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Communications in Computer and Information Science 1754

Optimization, Learning Algorithms and Applications

Second International Conference, OL2A 2022
Póvoa de Varzim, Portugal, October 24–25, 2022
Proceedings

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Editors

Ana I. Pereira
Instituto Politécnico de Bragança
Bragança, Portugal

Andrej Košir
University of Ljubljana
Ljubljana, Slovenia

Florbela P. Fernandes
Instituto Politécnico de Bragança
Bragança, Portugal

Maria F. Pacheco
Instituto Politécnico de Bragança
Bragança, Portugal

João P. Teixeira
Instituto Politécnico de Bragança
Bragança, Portugal

Rui P. Lopes
Instituto Politécnico de Bragança
Bragança, Portugal

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Preface

This CCIS volume 1754 contains the refereed proceedings of the Second International Conference on Optimization, Learning Algorithms and Applications (OL2A 2022), a hybrid event held during October 24–25, 2022.

OL2A 2022 provided a space for the research community on optimization and learning to get together and share the latest developments, trends, and techniques, as well as to develop new paths and collaborations. The conference had more than three hundred participants in an online and face-to-face environment throughout two days, discussing topics associated with optimization and learning, such as state-of-the-art applications related to multi-objective optimization, optimization for machine learning, robotics, health informatics, data analysis, optimization and learning under uncertainty, and Industry 4.0.

Five special sessions were organized under the following topics: Trends in Engineering Education, Optimization in Control Systems Design, Measurements with the Internet of Things, Advances and Optimization in Cyber-Physical Systems, and Computer Vision Based on Learning Algorithms. The OL2A 2022 program included presentations of 56 accepted papers. All papers were carefully reviewed and selected from 145 submissions in an single-blind process. All the reviews were carefully carried out by a scientific committee of 102 qualified researchers from 21 countries, with each submission receiving at least 3 reviews.

We would like to thank everyone who helped to make OL2A 2022 a success and hope that you enjoy reading this volume.

October 2022

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Monitoring Electrical and Operational Parameters of a Stamping Machine for Failure Prediction

Pedro Pecora[1(✉)], Fernando Feijoo Garcia[2], Victória Melo[1], Paulo Leitão[1], and Umberto Pellegri[3]

[1] Research Center in Digitalization and Intelligent Robotics (CeDRI), Instituto Politécnico de Bragança, Campus de Santa Apolónia, 5300-253 Bragança, Portugal
{pedropecora,victoria,pleitao}@ipb.pt

[2] Universidad de Burgos, C. Don Juan de Austria, s/n, 09001 Burgos, Spain
ffeijoo@ubu.es

[3] Catraport Lda, Zona Industrial de Mós, Lote n.° 1, 5300-692 Mós, Bragança, Portugal
u.pellegri@p-cautomotive.pt

Abstract. Given the industrial environment, the production efficiency is the ultimate goal to achieve a high standard. Any deviation from the standard can be costly, e.g., a malfunction of a machine in an assembly line tends to have a major setback in the overall factory efficiency. The data value brought by the advent of Industry 4.0 re-shaped the way that processes and machines are managed, being possible to analyse the collected data in real-time to identify and prevent machine malfunctions. In this work, a monitoring and prediction system was developed on a cold stamping machine focusing on its electrical and operational parameters, based on the Digital Twin approach. The proposed system ranges from data collection to visualization, condition monitoring and prediction. The collected data is visualized via dashboards created to provide insights of the machine status, alongside with visual alerts related to the early detection of trends and outliers in the machine's operation. The analysis of the current intensity is carried out aiming to predict failures and warn the maintenance team about possible future disturbances in the machine condition.

Keywords: Condition monitoring · Digital Twin · IoT

1 Introduction

The digital transformation occurring in the context of Industry 4.0 [11] stimulates the emergence of new concepts and technologies, reshaping the manufacturing world. One of the main foundations for this transformation is the

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adoption of cyber-physical components, which are represented by intelligent and connected assets and products that are part of a dynamic ecosystem. The integration of these components forms the Cyber-Physical Systems (CPS), that are complex engineering systems that integrates physical, computation/ networking, and communication processes [13], which can improve the resource productivity and efficiency, the production systems' performance, responsiveness and reconfigurability, can efficiently manage the complexity and uncertainty and enable more flexible models of work organization [4,16].

Industrial manufacturing environments are considered dynamic and chaotic. Therefore, the implementation of maintenance systems becomes the key to ensure production efficiency, since the occurrence of unexpected disturbances can cause system performance degradation and, consequently, loss of productivity and business opportunities, critical factors in terms of competitiveness [2]. In terms of maintenance decisions, machine diagnostics can be performed after a failure has occurred, being a reactive approach that cannot prevent downtime and associated costs. Although, a shift in maintenance strategy from traditional fail-and-fix (diagnostics) to a predict-and-prevent approach (prognostics) is required, performing the maintenance in a proactive manner to reduce its costs and ensure the greatest feasible machine uptime [14]. Therefore, one of the important tasks in the performance of industrial machines is the monitoring of their health condition, in order to identify their performance and to early determine failures and/or the need to optimize their operating parameters. Traditionally, this condition monitoring uses techniques that are very targeted, case by case, to the particularities and requirements of the machine in question.

Given the idea of condition monitoring, predictive maintenance (PdM) proactively plans maintenance tasks based on a system's current and predicted future condition. With the advent of new technologies, such as the Industrial Internet of Things (IIoT) or Cloud Computing, and the continuing decline of costs for necessary hardware, PdM is becoming more attractive for the whole production sector [6]. However, PdM still relies in the expertise of technicians for a correct interpretation of the data [9]. Moreover, the increasing quantity of available data increases the complexity of treatment and interpretation [23]. Each sensor, e.g., pressure, temperature, vibration, and electrical current, provides new dimensions to be analyzed. Artificial Intelligence (AI) is applied in this context, with time series data series automatically being classified in different categories corresponding to healthy, degradation and critical stages, or used to calculate healthy metrics, e.g., Time-to-Failure or Remaining Useful Life (RUL) [15]. Machine Learning algorithms are suitable to deal with multivariate problems. As an example, Susto *et al.* [21] applied a multiple classifier approach based on Support Vector Machine and k-Nearest Neighbors classifiers to define the PdM policy in semiconductor manufacturing process with data from 31 sensors. Lu *et al.* [17] proposed a clustering diagnostic method for bearings using features extracted from the vibration signal. Juez-Gil *et al.* [10] proposed a method to early detect multi-faults in induction motors based on Principal Component Analysis and multilabel decision trees using voltages, stator currents, rotational speed and vibrations. Carvalho *et al.* [3] provides a review on ML techniques and their application to PdM.

The adoption of emerging digital techniques in the context of Industry 4.0 allows leveraging the development of new solutions based on the collection of data from heterogeneous sources through the use of, e.g., sensor networks and IoT technologies. These sources can be combined with AI techniques for further analysis, aiming to make this data available for data-driven systems enabling, e.g., monitoring, diagnosis, prediction and optimization [18].

The Digital Twin concept is being largely adopted to enable the condition monitoring for manufacturing resources. According to [20], a Digital Twin is a digital copy of a physical object or system, that is connected and shares functional and/or operational data, enabling the collected data to be later analyzed to allow the optimization and improvement of the physical object. In this sense, this data is collected by machines' controllers and external sensors and used for the synchronous adjustment of digital models and their simulation, allowing the monitoring and prediction of the condition and status of the machines as a result from the simulation of physics-based models, without the use of invasive techniques commonly used in predictive maintenance solutions [1]. The use of the Digital Twin concept will significantly contribute to the development of Industry 4.0 compliant solutions, allowing the use of a virtual machine model that is aligned with real-time data and the integration of various emerging digital technologies for its operation, such as IoT, AI, and cloud computing. However, the implementation of the Digital Twin solution faces many difficulties in industrial environment. Mainly due to the shop floor constrains and the parameters to be analyzed, including also the need to ensure the security of this data to guarantee the integrity of the company's private data privacy [5].

Having this in mind, the objective of this paper is to develop a condition monitoring and prediction system that uses IoT, AI and cloud technologies, taking advantage of the fusion of operational and electrical data encapsulated in the Digital Twin concept. The designed condition monitoring system was deployed in an industrial metal stamping press, with the achieved preliminary experimental results contributing for the improvement of the system efficiency.

The rest of the paper is organized as follows: Sect. 2 describes the case study and introduces the Digital Twin based condition monitoring system architecture. Section 3 presents the deployment of the Digital Twin based condition monitoring for the industrial case study and Sect. 4 describes the implementation of a Recurrent Neural Network (RNN) algorithm to forecast the current intensity that will allow to predict failures in the machine. Finally, Sect. 5 rounds up the paper with the conclusion and points out some future work.

2 Digital Twin Condition Monitoring System Architecture

This chapter describes the designed condition monitoring and prediction system architecture for the industrial case study using the digital twin concept.

2.1 Description of the Case Study

The case study considered in this work considers an industrial metal cold stamping machine, hosted in the Catraport factory plant, illustrated in Fig. 1, that stamps metal parts to make complex shapes, applying up to 600 tons of force and operating in a range of 1 to 60 strikes per minute. As the machine has various stamping dies, the process can vary in the number of stamping steps it takes to make a final piece, and also in the pressure of each strike, among other variables.

Fig. 1. Metal cold stamping machine used as industrial case study.

This type of machine is supplied with a metal coil to be pressed through a feeding system, composed by an steel roll placed at one end point and a transfer system responsible for unrolling the steel sheet, which moves with each stroke. These systems operate synchronously through the use of a PLC (Programmable Logic Controller) alongside with motor controllers that are responsible of controlling all the three phases of the stamping machine. The machine is equipped with some loggers to collect the warnings and errors generated during its operation, accessible through excel spreadsheets, but operational and electrical data is not automatically available to support the condition monitoring and the failure prediction.

2.2 System Architecture

The architecture of the proposed condition monitoring and prediction system is illustrated in Fig. 2, and takes advantage of the analysis of the collected real-time data, to identify abnormalities and failures in advance, as well as to perform diagnosis and optimization in the machine operation. This architecture is based on the use of the Digital Twin concept, that brings the capability to digitize an asset as a virtual model that is fed with the real-time data to perform condition monitoring and failure prediction. The Digital Twin is complemented with the use of several digital technologies, namely IoT and AI, that will support the collection, transmission, storing and visualization of data and their posterior analysis to extract value and knowledge.

As seen in Fig. 2, the physical asset comprises a set of sensors to acquire the operational and electrical data, namely vibration, current intensity, power and power factor. This data is made available to the Digital Twin hosted in the cloud by using IoT communication protocols, e.g., publish-subscribe and request-response, allowing the scalable and loosely coupled design of condition monitoring solutions.

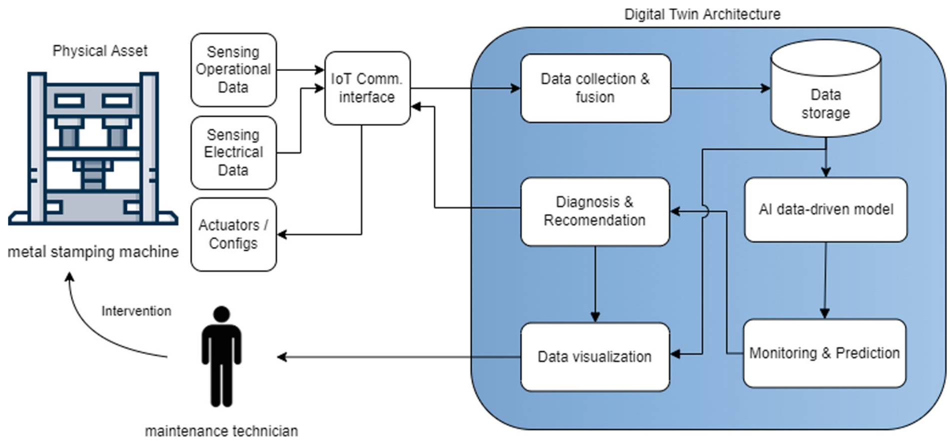

Fig. 2. Digital Twin based condition monitoring system architecture.

The *data collection and fusion* module is responsible for gathering the machine's electrical and operational data via a IoT communication protocol. The collected data is cleaned, aggregated and stored in a database for posterior analysis. Since heterogeneous data sources are considered, this module also includes data fusion tasks, particularly focusing multi-temporal and multi-spacial fusion. Key aspects to be considered in the data collection are related to the scale and frequency of the data acquisition as well as the clock synchronization to ensure the harmonization in the time stamps of different data sources.

The *data visualization* module allows the visualization of the collected data in an user interface through dashboards that makes use of time series graphs, gauges and icons to show the evolution of some parameters along the time, as well as some Key Performance Indicators (KPIs), illustrated through the use of statistical measures, like the average and the standard deviation. The dashboard must be designed to be illustrative and simple to be understood, and yet provide useful information regarding to the machine operation.

The *monitoring and prediction* module is responsible for the identification of anomalies and performance degradation, by applying abnormalities detection algorithms in the collected data and the early detection of possible failures, by applying trend detection and machine learning algorithms, that correlate the different machine parameters to forecast future occurrences. This task should consider the analysis of the streaming data.

The *diagnosis and recommendation* module is responsible to perform a diagnosis of the monitored data, as mentioned above, and make recommendations to improve and optimize the system performance. This recommendation can be simple alerts to the users, suggestions of the machine operation configuration or the need for maintenance interventions to the technicians, or even automatic change of the operation configuration in the machine. The information resulting from this module is also made available in the interface designed for the user to facilitate the understanding of the system's operation and support the necessary decision-making actions.

3 Deployment of the Digital Twin Based Condition Monitoring

The digital twin based condition monitoring and prediction system architecture described in the previous section is applied to the industrial case study, which special emphasis is in the data collection, visualization and monitoring to support the early prediction of failures.

3.1 Data Collection, Fusion and Storage

In the case study, data is collected from different data sources, focusing some operational and electrical parameters. The operational data, namely the vibration of the machine in the X, Y and Z axis, is collected with a frequency of 5 samples per second by a LSM303 compass that has a 3-axis accelerometer with 16-bit data output, supporting ± 16 g acceleration. This sensor is connected to an ESP8266 microcontroller through the Inter-Integrated Circuit (I^2C) protocol. The electrical data, namely voltage, current intensity and power-related data, is collected each 5 s using an IoTWatt device [8]. The installation of these devices is shown in Fig. 3.

These sensing modules constitute IoT nodes capable of acquiring and transmitting the collected data over Wi-Fi, following a JSON format, and publishing them onto a time-series driven database directly, using the HTTP protocol. In this work, the InfluxDB database was used, taking advantage of its high-performance time series engine [7] and its easy integration with data visualization platforms, such as Grafana. The collected data is published through the Influx's API service, being used a virtual machine running Ubuntu 20.04.4, with 16GB of RAM and AMD EPYC 7351 16-core processor to serve as an anchor point to the published data. It is important to point out that this is a private cloud, which ensure data security and privacy. Table 1 summarizes some collected electrical and operational parameters that are stored in the database (note that α represents the different measured electrical phases).

Data related to warning and machine breakdowns, such as lack of oil in the strike chamber, micro-stops, step adjustment, and tool change is also collected

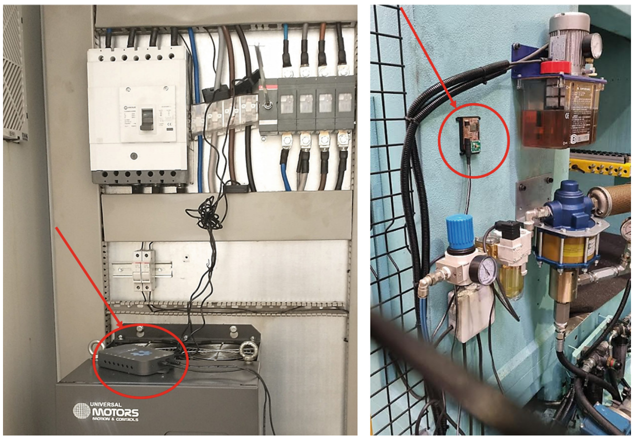

Fig. 3. IoT devices installed in the stamping machine. On the left, the IoTaWatt, and on the right, the ESP8266 including the LSM303 sensor.

using Excel files. This data is manually cleaned and fused, since each work order creates a new process order, containing more than only stops.

Table 1. Stored electrical and operational data

Parameter	Description
Curr_phaseα	Current intensity measured in the α phase [A]
PF_phaseα	Power factor measured in the α phase
Power_phaseα	Power measured in the α phase [W]
Frequency	Frequency of the reference power supply [Hz]
Voltage	Voltage of the reference power supply [V]
Accel_X	Vibration in the X axis [m/s^2]
Accel_Y	Vibration in the Y axis [m/s^2]
Accel_Z	Vibration in the Z axis [m/s^2]

The aggregated stored data becomes available for visualization, monitoring and prediction, through the other digital twin modules.

3.2 Visualization and Monitoring

The data visualization is performed by using the Grafana software platform, a web-server tool that is installed in the same virtual machine, allowing the easy communication between the database and the web-server. Aiming to develop an user-friendly and easy-to-understand interface, the dashboard displays some important electrical and operational parameters, as well as some alerts related to the system operation, KPIs, being illustrated in Fig. 4.

The left part of the dashboard is designed to illustrate the evolution of the power, current and power factor for the three phases over time. The middle part

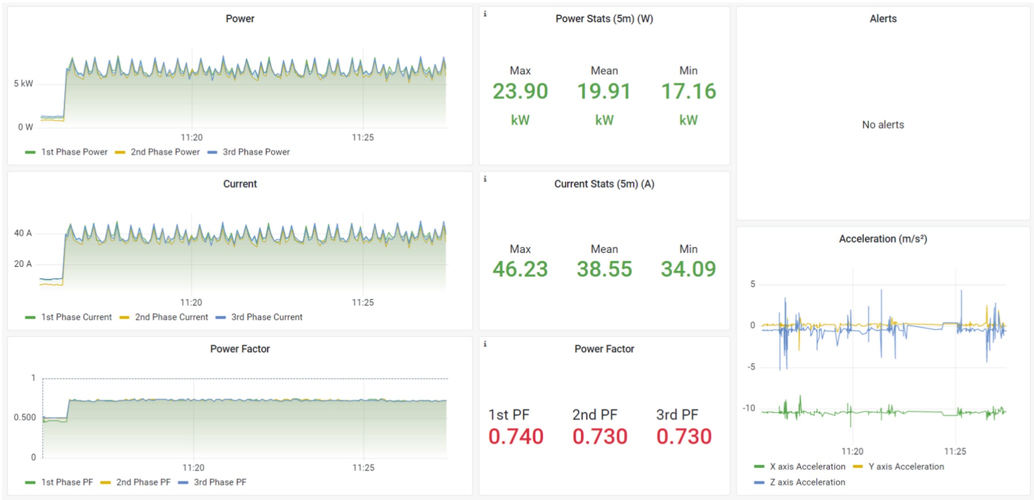

Fig. 4. Dashboard for visualization of the collected parameters.

shows the KPIs for these electrical parameters, namely the minimum, average, and maximum values, with a moving window that considers a predefined amount of last collected data, in this case 5 min. On the top right of the dashboard, an alert panel is presented, where the detected alerts regarding the monitoring can be shown. Lastly, on the bottom right the acceleration measurements are presented using time series graphs for the three axis.

A color scheme is used to highlight the particularities of the data, giving the user a better understanding of the values. For this purpose, the illustrated values regarding the electrical parameters are color-coded. Similar dashboards were deployed to illustrate the vibration data and the machine's stops/warnings.

Aiming to monitor the health condition of the stamping machine to support its correct operation and also to detect abnormal situations, preferably in advance, the collected data is analyzed in real-time. For this purpose, alerts are generated to warn risk situations related to the functioning of the stamping machine, e.g., in case of peaks in the current or power, or excessive vibration in one axis. These alerts are generated by applying Nelson rules [19], which is a process control method that use the mean value and the standard deviation to determine if a measured variable is out of control or presents a trend that shows that the variable is near to be out of control. In the deployed system, Rules 1, 3, 4 and 6, illustrated in Fig. 5, are implemented.

Briefly, rule 1 is used to detect an outlier in the operation of the stamping machine and is triggered when a value of the variable being analyzed is greater, or lower than 3σ from the mean. Rule 3 allows identifying a continuous growth trend in values of the measured variable, i.e. six successive increasing values in a row, allowing to detect in advance possible failures. Rule 4 uses fourteen or more values in a row, to pinpoint a variance that is not more a standard noise. It disregards their position relative to mean, checking only if they alternate in direction, increasing and then decreasing. Rule 6 identifies a tendency of the machine to be slightly out of control during the stamping process, by checking four successive values that are more than 1σ both above or below from the mean.

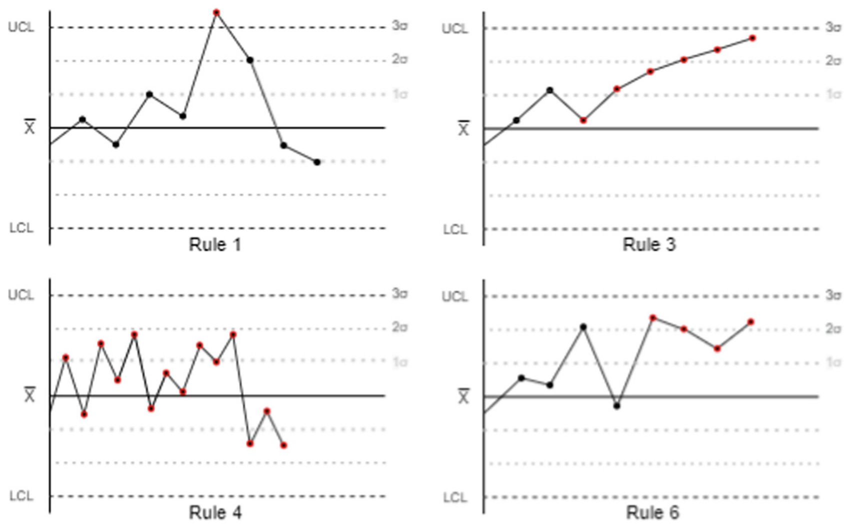

Fig. 5. Implemented Nelson rules, with red dots representing values that may trigger the rule (adapted from [19]). (Color figure online)

These rules were applied for the variables of current and vibration in all three axis, according to their mean and standard deviation values considering the normal operation. The monitoring of the vibration in Z axis is illustrated in Fig. 6. The distinct red and green areas show the corrected threshold for Rule 1 to be fired, and the red circles are examples of when the rule is fired. The generated alerts appear on the dashboard as notes, showing which measure is near to be out-of-control and also triggering emails that are sent to the maintenance department, notifying the type and time of problem that has occurred.

Upon analyzing the electrical data, the power factor value stood out as being a low number. A more in-depth analysis showed that the power factor value for every phase was below the legally desired value of 0.96 (since 2010, Portugal actively penalizes industries with a power factor lower than 0.96). A further study about this problem was triggered and a cost-effective solution was proposed, based on the implementation of a capacitor bank, to correct this lag between the measured power factor value and the desired value.

4 Prediction of Failures

Besides the monitoring, the developed system was also able to predict the failures that occurs in the machine operation.

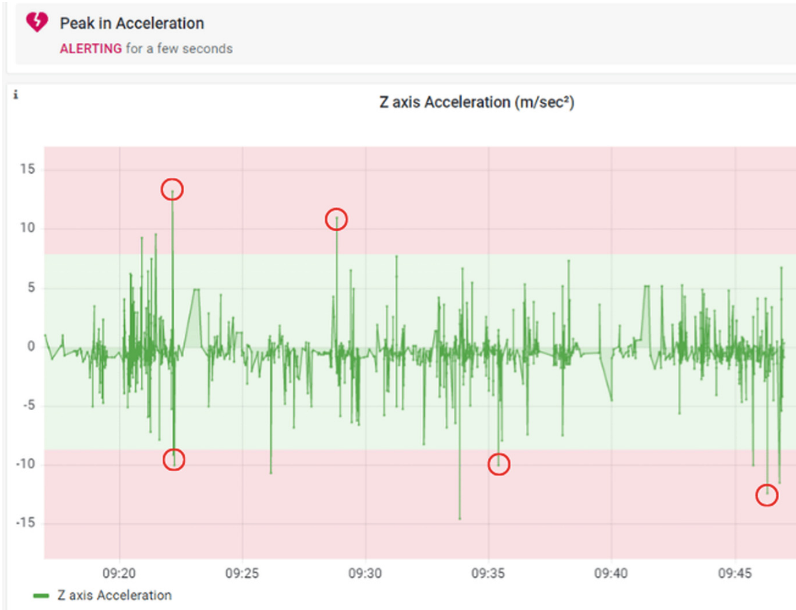

Fig. 6. Monitoring Z vibration and alerts triggered by the implemented rules. (Color figure online)

4.1 Clustering Technique Applied to Oil Alarms

A first evaluation of the press machine operation was performed to analyse possible failures due to the high pressure in the oil. Interruptions due to high oil pressure alarm, which prevents further damage in mechanical parts due to overstress, occurred 12 times during the one month data collection period. The feasibility of prediction of this alarm has been studied using the electric data obtained from the data collection and fusion module.

The data has been divided into 12 series corresponding to the data collected between oil alarms and subjected to summary statistics, such as mean, standard deviation, skewness, and kurtosis that are illustrated in Table 2, which can provide aggregated information of the time series [17,21,22]. They have been calculated using a 30 samples (2.5 min) sliding window over the phase 1 current. Three series have been discarded because they were too short for the sliding window.

Table 2. Summary of statistical features: mean (F1), standard deviation (F2), skewness (F3) and kurtosis (F4).

$F_1 = \bar{x} = \frac{1}{n}\left(\sum_{i=1}^{n} x_i\right)$	$F_2 = \sigma = \sqrt{\frac{\sum_{i=1}^{n}(x_i-\bar{x})^2}{n-1}}$
$F_3 = \frac{\sum_{i=1}^{n}(x_i-\bar{x})^3}{(n-1)\sigma^3}$	$F_4 = \frac{\sum_{i=1}^{n}(x_i-\bar{x})^4}{(n-1)\sigma^4}$

Figure 7 shows the results of plotting the complete set of features for one case of failure. The data have been divided in 3 categories: values corresponding to 10 min prior to the failure are classified as 3, values between 60 min and 10 min before the failure are classified as 2, and the values from the starting of the process to 60 min before the failure are classified as 1. In addition to the classification, the points were colored for an easier understanding: points over 60 min are designed a gray color, points between 60 and 10 min are colored as yellow, and points below 10 min are colored as red.

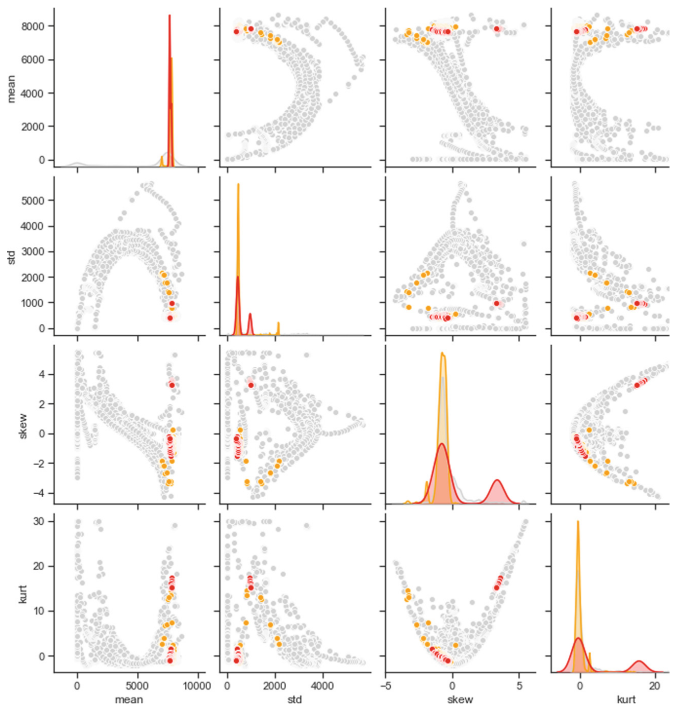

Fig. 7. Relationship between features for one failure type (oil alarm). (Color figure online)

Upon plotting the statistical features, it was desirable to find a potential cluster of values near-failure. However, it can be observed that for each correlation, the red and yellow points are disperse and with many gray dots in the vicinity, not allowing an accurate prediction. In the other hand, this analysis unveiled a new view point of the data, where the analysis of the physical data should be used along to analyze possible correlations, using vibration data and additional features in time and frequency domains.

4.2 Forecasting the Current Intensity

As stated before, due to overlapping points between near-failure conditions and normal working conditions, it is hard to create a classification algorithm. However, the proposed approach considers a ML algorithm to predict the current intensity, since it is one of the parameters being monitored by the Nelson rules, aiming to predict of anomalies, such as spikes or trends, to provide early triggers to the maintenance team to work quickly and mitigate the failure occurrence.

The chosen ML algorithm is the Convolutional Neural Network (CNN) Bi-directional-LSTM (Bi-LSTM), named EECP-CBL. The CNN part extracts the key information over the desired variables, and the Bi-LSTM part analyzes the data by forward and back propagation to make the predictions. The network's inputs are the current intensity, power factor and power for each phase.

The LSTM's layout is based in the layout presented in [12], consisting of a CNN to conglomerate the input variables. Two Bi-LSTM layers are considered, consisting of 64 units each. The output is composed of two standard densely connected layers, the last one, with the number of units equals to the number of samples to predict, an illustration of this layout is presented in Fig. 8. The compiled model have the Adaptive Moment Estimation (Adam) function as the optimizer, and the mean squared error as the loss function.

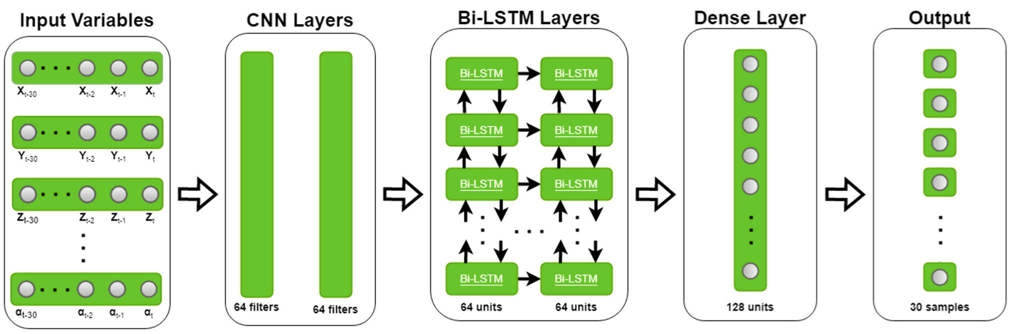

Fig. 8. The proposed network layout. Adapted from [12].

The cleaned data consists of 43,845 points, sampled every 20 s over the span of a month. The data points were splited in 80% for training, and 20% for tests. During all the tests, the amount of timesteps for the forecasted data and previous data is the same, i.e. for a forecast of 3 min, 3 min of previous data is used.

For means of comparison, Table 3 compares some common metrics such as the Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) on the test data. These metrics are widely used as a way to check the generalization capabilities of the trained network. As a ground truth to check the model's performance, the model predicted 20 s (1 sample), 3 min (9 samples) and 5 min (15 samples) ahead, against the autoregressive integrated moving average (ARIMA) model, with an order of $p = 8$, $d = 0$ and $q = 2$, that corresponds to the autoregressive, the differentiative, in case of a data with trends, and the moving average components.

The achieved results show that the EECP-CBL network performed better than the ARIMA model for a single step ahead, and upon further testing, the EECP-CBL out scales the ARIMA, since ARIMA tends to converge to the mean

Table 3. Comparison between the proposed EECP-CBL and ARIMA model

Model	Forecasted steps	RMSE [A]	MAE [A]	MAPE [%]
EECP-CBL	1	5.40	2.83	39.62
	9	11.30	8.48	26.64
	15	8.30	6.83	40.45
ARIMA	1	11.93	11.93	97.95
	9	13.53	13.41	49.31
	15	13.83	13.76	76.38

of the data, and the proposed model learned from the train data, being a more generalized model for the problem. A live-data application of the model is illustrated on Fig. 9, where the yellow line is the forecast intensity and the green line the real intensity. It is possible to visualize that, although the prediction is not as accurate, the model was able to successfully generalize the high peaks in the current intensity, therefore being able to generate an alert to the technician as intended.

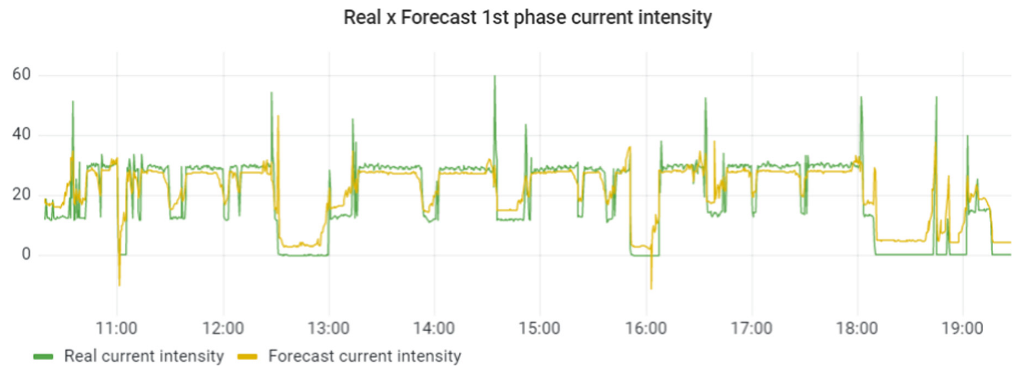

Fig. 9. Real and forecast current intensity comparison. (Color figure online)

Note that the trained model was implemented in the monitoring and prediction system, gathering live data from the data storage module as part of the Digital Twin, as its inputs. For each forecast value, the Nelson Rules were applied allowing to trigger alerts to the maintenance team.

5 Conclusions

The condition monitoring, as part of the predictive maintenance of industrial machines, is currently a critical issue aiming to increase the system performance. The use of emergent digital technologies under the scope of Industry 4.0, e.g., IoT, AI, and Digital Twin, can contribute to develop more efficient systems.

This paper describes the implementation of a Digital Twin approach developed for monitoring electrical and operational parameters of an industrial cold stamp machine. This approach allows extracting information from the collected data to supervise machine's condition operation and to detect anomalies and performance degradation in advance, supporting the diagnosis, prediction and optimization of the machine's operation. For the visualization of the system's data, a user interface was created, displaying the system data, statistical information and the alerts generated through the implementation of control rules.

The monitoring of the system is carried out via Nelson Rules, that can detect samples out of control, trends, and uncommon oscillations while the machine is working. Aiming to foresee potential dangers, The prediction of failures was performed by using the EECP-CBL algorithm to forecast the value of the current intensity 5 min ahead, which allows the maintenance team to react aiming to mitigate the possible occurrence of such failure.

The application of ML techniques in industrial environments faces multiple difficulties due to the peculiarities of this environment. While most of the works consider data sets obtained in a laboratory, with controlled conditions, in this case the capture of data had to cope with the noise and daily movements of a factory, which makes more difficult to obtain steady data. Future work will be devoted to implement more powerful ML algorithms to identify more complex correlations among the collected data in the industrial case study, as well as to implement the diagnosis and recommendation module using also ML algorithms.

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