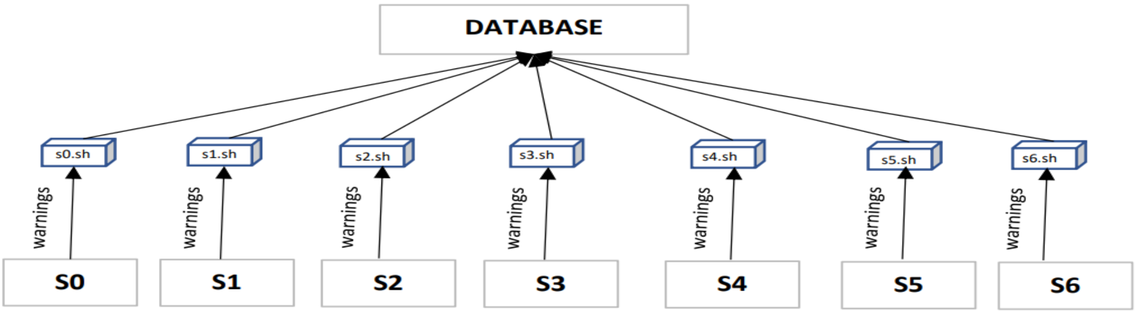

Figure 6. Data aquisition

Fig. 7 presents an example for one station (S0) of the displayed messages stored in each database for each equipment from the production line.

```
---------------------------------
0 Warning Gearbox_vibration_limit on:outfeed_gearbox
1 Warning Motor_Overheat on:Motor_4
2 Warning Motor_Overheat on:Motor_1
3 Warning Sensor_Faulty_Signal on:Sensor_2
4 Warning Gearbox_vibration_limit on:infeed_gearbox
5 Warning Motor_Overheat on:Motor_5
6 Warning Sensor_Faulty_Signal on:Sensor_2
7 Warning Gearbox_vibration_limit on:Main_gearbox
8 Warning Sensor_Faulty_Signal on:Sensor_1
9 Warning Sensor_Faulty_Signal on:Sensor_2
10 Warning Motor_Overheat on:Motor_5
11 Warning Sensor_Faulty_Signal on:Sensor_1
12 Warning Motor_Overheat on:Motor_3
13 Warning Motor_Overheat on:Motor_5
14 Warning Motor_Overheat on:Motor_3
15 Warning Gearbox_vibration_limit on:infeed_gearbox
16 Warning Motor_Overheat on:Motor_3
17 Warning Motor_Overheat on:Motor_1
18 Warning Motor_Overheat on:Motor_4
19 Warning Motor_Overheat on:Motor_4
20 Warning Gearbox_vibration_limit on:infeed_gearbox
21 Warning Sensor_Faulty_Signal on:Sensor_3
22 Warning Sensor_Faulty_Signal on:Sensor_2
23 Warning Gearbox_vibration_limit on:infeed_gearbox
24 Warning Gearbox_vibration_limit on:Main_gearbox
25 Warning Gearbox_vibration_limit on:infeed_gearbox
26 Warning Gearbox_vibration_limit on:Main_gearbox
27 Warning Sensor_Faulty_Signal on:Sensor_3
28 Warning Sensor_Faulty_Signal on:Sensor_3
```

Figure 7. Messages displayed in the database for S0.

IV. DATA ANALYSIS AND DECISION MAKING

Our approach for predict future malfunctions is to look and identify patterns in historical warning of the equipment in the database. In order to achieve this, we will define as a perfect condition equipment, an equipment with zero alarms in the last 30 days that will have a technical score of 1000 points.

Each category of warning will have different weights (ω) based on frequency (n) and the level of impact in the equipment functionality. In the following equations, heuristic knowledge, derived from experience will be defined.

The technical score is defined as:

$$\text{Technical score} = 1000\text{-}n1\times\omega1\text{-}n2\times\omega2\text{-}n3\times\omega3 \qquad (5)$$

Where:

n1- number of Motor_overheat warnings.

n2 - number of Sensor_faulty_signal warnings.

n3 - number of Gearbox_vibration_limit warnings.

ω1 - weight of the motor_overheat warnings.

ω2 - weight of the Sensor _faulty_signal warnings.

ω3 - weight of the motor_overheat warnings.

$$\omega1 = b1 + n1/10 \qquad (6)$$

$$\omega2 = b2 + n2/10 \qquad (7)$$

$$\omega3 = b3 + n3/10 \qquad (8)$$

b1, b2, b3 - are constant factors for warnings weights that can be modified by the user according to experience.

In our research work, reported in this paper, we used for b1, b2, b3 the following set of constants:

- b1=5
- b2=2
- b3=3

Based on a scale from 1 to 5, these constants have been set to these values based on the level of impact of the warnings in the equipment functionality (1- low impact, 5- high impact).

Our plan is to ensure a condition-based maintenance for each equipment of the production line and by using the technical score of the equipment we can estimate the time until next equipment maintenance.

Based on the technical score of every equipment, will offers a clear vision regarding the technical status for the entire line. Knowing the importance of each equipment in the line functionality (S0 and S1 are critical, S6 has a backup), the maintenance intervention can be planned taking into account the resources needed (spare parts or personnel: electricians/mechanics) or the line production plan (not able to stop due to high demand to produce).

Starting from perfect condition equipment, we can estimate that in order to have flexibility in both line functionality and in the maintenance planning it is best to keep the “next needed equipment maintenance in” to always greater that 14 days.

In Fig. 8, the technical score for S0 is displayed. Based on this score, the system predicts the next needed equipment maintenance in 22 days.

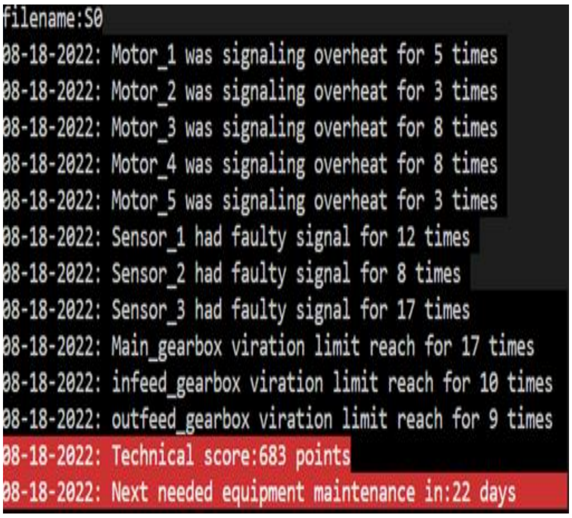
```
filename:S0
08-18-2022: Motor_1 was signaling overheat for 5 times
08-18-2022: Motor_2 was signaling overheat for 3 times
08-18-2022: Motor_3 was signaling overheat for 8 times
08-18-2022: Motor_4 was signaling overheat for 8 times
08-18-2022: Motor_5 was signaling overheat for 3 times
08-18-2022: Sensor_1 had faulty signal for 12 times
08-18-2022: Sensor_2 had faulty signal for 8 times
08-18-2022: Sensor_3 had faulty signal for 17 times
08-18-2022: Main_gearbox viration limit reach for 17 times
08-18-2022: infeed_gearbox viration limit reach for 10 times
08-18-2022: outfeed_gearbox viration limit reach for 9 times
08-18-2022: Technical score:683 points
08-18-2022: Next needed equipment maintenance in:22 days
```

Figure 8. Technical score for S0 and recommended equipment maintenance.

In Fig. 9, the technical score for S5 is displayed. Based on this score, the system predicts the next needed equipment maintenance in 12 days.

.

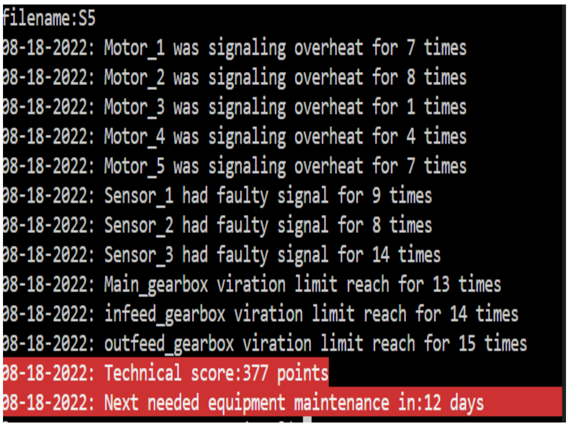
```
filename:S5
08-18-2022: Motor_1 was signaling overheat for 7 times
08-18-2022: Motor_2 was signaling overheat for 8 times
08-18-2022: Motor_3 was signaling overheat for 1 times
08-18-2022: Motor_4 was signaling overheat for 4 times
08-18-2022: Motor_5 was signaling overheat for 7 times
08-18-2022: Sensor_1 had faulty signal for 9 times
08-18-2022: Sensor_2 had faulty signal for 8 times
08-18-2022: Sensor_3 had faulty signal for 14 times
08-18-2022: Main_gearbox viration limit reach for 13 times
08-18-2022: infeed_gearbox viration limit reach for 14 times
08-18-2022: outfeed_gearbox viration limit reach for 15 times
08-18-2022: Technical score:377 points
08-18-2022: Next needed equipment maintenance in:12 days
```

Figure 9. Technical score for S5 and recommended equipment maintenance

CONCLUSION

In conclusion, we can say that using the historical alarm data (warnings, alarms) gathered from equipment offers a deep understanding of the equipment status. This paper presents an example of how this data can be used in predicting future malfunctions and is a step further in obtaining a condition-based maintenance for each equipment. Heuristic knowledge derived from experience was applied to data analysis.

As a future work we intend to integrate the ontology with the data analysis and decision-making subsystem.

REFERENCES

[1] Polenghi A., Roda I., Macchi M., Pozzetti A., Panetto H.,"Knowledge reuse for ontology modelling in maintenance and industrial asset management", Journal of Industrial Informatics Integration, 27,2022.

[2] Ramírez-Durán V. J., Berges I., Illarramendi A. , "ExtruOnt: An ontology for describing a type of manufacturing machine for Industrie 4.0 systems", Semantic Web, 11(6), pp. 887-909,2020.

[3] Roldán-Molina G. R., Ruano-Ordás D., Basto-Fernandes V., Méndez J. R., "An ontology knowledge inspection methodology for quality assessment and continuous improvement", Data & Knowledge Engineering, 133,2021.

[4] Cao Q., Zanni-Merk C., Samet A., Reich C., de Bertrand de Beuvron F., Beckmann A., Giannetti C. (2022). KSPMI: "A knowledge-based system for predictive maintenance in Industrie 4.0", Robotics and Computer-Integrated Manufacturing, 74.

[5] Hartmann C., Opritescu D., Volk W., Schmiedl F., Ritter M., Gritzmann P. (2022), "A knowledge-based automated driving approach for flexible production of individualized sheet metal parts", Knowledge-based Systems, 244.

[6] Kang Z., Catal C., Tekinerdojan B. (2022), "Product failure detection for production line using data-driving model", Expert Systems with Applications, 202.

[7] Grabot B. (2020), " Rule mining in maintenance: Analyzing large knowledge bases", Computers & Industrial Engineering, 139.

[8] Morosan A.D. (2013),"Efficient software system for flexible manufacturing lines", in Romanian, PhD Thesis, University of Transilvania, Brasov.

[9] Tao F. (2018), "Data-driven smart manufacturing", Journal of Manufacturing Systems, 48, pp. 157-169.

[10] Dalota M.D. (1996),"The enterprise of the future implementation strategy" (Romanian), Published by Sedona, Timisoara.

[11] Peter P., David Ž., Josef B., "Historical Overview of Maintenance Management Strategies: Development from Breakdown Maintenance to Predictive Maintenance in Accordance with Four Industrial Revolutions", Proceedings of the International Conference on Industrial Engineering and Operations Management Pilsen, Czech Republic, July 23-26,2019.

[12] Mehrabi M.G, Ulsoy A.G., Koren Y. and Heytler P. ,"Trends and perspectives in flexible and reconfigurable manufacturing systems", Journal of Intelligent manufacturing, pp.135-146, April 2002.

[13] Eversheim W. and Herrmann P. (1982)," Recent trends in flexible automated manufacturing", Journal of Manufacturing Systems, Volume 1, Issue 2, pp. 139-148.

[14] https://www.reliableplant.com/Read/11785/overall-equipment-effectiveness

[15] https://www.tibco.com/reference-center/what-is-overall-equipment-effectiveness