A Smart Node (Maintenance & Lifespan Prediction System)

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Abstract

Failure doesn't occur overnight, as the warning signal from many different sources emerge, and even the production quality/quantity evolve prior to the failure. Hence, surveillance of these signals 'sources could be used as an input for a system that depends on smart factory principles in order to predict failure and parts' lifespan in advance. This idea was echoing for few years but now it became achievable due to the development of the artificial intelligence (AI), machine learning, data mining and data reservoir technologies.

Keywords: AI, SAS, IoT, Failure prediction, Machine learning.

1. Introduction

Since the present business environment is suffering uncertainty due to the economic fluctuations, not only the failure anticipation of production lines is fundamental, but also it is critical to preserve company's capital and production flowing. The project aimed to develop novel maintenance mechanism based on industry 4.0 principles, implementing of the IoT monitoring system on manufacturing line and verifying and validating the performance of the maintenance system. Industries appoint (15-60) % of their revenues for maintenance execution, and 33% of these expenses is unnecessary [1]. Failure prediction system develops and propagate the boundaries/thresholds, the saved approaches are not explicit considering the different variables [2]. Parallel to the real-time data, this system provides an analysis of the historic data of the parts since the implementation date till the current date. The data are being collected via sensors and invertor at the real time, modified according to the load and the production-line characteristics. Then being updated every 20 minutes (comparison interval) by the scanned data during working time in order to ascend the prediction accuracy.

The log files represent the changes of the system, each interval enables the system to form a pattern that can be analyzed and used to predict failures. The continuous collecting of the pattern illustrates the possible failure development and enables the system from predicting the lifespan of the parts accurately.

The data has been collected, the charts have been organized and the medians showed distinguish changes according to the scrutinized item (lubrication), vibration and noise charts showed the changes of the medians within the failure development and the prediction accuracy achieved 99.998%.

The process didn't finish there, it requires series of decision making, analyzing data, changes observation and consequences prediction [3]. The decision supporting system forms the backbone of any diagnostic system, the most efficient method have been the implementing of artificial neural network [4] because sometimes the other methods perform false alarms signals. To avoid all these faults, a few conditions must be followed, resilient configuration, fast data acquisition, simplicity and reliable in hard circumstances. These requirements are achievable by using intelligent sensors and control system provided with microprocessor [5].

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2. Methodology

SAS/Open source software collected organized, processed data (that have been acquired by sensors and inverter) and adapted the thresholds according to the working conditions. These data are being integrated during the different intervals to check the development of the status of the studied part without checking the whole system. Here comes the turn of AI and machine learning technologies where they arrange and manage the components then the monitor will be able to predict the failure prior to its due time. This novel idea has been applied on conveyors, drivers and idlers in order predict the failure and the fatigue of the part besides monitoring oil leaking of the gear box.

3. Experiment tools

Modular conveyor, driver (0.55 Kw), idler, gearbox, Siemens Inverter that provides (speed, frequency, current, power, voltage and temperatures) and the motor velocity, acceleration, crest and temperature by IFM. Besides, Bosch XDK scrutinizes the vibration, noise and ambient temperature of the gearbox. SAS Viya/Open source.

3.1. *Machine Learning Model*

The input dataset was used to build and train machine learning models. The input data consists of 7506 rows and the ratio used for train; test validations are 6:2:2 respectively. The platform used to train and deploy the machine learning models is SAS Visual Data Mining and Machine Learning (VDMML) V.03.05. A total of 6 machine learning models were trained, which were stepwise logistic regression, neural network, forward logistic regression, random forest, decision tree and gradient boosting. Data pre-processing step of imputation (impute missing values) was carried out on forward logistic regression while both imputation and variable selection were carried out for stepwise logistic regression and neural network model to improve the accuracy. The cross-validation technique employed for neural network, random forest, decision tree, and gradient boosting was K-fold cross validation with cross validation number of folds set to 5. After comparing the performance of all 6 models, the gradient boosting model was found to have the highest accuracy in terms of misclassification rate and Kolmogorov-Smirnov statistic (KS). Thus, gradient boosting model was chosen to be deployed.

3.2. *Gearbox Lubricant's temperature*

The previous studies showed that the lubricant level can impact the power consumption [6]. The ammeter charts illustrate that the (low lubricant level) makes the current reading irregular which makes the line erratic, while adding more lubricant oil makes the line smoother and more consistent. This power consistency can be ensured

by the efficiency of the lubricant and the used equipment [6].
The correspondent lubricant contributes in several cases that increases the lifespan of the motor via preventing abrasion, galling, sliding friction, seizing, rust and corrosion, besides resisting the low and high temperature. The association among these factors reduces the friction and the energy consumption [6].
The orientation of the driver has been chosen and the experiments will depend on studying the effect of the lubrication oil (low, medium and high) in the gearbox. Each case will be providing different lubrication system (dry, splash and oil-bath). Hence, this experiment will show the effect of the lubrication oil on the temperature, noise and oscillation.

3.3 Noise calculation

The functioning conveyor is a source of a complex of noises that are being originated from drivers' gear, idler, chains and friction among the moving parts. These noises are being affected by many different factors including the conveying type, these noises an enable the operator from understanding the consistency and the behavior of the whole system. Several strategies have been applied in order to reduce the noise by using different materials in producing the moving materials or improving the damping procedure.
The gear motor is one of the major sources of noise in the modular conveyor system, thus the lubrication of the gear contributes in reducing friction which in turn reduces the emitted noise. In this study the lubricant has been standardized thus all the factors related to the lubricant will be neglected. While, the manipulation implied only the level of the lubrication in the gearbox trying to understand the effect of it on the noise level and vibration.

3.4 Tensile

The tensile samples' results were collected from five tests, the data showed that the break began to occur under the load of 539 kgf and higher with a maximum increment in the required force to cause the breakage with 4%. The threshold that must be studied is 539 because the smart conveyor must be alerting before it reaches this value. The elongation can be the studied value that will illustrate that the force is close to the breakage threshold by finding the companion elongation that attends the breakage force is almost (12.76%) (30mm/235mm) at least before the breaking which should be the threshold that alerts the system to prepare itself for the preventive maintenance, also the ratio of the elongation can prepare the due date of the preventive maintenance where it must be postpones (the red zone).

The system detects the lengthening by calculating the (the consumed time per full cycle), the designated speed facilitates the system's duty in calculating the lengthening ratio. The tests showed that the 12.76% is the lengthening before the links starts to break, so the system will be alarming the operator according to the lengthening ratio per time and the more data collected in the system the higher the accuracy of the breakdown timing prediction. To facilitate this process, it can be divided into three stages:

- (0-4) % lengthening, this stage shall be used to collect accurate data regarding the intervals and the lengthening ratio.
- (4.1-8) % lengthening, this stage is safe as well and provides more accurate data in order to find the failure acceleration ratio.
- (8.1-13) % lengthening, it provides precise prediction regarding the breakdown so the maintenance supposed to be done during the closest rest before/after entering this zone (according to the sensitivity of the production line).

The vibrations of the conveyor make the static load affect the system like a dynamic impact load, and as the vibration is frequent and inconsistent which forbids the damping. Thus, the lifespan of the moving parts become shorter because of the dynamic load impact. The safety factor should be pretty high as the tension test is being applied discretely while the chain is being affected by many different factors not only tension (heat, abrasion, vibration, dynamic load…). The amplitude of the vibrations and the temperature of the ambient/parts integrate to define the critical point. The accumulation among these factors is similar to the Coriolis of the harmful forces. Thus, the relationship between these factors and the lengthening ratio is indirect proportion.

4. Results and discussion

Please This study developed an approach of creating a predictive maintenance system that can be used in all industrial machines depending data that has been extracted from tangible and intangible variables. The prediction accuracy ascended to reach 99.998% based on misclassification rate on validation portion. Factors like noise, vibration, voltage, current, power and rms's were the most influencing variables. This study has many useful impact not only by alleviating the failure effect, reducing the breakdown of the production line but also it reduced the power consumption by integrating the aforementioned factors with the load.

Fig. 1. Conveyor setup.

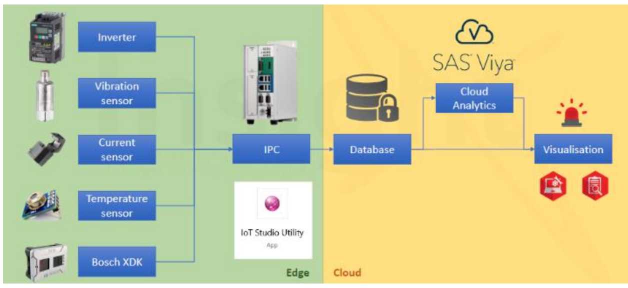

Fig. 2. The system architecture

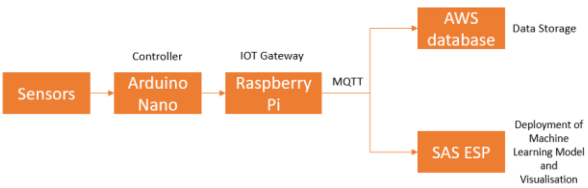

Fig. 3. Architecture of data flow

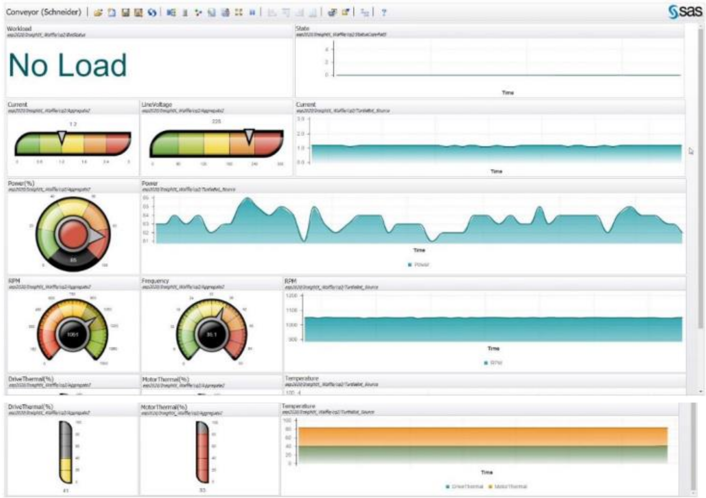

Fig. 4. real time dashboard (interface)

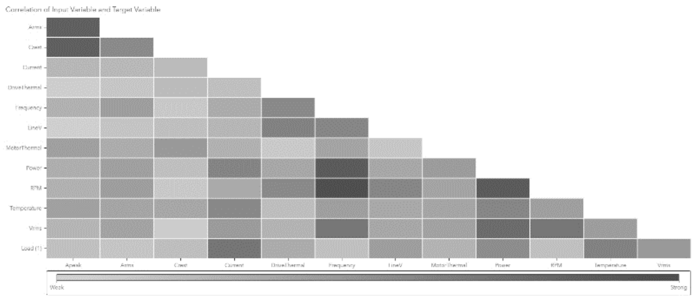

Figure 5 Correlogram of input variables and target variable

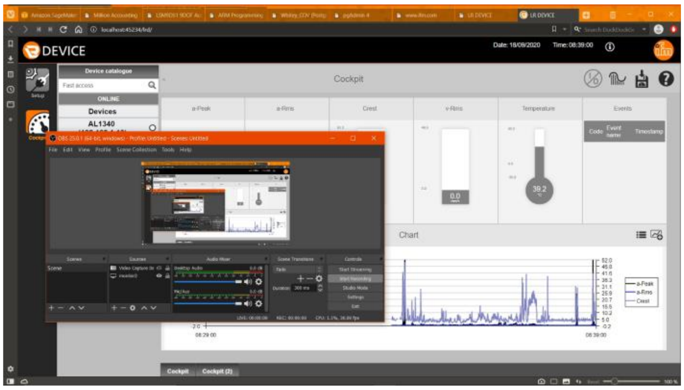

Fig. 6. IFM Vibration sensor data

Acknowledgements

The authors would like to thank MODU company management for funding this project, also, to express the gratitude towards the support from the UCSI University, and its Research and CERVIE units who are supporting the research.

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