Conceptual Framework of Predictive Maintenance in a Canning Industry

Panagiotis Mallioris [1], Georgios Kokkas [1], Alexandros Styliadis-Heinz [1], Ioannis Margaritis [2], Fotios Stergiopoulos [1] and Dimitrios Bechtsis [1]

[1] *International Hellenic University, Department of Industrial Engineering and Management, P.O. Box 141, Sindos, 57400, Greece*
[2] *SAVVYCAN S.A., Karavaggeli 6, Kalohori, 57009, Greece*

Abstract

In the context of Industry 4.0, Industrial Internet of Things devices, Cyber Physical systems and Big Data solutions constitute the main core of state-of-the-art industrial production. The majority of research in this area focuses on smart manufacturing in order to improve the production process, increase the reliability and safety of industrial machinery, reduce downtimes and optimize the maintenance schedule. This paper proposes a smart solution for production monitoring incorporating a decision support system for failure diagnosis in a tin can manufacturing process. This study focuses on a predictive maintenance strategy framework that will prevent machine malfunction, bottlenecks in the production process and long downtimes. In this paradigm, optical sensors will be embedded alongside vibration and environmental sensors (i.e., humidity, temperature) for the data acquisition of important Key Performance Indicators (KPI). Programmable Logical Controllers and the KEP Open Platform Communications (OPC) Server will be utilized in order for the acquired data to be dynamically transferred and stored in a MySQL relational database. Afterwards, the database will be integrated with a Big Data analytics platform for the process of data mining and decision making. As a final step, a dashboard with real time descriptive statistics and an alarm-based system will inform the maintenance personnel for upcoming potential failures. This approach will connect malfunctions with features/sensors and improve the existing production process which will eventually lead on minimizing the production costs and increasing machine reliability.

Keywords

Canning Industry, Big Data, Decision Support System, Predictive maintenance

1. Introduction

Big data solutions in manufacturing process have been widely researched in recent years. The advent of information technologies combined with big data approaches, enable a flexible, responsive and decentralized process which leads to smart manufacturing [1]. In order to be competitive, modern enterprises will be prompted to modify their production processes and manipulate efficiently data of high velocity, variability, veracity, volume and value [2]. In this context, industrial machinery should be capable of analysing real-time data and prognosing upcoming potential malfunctions, preventing production disruptions (Gokalp et al., 2017).

This paper focuses on developing a smart manufacturing solution by integrating Industry 4.0 technologies namely Industrial Internet of Things (IIoT), Cyber-Physical Systems (CPS), Big data in a Can manufacturing process. Our research will significantly impact the competitiveness and productivity

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EMAIL: panmalliw@gmail.com (A. 1); geokokkas87@gmail.com (A. 2); alexstyliad@gmail.com (A. 3); i.margaritis@savvycan.gr (A. 4) fstergio@ihu.gr (A. 5) dimbec@ihu.gr (A. 6)
ORCID: 0000-0001-5781-8362 (A. 1); 0000-0002-9351-5542 (A. 5); 0000-0003-3110-7292 (A. 6)

of the organisation by constructing an autonomous real-time data processing approach. In addition, a predictive maintenance solution with data-driven methodologies will be examined in order to increase the reliability and safety of production machinery. Several examples exist in literature of predictive maintenance applications and bottleneck reduction solutions. A machine learning solution for failure classification and identification on motor shafts was presented [4]. The MatrikonOPC simulation server was used for the interface between data sources, while the National Instruments (NI) LabVIEW software has been used for data acquisition and for developing the solution systems. Accelerometers were installed on the motor shaft to measure the vibration on different axes to be used as an input on the classification algorithm. The proposed implementation successfully detected the vibration failure of the motor shaft. Additionally, [5] presented a machine learning approach for anomaly detection and production bottleneck prediction in cold forming manufacturing line. Acoustic emissions, maintenance logs and statistical measures, such as mean and standard deviation, were implemented as the input features of the classification algorithm. The results indicated a classification of the healthy state of cold forming manufacturing line using acoustic emissions with an F1 score of 0,632.

In more depth, in our research optical sensors will be implemented in each production stage, vibration sensors in the frequently malfunctioning beader machine and temperature and humidity sensors in the oven respectively. Moreover, the sensors will be integrated in an OPC Server through Programmable Logic Controllers (PLCs). As a next step, the OPC Server will establish a real-time connection with a relational MySQL database for data storage and further analysis. Furthermore, the Pandas big data analysis library and python programming language will be implemented for the process of data mining and decision making on critical production processes, i.e. predicting the failure of machinery and preventing production bottlenecks. Finally, real-time statistical measurements of KPI parameters, prediction outcomes and an alert-based system will inform the production engineers. Figure 1 shows the proposed methodology as a stepwise process.

This paper is organized as follows. Section 2 describes the framework of OPC server and the connections between PLC and database. Section 3 presents the Big data platform and the conceptual methodology of data mining. Section 4 concludes with some remarks and propositions for future research.

2. PLC- OPC Server – Database

The main scope of the proposed Decision Support System (DSS) is improving the productivity through a dynamic process of data acquisition and analysis. The monitoring framework will ensure the reliability and safety of machinery, determine production losses at various stages and collect quantitative and qualitative characteristics related to the use of raw materials (namely, tinplate, lacquer, powder). In combination with photo electric sensors used for controlling the operation of the production line in order to avoid bottlenecks, a variety of sensors will be integrated at different production stages collecting important measurements of vibrations temperatures, humidity. The acquisition of such important indicators will enable the researchers to output descriptive statistical information regarding the production process and additionally implement a set of data-driven algorithms for predictive maintenance. A set of Siemens PLC will be used in order for the acquired data to be transferred in real time with a sampling period of 10sec to the KEP OPC Server. As a proof-of-concept, basic hardware connection between a PLC and optical sensors is presented in Figure 2.

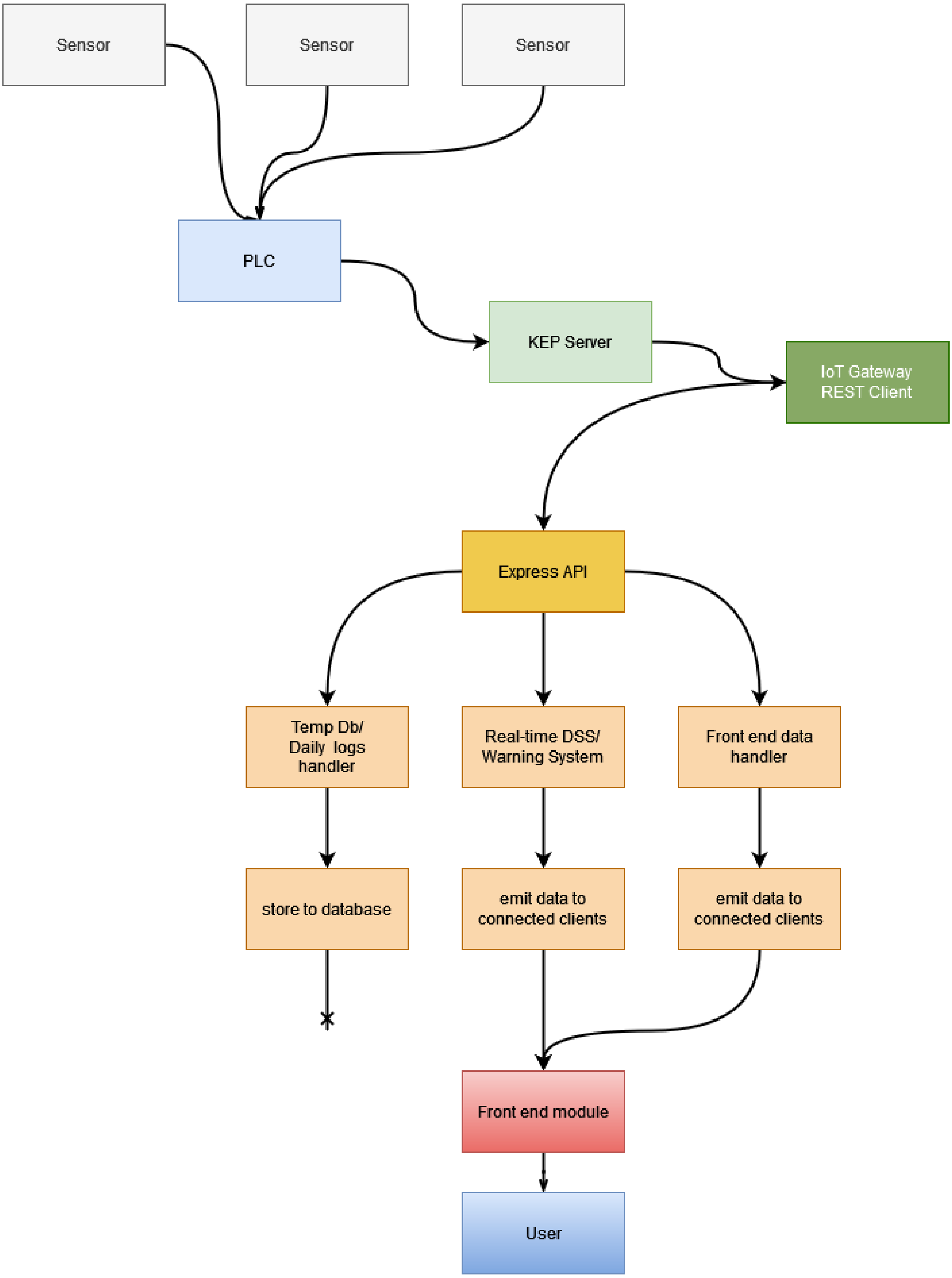

Figure 1: Proposed methodology as a stepwise process

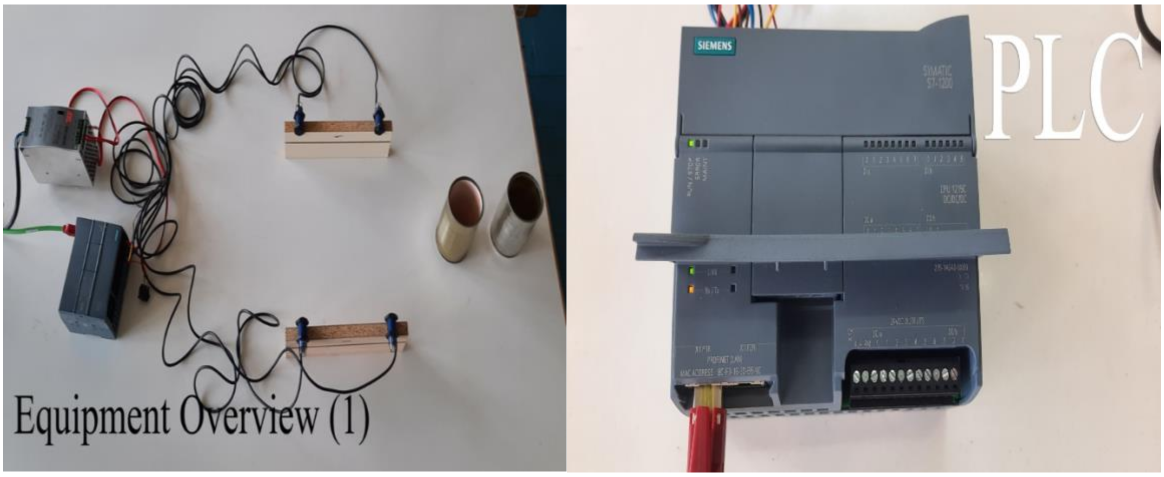

Figure 2: Connection of a PLC to optical sensors (proof-of-concept)

As a next step, the OPC Server inherently stores production data in a relational database and provides three data sources to the rest of application. More specifically, the data sources consist of a Data Logger, a HTTP Server and a HTTP Client.

- A **data Logger** is used to store data directly into a MySQL database at a steady rate of 10 seconds. The database, being static, also serves as a long-term repository for storing historic data of the production line.
- An **HTTP Server** is an endpoint that enables bilateral communication between the webserver and the OPC Server permitting remote Read/Write functionality for the rest of the application.
- An **HTTP Client** broadcasts sensor generated data to a designated web endpoint in real-time.

Our proposed framework is quite innovative, reducing the otherwise complicated process of aggregating heterogenous data sources of production process and facilitates their presentation to all the stakeholders using state-of-the art software tools. In the following section the process of data mining and decision making will be described thoroughly.

3. Decision Support Systems (DSS)

In a decision support system where a huge amount of heterogenous is processed, data mining is essential. Data mining is the process of manipulating raw data through cleaning techniques, finding patterns, creating models, and evaluating the outputs. It includes descriptive statistics and data-driven methodologies for decision making. Furthermore, data mining can be divided in three different subsections namely, data cleaning or cleansing, data pre-processing and decision making. [6], [7] presented an extensive research of data manipulation and data analysis. In the following sections the procedure of data mining is described.

3.1. Data Cleaning

It is essential for a decision support system that the processed data to be complete and in the proper format. In a production process, where real-time data is collected in large quantities from heterogeneous sources, data cleaning techniques avoid processing them in the wrong or incomplete form. The data cleansing process involves identifying incorrect, incomplete or inaccurate data and replacing or deleting them. In our use case we implement NumPy and Pandas libraries of the python programming language for data cleaning. Additionally, commonly used software is Apache Spark and pyspark libraries.

3.2. Data Pre-processing

Data pre-processing in a data-flow application further manipulates important variables prior to their implementation in the decision algorithms. Data-pre-processing can be divided as follows:

- Conversion of the data type into an appropriate format, thus avoiding inequalities between the variable types of each column.
- Data normalization which is important when variables from heterogenous sources show high redundancy and thus improving data integrity.
- Homogenization of the data in order to avoid biased results and ensure data consistency for the prediction algorithm.
- Fabrication of additional features which can be produced by dividing the information of a crucial parameter (namely datetime).
- Deviating the structure of the columns in order to provide the prediction algorithm the possibility to find additional correlations.
- Further analysis with descriptive statistics, i.e. mean, median, mode, standard deviation, variability.
- Additional correlation examination using methods such as Pearson, Kendall, Spearman, Point-Biserial.

Figure 3 shows a heatmap of important manufacturing variables using the Spearman correlation method, python programming language and the seaborn library.

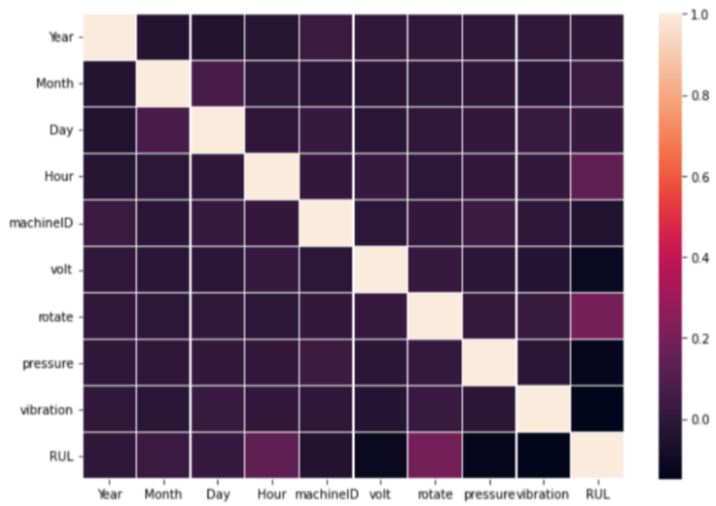

Figure 2: Heatmap of important manufacturing variables

3.3. Decision-making

Prior to data visualization, the final step in the decision support process is decision making. Depending on the predicted value the researcher is opted to select and examine a variety of predictive algorithms in order to output an accurate solution. Relatively, the confronted issue can be defined as classification, regression, remaining useful life (life expectancy) or a clustering problem. It is essential for the decision-making process, the input features and the predictive value through the data mining procedures to be thoroughly analyzed and categorized [8]. The limitations of a decision-making algorithm is that it requires a large dataset containing non-failure and failure measurements and it can be computationally expensive. In this research, where we have to examine heterogenous data, we will select the optimal predictive solution relatively to the emerging issue and the production needs. Python programming language and the scikit-learn, TensorFlow and keras libraries will be used for the algorithm implementation.

3.4. Data Visualization

A dashboard containing real-time crucial parameters and predictive outcomes of the production process in combination with an alarm-based system are designed for the proposed use case. As part of this process, a service that filters the incoming data is set up before it is stored in the database. If the algorithm detects an anomaly, a warning message is triggered and forwarded to the front-end application to prompt the user for corrective action. The visual data presentation (Figure 4) is implemented using the React framework in combination with a charting engine of the echarts library developed by the Apache Foundation. More specifically, the frontend web application queries an Express server upon user request and, upon receiving a response, forwards the requested data to the echarts React component library in order to be visualized for the user.

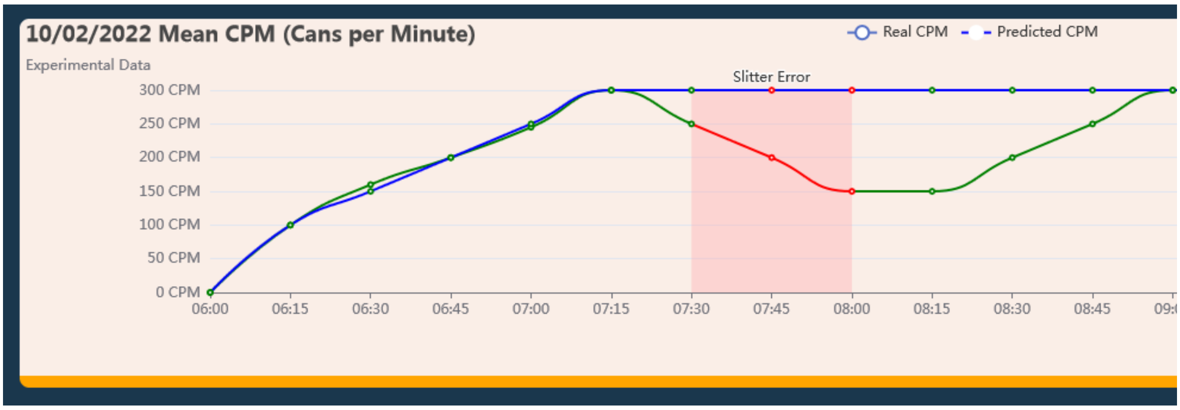

Figure 3: Example of visual data presentation

4. Conclusion

In this article a conceptual framework of a predictive maintenance process for a canning industry has been proposed. The added value of the research is the proposition of a smart manufacturing framework which enables a real-time condition monitoring significantly improving the manufacturing process. The complete data-flow process from heterogenous sources up until the data visualization was extensively presented and analysed proposing the implemented software and algorithms for each process respectively. As future research, a more extensive analysis on the data-driven algorithms for the improvement of the decision-making process and the reliability of industrial machinery is proposed.

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