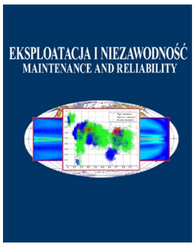

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Short and long forecast to implement predictive maintenance in a pulp industry

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Highlights

- This article presents a predictive model for a wood chip pump system.
- The Ishikawa diagram and the FMECA analysis were used to identify possible causes of system failures.
- Development of an algorithm for predicting the values of equipment sensors in the short and long term.
- The prediction made through Neural Networks had a mean absolute percentage error in all variables lower than 10%.

Abstract

Predictive maintenance is very important for effective prevention of failures in an industry. The present paper describes a case study where a wood chip pump system was analyzed, and a predictive model was proposed. An Ishikawa diagram and FMECA are used to identify possible causes for system failure. The Chip Wood has several sensors installed to monitor the working conditions and system state. The authors propose a variation of exponential smoothing technique for short time forecasting and an artificial neural network for long time forecasting. The algorithms were integrated into a dashboard for online condition monitoring, where the users are alerted when a variable is determined or predicted to get out of the expected range. Experimental results show prediction errors in general less than 10 %. The proposed technique may be of help in monitoring and maintenance of the asset, aiming at greater availability.

Keywords

predictive maintenance, condition based maintenance, time series, artificial neural networks, forecasting.

1. Introduction

As technology evolves, industrial processes are forced to adapt. That is currently the case with Industry 4.0, which may require process changes in all areas, including tracking products[2], monitoring and predicting production [36], quality control [37], or condition-based maintenance [4], among other uses of sensor networks and algorithms.

Due to this fact, there is a need for maintenance departments to reorganize, integrate new sensors, and process collected data for better performance. Machine learning can be beneficial in quality management and control, reducing maintenance costs, and improving the overall manufacturing process. That can make a key difference in modern industries.

This article presents a case study, where data analysis is performed and a predictive system is developed for a wood chip pump system, operating in an industrial paper company. This asset had frequent failures on an axis. The pump shaft and its entire fastening system had a much shorter life cycle than recommended by the manufacturer. The shaft opened cracks quickly. The analysis aimed to determine the cause of failure, as well as other potential failures.

To identify all possible causes of malfunction, Ishikawa Diagram, and Failure Mode, Effects, and Criticality Analysis (FMECA) were used. After identification of the actual cause, sensors were installed for monitoring key condition variables of the system's equipment to improve its reliability.

A global analysis of the data collected from the sensors installed in each equipment, including their minimum and maximum expected values, is presented. The variables' behaviour is studied, including graphical analysis for visualization, and forecast algorithms based on time series and Artificial Neural Networks (ANN) are applied.

A short term prediction model, with a gap of 5 days, was implemented, based on the common technique of exponential smoothing. A long term prediction model, with a gap of 3 months, was implemented, based on artificial neural networks. The short term gap of 5

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days is adequate for the company to prepare small interventions. The long term gap allows the company to adequately prepare and schedule maintenance interventions, thereby avoiding loss of production and optimizing downtime. The duration of the gaps was decided so that a competitive advantage is achieved by reducing maintenance downtime and increasing production time.

A dashboard was developed, in which some alerts are displayed through semaphores, along with some quantitative and graphical information.

The system is designed to avoid unexpected failures and to reduce costs as much as possible, which are two of the main objectives of a good maintenance policy [22].

The present paper describes a case study where different diagnostic and prediction tools are combined to improve maintenance performance and maximize equipment availability. The fault diagnosis methodology as well as the prediction method proposed can be adapted and applied to other equipment. Fault diagnosis methods are suitable for any type of equipment, while the machine learning methods can be applied to any dataset with adaptations and proper training.

The paper is organized as follows. Section 2 presents related work and the theoretical framework. Section 3 describes the chip pump system and its diagnosis. Section 4 presents the system's condition monitoring variables. Section 5 is about the condition variables global analysis. Section 6 presents the approach about short time forecast. Section 7 proposes the approach of long- time forecast. Finally, section 8 draws some conclusions and proposes future work.

2. Background

2.1. Predictive Maintenance and Diagnosis

Predictive maintenance aims to maximize the system's availability, based on the identification of the weakest components of this physical asset [29].

According to the European Standard EN 13306:2017, a failure is the loss of the ability of an item to perform a required function after its failure, which may be complete or partial [38].

Predictive maintenance currently uses a lot of hardware to collect and store data and software to analyse it. Farinha (2018) presents an overview of the subject [9]. The purpose of predictive maintenance is to enable proactive scheduling of corrective work and thus avoiding unexpected equipment failures [33].

Maintenance optimization is a priority, due to the great trend in simulation-based optimization [28]. Currently, the best maintenance plans are tirelessly sought to minimize the overall cost of maintenance or to maximize the production and availability of assets [31]. Maintenance costs can reach 50% of production costs, which reinforces the importance of improving this area [1][26].

Predictive maintenance has evolved since visual inspection, which was its first method. Currently, with the advance of sensors and computer power, several advanced signal processing techniques are used based on pattern recognition, classification, clustering, and prediction algorithms [25].

According to FMECA reliability theory process, several types of failure mode, reasons, effects, and criticality of assets can be determined [16].

After detecting all possible failures through the Ishikawa Diagram and subsequent FMECA analysis, the main objective of predictive maintenance is to avoid the same failures by predicting them in advance.

2.2. Industry 4.0 in Industrial Maintenance

As hardware prices decrease and computing power increases, the Internet of Things (IoT) is increasingly more present in the industry [12][6]. That is a key factor to make processes predictable, simpler, controllable, and efficient, thus reducing equipment manufacturing and maintenance costs as much as possible [35].

Industry 4.0 is a result of the technological revolution, thus helping predictive maintenance [19][34]. In such a globalized and competitive market, it is necessary to make decisions about people and equipment all the time. Predictive maintenance decisions of this kind, in general, depend on massive amounts of data [7][30]. Predicting with low error the need to perform maintenance operations on the assets at a certain future point in the medium and long term is one of the main challenges in this field [14].

Due to the importance that IoT has acquired in recent years in industry and maintenance, a new concept applied specifically to the industrial sector has emerged, which is Industrial Internet of Things (IIoT).

To have an accurate forecast, it is imperative to have timely calibration and certification of industrial sensors. This is indispensable because, without the support of metrology based on measurement quality, there could be evaluation errors and discrepant data, which can result in prediction errors, poor forecasting, risks, large costs, and, consequently, loss of confidence from the market [23].

According to Hashemian, condition-based maintenance techniques for equipment and industrial processes are divided into three categories. The first category uses signals from existing process sensors, such as resistance temperature detectors and thermocouples, to help verify the performance of assets [13]. The second category depends on signals from test sensors that are installed on the equipment. The third category involves injecting a test signal into the equipment. The present work falls into the second type, as it depends on sensor signals that are installed in the equipment to measure the operational parameters.

2.3. Other Related Work

In this section some works are presented, whose aim is to predict the values of sensors installed in equipment, stressing the important of this research field for predictive maintenance using Artificial Intelligence (AI).

Kanawaday *et al.* took advantage of the machine data generated by various sensors by applying different data analysis algorithms to obtain information that help in making decisions [17]. The data captured by the sensors were always accompanied by the date and time, both of which are vital parameters for predictive modelling. The same authors used the Auto Regressive Integrated Moving Average (ARIMA) forecast in the sensor database of a longitudinal cutting machine [11][10][8].

Short-term forecasting work in maintenance has also been carried out by other authors. However, it should be noted that those studies are only focused on short-term forecasting, which shows a clear limitation in the area of long-term forecasting. An example of this type of study is the work presented below.

Kolocas *et al*. presented a predictive maintenance methodology to predict possible equipment failures of an industrial equipment in real time, using data from process sensors of operation periods. The alert period for the failure of the asset is forecasted in short-term, since a forecast gap was defined around 5-10 minutes before the incident occurred [20].

The following review section demonstrates a promising avenue of research in the use of neural networks in the area of predictive maintenance.

Tian [32] developed an Artificial Neural Network (ANN) based method designed to achieve more accurate remaining life prediction of equipment subject to condition monitoring. The proposed ANN method is validated using vibration monitoring data collected from pump bearings. The ANN model has as input to the network the age of the equipment and current condition measurement values and inspection performed. The network gives a percentage of the asset's life as an output.

Rafiee *et al*. [27] used a 2-layer perceptron neural network to detect gear and bearing failures and identify gearboxes using a new feature vector updated by the standard deviation of wavelet packet coefficients of vibration signals. Synchronization of vibration signals used cubic Hermite interpolation by parts.

Heidarbeigi *et al*. [15] developed a neural network built to predict gearbox failures. In this project a backpropagation learning algorithm and a multilayer network were used. The network has three classification outputs, which are: worn, broken teeth of gear, and faultless condition. The ideal Multilayer Perceptron Neural Network (MLP) selected for classification exhibited a 489-10-3 layer structure and had 87% accuracy. The model shown works based on vibration differences, so it can be used in other applications.

Karpenko [18] developed a neural network pattern classifier to diagnose and identify failures in an actuator of a Fisher-Rosemount 667 industrial process valve. The network is trained with experimental data obtained from the asset. The test results show that the resulting multilayer feedforward network can detect and identify various types of failure.

Wang [33] presents an artificial intelligence algorithm based on neural networks to identify failures in diesel engine lubrication pumps using vibration data. The algorithm has been tested on more than fifty lube pumps which have proven its effectiveness.

The studies mentioned above show that neural networks using monitoring data such as vibration and temperature can detect and even anticipate failures. That is useful in the diagnosis of faults with high reliability, as well as foreseeing potential failures and preventing them from happening. The research carried out also shows that there is gap in a long-term forecasts, specially predicting with 3 months advance. Nonetheless, this should be a research goal, because industries often need several weeks to prepare and carry out complex maintenance operations with minimum downtime.

3. Chip Pump System: Problem and Diagnosis

The chip pump system is depicted in Figure 1. It comprises three chip pumps, each one fed by one asynchronous motor through a mechanical connection. The inputs of the system are wood chips and liquor. The final product is a mixture of them.

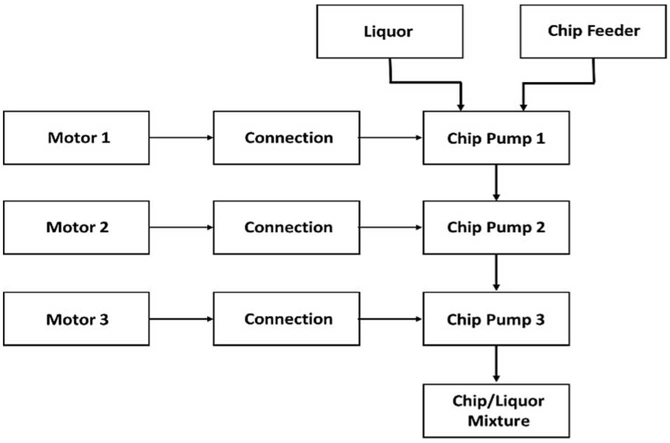

Fig. 1. Chip Pump System

The company found that the shaft of the chip pump 3 depicted in Figure 1 had shorter life services than expected. Frequent failures on that chip pump had led to cracks in the shaft, damaging its fixation cones.

Pressure is an important parameter in diagnosis, and active diagnosis is a proposal for future work to be developed after this manuscript. After several measurements, it was concluded that the pressure exerted by the mixture at the output of the chip pump increases, as shown in Figure 2.

Ishikawa diagrams allow to carry out an exhaustive diagnosis of the potential causes of equipment defects [5]. Figure 3 shows the Ishikawa diagram carried out for the fissure or breakage of the shaft and cone of the chip pump 3.

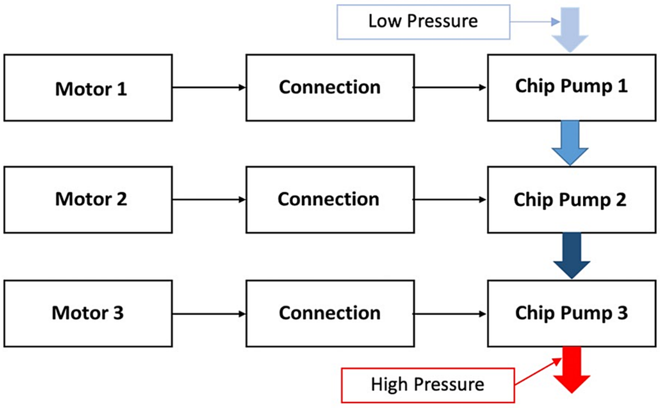

Fig. 2. Pressure increases throughout the system

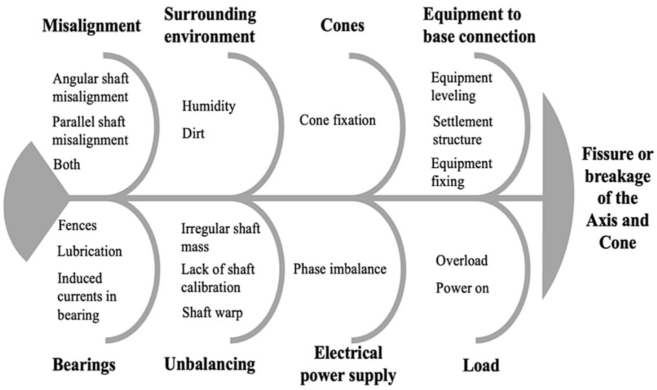

Fig. 3. Ishikawa diagram about fissure or breakage of the shaft and cone

The previous root-cause approach was complemented by a FMECA following the guidelines given by the IEC 60812:2018 [24].

FMECA allows the identification of the main possible problems in the asset. This type of analysis can be developed through a hierarchy of potential failures, complemented by a list of recommendations for avoiding them through maintenance techniques.

Through FMECA it is possible: to develop a working method; to evaluate modes of failure and their impact, to organize them; to identify the points of failure and verify the integrity of the system; to resolve failures faster; and, finally, to define criteria for tests and verifications that must be included in the preventive maintenance plan. A failure analysis can be used to understand the asset's failure mechanism. FMECA includes Failure Mode and Effect Analysis (FMEA) and the Criticality Analysis (CA) [3], [21].

The main problem was identified as the "fissure or breakage of shaft and cone", according to the FMECA matrix illustrated in Figure 4.

Based on the Ishikawa diagram and the FMECA analysis, and subsequent vibration analysis, it was possible to conclude that the actual cause of the defects was the poor seating of the chip pump machine, which was causing excessive vibration, cracking the shaft and consequently damaging the cones.

4. Chip Pump System Monitoring

Following the correction of the problem, the company decided to install a monitoring system over the key variables identified in the Ishikawa and FMECA analysis.

The system has the following sensors to monitor its condition: accelerometers; temperature sensors in roller bearings, in oil circuits, and in motor windings; load sensors; pressure sensors; flow meters; and rotation meters. Sensor readings are recorded every minute.

Figure 5 gives a global vision of the variables that are continuously monitored.

Equipament	Chip Pump				Prepared by		Team Company					
Team	Company				Date		2021					
Equipment Module	Function	Failure Mode	Failure Effect	Severity	Potential Cause of Failure	Occurrence	Preventive Action	Detection Action	Detection	RPN	Recommended Actions	Responsible and Deadline
Chip Pump (412-306)	Mechanical Traction / Mechanical Transmission	Crack or breakage of shaft and cone	Stop system for Chip Pump (412-306) and production system		**Misalignment**							
				2	Angular shaft misalignment	1	Angular alignment	Vibration Analysis	3	6	Perform alignment	
				2	Angular shaft misalignment	1	Angular alignment	Vibration Analysis	3	6	Perform alignment	x
				3	Angular and parallel shaft misalignment	2	Angular and parallel alignment	Vibration Analysis	3	18	Perform alignment	
					Imbalance							
				3	Irregular shaft mass	1	Regulate the mass	Vibration Analysis	4	12	Replacement	
				3	Lack of shaft calibration	1	Calibration	Vibration Analysis	3	9	Perform calibration	
				3	Wash Shaft	1	Replacement	Vibration Analysis	3	9	Replacement	
					Cones							
				4	Cone fixing	1	Fix the cone	Vibration Analysis	3	12	Perform predictive inspection	
					Connecting the equipment to the base							
				4	Leveling of equipment	2	Leveling the equipment	Vibration analysis and leveling check	3	24	Inspect settlement	
				4	Equipment laying structure	4	Fix the equipment	Visual displacement of the equipment	1	16	Inspect settlement	
				4	Fixing the equipment	4	Fix the equipment	Visual displacement of the equipment	1	16	Using standard screws	
					Environment							
				2	Humidity	1	Correct infiltrations	Existence of fungi	1	2	Perform isolation	
				2	Dirtiness	1	Check the cleaning of the equipment	Existence of dirt	1	2	Perform a clean-up	
					Bearings							
				2	Seals	4	Leak control or replacement	Leak checking	1	8	Perform lubrication	
				2	Lubrication	1	Lubricate bearings	Excessive friction in bearings	2	4	Perform lubrication	
				2	Induced currents in bearing	1	Improve housing insulation	Measurement of the current in the rotor	4	8	Improve housing insulation	
					Electric Power							
					Engine windings temperature		Download load	Temperature Measurement of windings			Do not exceed the recommended load	
				3	Phase imbalance	2	Balance phases	Phase measurement	1	6	Systemic phase control	
					Load							
				4	Overload	4	Respect the maximum recommended load	Analysis of Vibrations, Temperature and Electric Currents of the Motor	3	48	Follow the equipment standard	
				4	Start	4	Start at the proper speed in sequence and in conjunction with the start-up of the previous pumps	Tachometers / Voltimeters and Amperimeters	4	64	Follow the manufacturer's procedures	

Fig. 4. FMECA analysis of fissure or breakage of shaft and cone

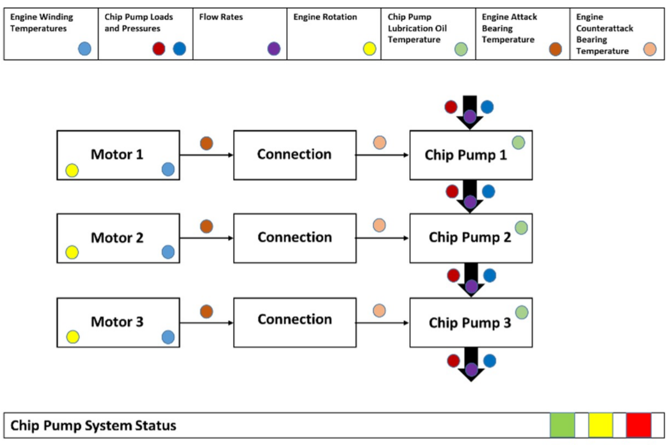

Fig. 5. Global vision of the variables that are continuously monitored

A more sophisticated algorithm to determine the relationship between predicted variables and the possibility of asset failure is out of the scope of the current project. That is a work to be developed in the future, in a separate project. The goal of the present project is just to monitor the equipment status and to predict future values. A short time prediction is performed, to anticipate future values five days in advance. A long-time prediction is performed, for three months in advance.

Relying on the forecast results, the company can anticipate malfunctions when peaks or ebbs in the predicted parameters are detected. By preventing and anticipating these failures, the company reduces its operating and maintenance costs.

5. Condition variable global analysis

The first analysis made on the condition monitoring variables was about their average and amplitude. The average, minimum and maximum values, and the time when the two latter occurred, were analyzed for all variables: vibration; temperature of attack and counterattack bearings, oil, and motor windings; load; pressure; flow; and rotation velocity.

This section presents statistics of temperature and pressure values for the three chip pumps from May 2017 to August 2019 (Tables 1-4). Pressure increases significantly throughout the system, as the mixture increases density.

Table 2 presents a comparison of engine winding temperatures from May 2017 to August 2019.

6. Short Time forecast

The short time forecast is based on an Exponential Smoothing self-adaptive, model according to Formula (1).

$$S_{t+1} = \alpha_t \times X_t + (1-\alpha_t) S_t \tag{1}$$

Table 1. Analysis of Pressures before and after each Chip Pump

	Pressure before chip pump 1			Pressure after chip pump 1			Pressure after chip pump 2			Pressure after chip pump 3		
Year	**Average value (kPa)**	**Max. value (kPa)**	**Max. value date**	**Average value (kPa)**	**Max. value (kPa)**	**Max. value date**	**Average value (kPa)**	**Max. value (kPa)**	**Max. value date**	**Average value (kPa)**	**Max. value (kPa)**	**Max. value date**
2017	-	-	-	357.67	1031.45	2017-12-05 11:01	678.12	1492.63	2017-08-09 12:22	1007.29	1201.84	2019-06-17 16:47
2018	46.57	160.16	2018-12-12 21:51	357.19	565.89	2018-02-04 02:50	685.23	1547.28	2018-11-16 12:14	995.44	1187.94	2018-06-26 11:22
2019	48.31	162.68	2019-01-23 08:03	361.64	558.97	2019-07-18 12:32	676.26	909.47	2019-06-05 11:29	1023.69	1244.60	2019-07-22 11:54

Table 2. Chip pump lubricating oil temperature

	Chip pump 1 lubricating oil temperature			Chip pump 2 lubricating oil temperature			Chip pump 3 lubricating oil temperature		
Year	**Average value (°C)**	**Max. value (°C)**	**Max. value date**	**Average value (°C)**	**Max. value (°C)**	**Max. value date**	**Average value (°C)**	**Max. value (°C)**	**Max. value date**
2017	36.1	43.11	2017-11-03 21:26	37.47	51.42	2017-01-16 13:26	36.56	44.56	2017-11.03 21:26
2018	-	-	-	42.54	108.19	2018-09-28 15:44	42.71	64.87	2018-10-04 12:43
2019	54.18	61.72	2019-07-26 13:18 2019-07-06 13:19	54.07	62.5	2019-07-26 13:15	54.28	62.23	2019-03-24 12:22

Table 3. Temperature analysis of the drive pump bearing for the chip pump

	Temperature analysis of the drive pump bearing for the chip pump 1			Temperature analysis of the drive pump bearing for the chip pump 2			Temperature analysis of the drive pump bearing for the chip pump 3		
Year	**Average Value (ºC)**	**Max. Value (ºC)**	**Max. Value Date**	**Average Value (ºC)**	**Max. Value (ºC)**	**Max. Value Date**	**Average Value (ºC)**	**Max. Value (ºC)**	**Max. Value Date**
2017	53.58	76.87	2017-08-03 13:06	58.99	83.36	2017-10-01 16:48	68.53	95.58	2017-10-27 15:03
2018	63.75	94.62	2018-08-03 18:28	71.69	93.29	2018-08-03 18:31	72.16	105.78	2018-09-25 14:06
2019	62.02	89.37	2019-05-30 15:14	64.33	95.71	2019-05-12 17:33	68.46	105.32	2019-07-09 18:57

Table 4. Temperature analysis of the counterattack bearing to the chip pump motor

	Temperature analysis of the counterattack bearing for the chip pump 1			Temperature analysis of the counterattack bearing for the chip pump 2			Temperature analysis of the counterattack bearing for the chip pump 3		
Year	**Average Value (ºC)**	**Max. Value (ºC)**	**Max. Value Date**	**Average Value (ºC)**	**Max. Value (ºC)**	**Max. Value Date**	**Average Value (ºC)**	**Max. Value (ºC)**	**Max. Value Date**
2017	27.36	46.22	2017-06-20 12:12	27.71	53.90	2017-06-20 12:12	24.45	57.38	2017-06-20 14:22
2018	27.83	55.95	2018-10-03 15:02	27.93	58.86	2018-10-03 15:08	25.60	56.68	2018-10-03 15:04
2019	27.98	48.32	2019-07-11 13:49	28.78	50.77	2019-07-11 14:08	26.70	53.67	2019-07-11 14:00

where:

S_{t+1} is the expected value for time t+1

α_t is the the Auto Adaptive Smoothing Coefficient for time t ($0 \le \alpha_t \le 1$)

X_t is the variable value at time t

S_t is the expected value for time t

The Auto Adaptive Smoothing Coefficient α_t is calculated through Formula (2):

$$\alpha_{t+1} = Min(1, k_t) \tag{2}$$

where:

$$E_t = X_t - S_t \tag{3}$$

and:

$$k_t = \left|\frac{A_t}{M_t}\right|, \text{ if } M_t > 0, \text{ 0 otherwise} \tag{4}$$

$$A_t = \beta \times E_t + (1-\beta) \times A_{t-1}, \ 0 \le \beta \le 1 \tag{5}$$

$$M_t = \beta \times |E_t| + (1-\beta) \times M_{t-1}, \ 0 \le \beta \le 1 \tag{6}$$

E_t is the forecast error for time t. β is a parameter of the algorithm – a larger value will result in faster response of the filter.

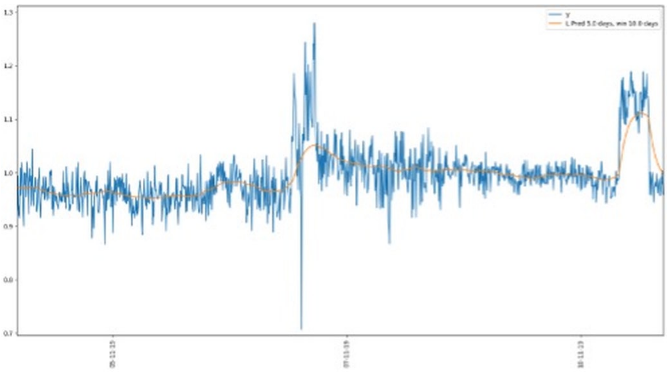

Fig. 6. Result of the short time prediction algorithm for variable Vibration

The short-term algorithm was implemented in Python. Figure 6 shows an example of the output produced by the short time prediction algorithm for vibration, with a $\beta = 0.4$. As the plot shows, the prediction follows the trends of the signal very closely. Since it is smoothed, the prediction is much more stable and immune to short spikes. For vibration, the Mean Squared Error (MSE) is 0.068 and the Mean Average Percentage Error (MAPE) is 5.61%. For pressure, the MSE is 990.64 and the MAPE is 1.36%. For the U, V, W motor winding temperatures, the MSE are 0.18, 0.21, 0.18 and the MAPE are 0.39, 0.41 and 0.36 %, respectively. For flow, MSE is 322.5, MAPE is 0.45. For the temperature of the attack roller bearing, MSE is 0.30, and MAPE is 0.59 %. For the counterattack roller bearing, the errors are 3.14 and 5.76 %. For velocity and temperature oil temperature, MSE are 254.07 and 0.15m and MAPE are 0.37% and 0.29%.

7. Long Time Forecast

To forecast the parameters, a dataset provided by the company was used. The dataset contains sensor data from 2017 to 2020, with a sampling period of 1 minute, as stated above.

The dataset was divided into two parts, 80% for training and 20% for testing. Each training iteration takes between six hours and eight hours on a computer with Intel Xeon E5-2680v2 CPU.

The code used was developed by the authors in Python, using the the ScyPy Sk-learn Library. Several mode tests were carried out and based on the results the best parameters were chosen.

It was ensured that there were no overfitting problems, as graphs were developed about the network's learning history, having presented a converging curve. The final Neural Network has two hidden layers (140-2).

7.1. Dataset, filter, smoothing and normalization

The dataset was composed of 11 variables: Vibration, Pressure, Velocity, U Winding temperature, V Winding temperature, W Winding temperature, Oil temperature, Flow, Temperature of Attack Roller Bearing, Temperature of Counterattack Bearing and Load. It should be noted that the load will not have a forecast, as it is only used as an input to the neural network.

Missing data in the dataset were filled with last known value for that variable, *i.e.* all missing or null values are replaced.

Then a median filter was applied using a sliding window with the previously defined window width (w, in samples). Finally, the data of all variables under study were normalized using the python Standard-Scaller library. The normalization interval used was [0, 1].

7.2. Input vector creation

To create the input vector for the neural network, a sliding window of width *wn* is applied. The following diagram illustrates the application of the window to the time series *u*.

u[n - ...]	u[n-*wn*-2]	u[n-*wn*-1]	u[n-wn]	...	u[n-1]	u[n]
			W[*wn*]	...	*W*[2]	*W*[1]

Fig. 7. A sliding window W, with size wn, is applied to the time series u, so that wn samples of the sequence u are selected to create the input to the neural network

Applying the sliding window *W* to sequence *u*, *wn* samples, from *u[n]* to *u[n-wn],* are selected to create the input vector to the neural network.

Once the *wn* samples are selected, a signature *Sn* of the window is calculated to feed as input to the neural network.

The signature *Sn* comprises the mean value of the window (m_w), the Standard Deviation (std_w), the median (med_w) of the *wn* samples, and the Power Spectrum Density (psd_w), as represented in (7). Experiments with other vectors were performed, but for succinctness the results are not presented in the paper.

$$Sn(n) = [m_w, std_w, med_w, psd_w] \tag{7}$$

Once the sequence of signatures of each window is created, a transformed dataset is constructed, with the structure represented in Figure 8.

Sn[n - ...]	Sn[n-5]	Sn[n-4]	Sn[n-3]	Sn[n-2]	Sn[n-1]	Sn[n]

Fig. 8. Representation of the transformed dataset, containing the signatures of each window wn

To train the model to predict future values, a time gap g, in samples, is applied to create the desired output vector. The vector is introduced, so that the predicted value p for time $n+g$ is a function of *Sn[n],* as shown in (8).

$$p[n+g] = f(Sn[n]) \tag{8}$$

Figure 9 schematically shows the correspondence between signature *Sn* in the dataset and the predicted value *p*, where *Sn[n]* is used to predict *p[n-g]*. In the figure, *g=3*. In the experiments, *g* was the number of samples in 90 days.

wn[n - ...]	wn[n-5]	wn[n-4]	wn[n-3]	wn[n-2]	wn[n-1]	wn[n]
p[n - ...]	p[n-5]	p[n-4]	p[n-3]	p[n-2]	p[n-1]	p[n]

Fig. 9. Representation of the prediction model, where the signature of the signal at time n-3 is used to predict the value at time n

The machine learning model used to make the predictions was an Artificial Neural Network, namely the MLPRegressor of the Sklearn library. The neural network after several training procedures, achieved good results. Figures 10-12 show the original signal and the prediction for different values. Those results were obtained using a multilayer neural network with two hidden layers, with 200 and 10 neurons, respectively, using the ReLU activation function. The sliding window applied on the data comprised 7 days of data.

For better stability of the values predicted, they were smoothed using median filter with window size 20.

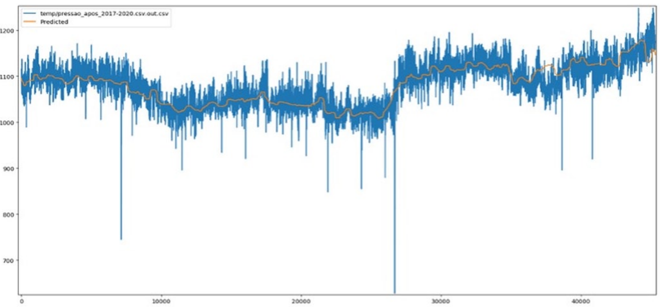

Fig. 10. Results of prediction for temperature. The signal is in blue, the prediction in orange

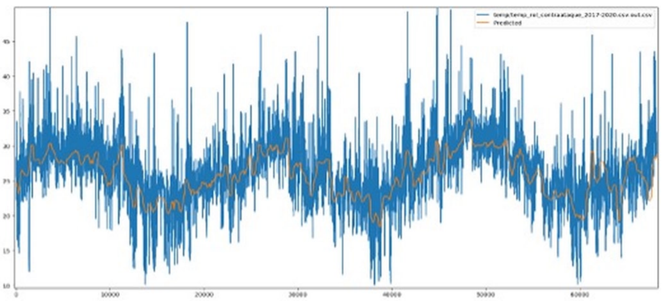

Fig. 11. Results of prediction for counterattack bearing temperature

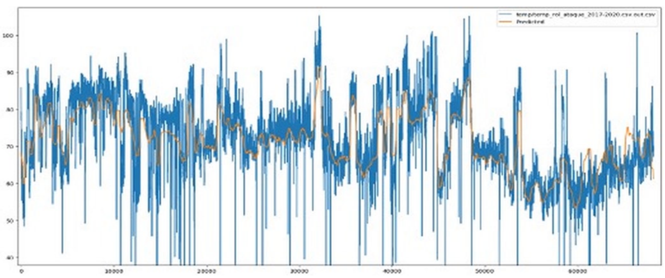

Fig. 12. Results of prediction for attack bearing temperature

To better understand the efficiency of the neural network, Table 5 shows the Mean Absolute Percentage Errors and the Mean Squared Errors for all the predicted variables.

Table 5 shows that it is possible to predict the status of the equipment in advance, with errors on average less than 10 %.

Table 5. MAPE and MSE of the 3-month forecast of all variables.

VARIABLE	MAPE	MSE
Vibration	9.47	0.19
Pressure	1.59	507.08
Velocity	1.32	847.25
Winding temperature U	4.26	25.93
Winding temperature V	4.32	28.13
Winding temperature W	4.47	29.89
Oil	5.34	31.75
Flow	3.35	5652.65
Temperature Attack	6.63	39.16
Temperature Against Attack	9.72	10.13

7.3. User end interface

The end user interface was implemented through semaphores, quantitative values, and graphs, aiming to give, in an intuitive way for the user, a global vision of the system behaviour.

In this colour system, red is for the anomaly, yellow for lookout, and green for good working. This choice of colours was chosen to be like the traffic light system used on roads, making it easy to interpret and assimilate by everyone.

Through this system, it is easy, quick, and simple for the operator to know in which state of operation the equipment is, which can also contribute to prevent serious failures or malfunctions (when it is yellow or red).

The limits for green, yellow, and red were proposed by the company technicians, based on previous experience and manufacturer's information.

8. Conclusion

Failures in industrial plants can cause huge losses, or even endanger people and property. A case study of chip pumps has been described, where a dataset of approximately three years of sensory data and factory inspections were used to diagnose problems and develop a model to predict future behaviour. FMECA analysis identified that the last of three chip pumps was subjected to huge strain. Such effort was justified by the fact that it must transport its load vertically, while the predecessor chip pumps do it horizontally.

The same chip pump has deficiencies in its settlement which exponentially increase its vibration. Such vibration associated with a greater Strain effort make the shaft of the chip pump to suffer more stress than recommended, hence its useful life is doomed to be much shorter than required.

The forecast of sensor values to three months offers a great advantage for decision-making in equipment maintenance management. The temporal dimension of the forecast is totally innovative since, in the review of the state of the art, only short/medium-term forecasts were found.

Prediction made through Neural Networks proved to be valid for this type of problem. The Mean Absolute Percentage Error in all variables was below 10%.

Given the results achieved, this work offers the industry concerned the possibility of making more informed scheduled maintenance stops. This contributes very positively to increase the availability of assets as well as to reduce costs, as it reduces unexpected breakdowns. One limitation of the approach is that it relies on past sensory data. Changes in one or more key variables, for example due to differences in parts, environment, or other changes, can result in more uncertain predictions.

This methodology can be applied to other equipment by training the neural networks with appropriate data, although there is no guarantee that the same results can be achieved in another asset. The results can be better or worse, depending on the type of patterns present in the data.

This problem may be subject to future work. Other future work includes the study of more variables, as well as other machine learning models.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
ANN	Artificial Neuronal Networks
ARIMA	Auto Regressive Integrated Moving Average
FMEA	Failure Mode and Effect Analysis
FMECA	Failure Mode, Effects and Criticality Analysis
MAPE	Mean Absolute Percentage Error
MLP	Multilayer Perceptron
MSE	Mean Squared Error
NN	Neuronal Networks
WS	Windows Size
IoT	Internet of Things
IIoT	Industrial Internet of Things

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