Available online at www.sciencedirect.com

ScienceDirect

Procedia Computer Science 200 (2022) 111–120

Procedia Computer Science

www.elsevier.com/locate/procedia

3rd International Conference on Industry 4.0 and Smart Manufacturing

A Two-Phase Machine Learning Approach for Predictive Maintenance of Low Voltage Industrial Motors

Mohsen Nikfar[a], Julia Bitencourt[a], Konstantinos Mykoniatis[a]*

[a]*Auburn University, 3301A Shelby Center, Auburn, Alabama, 36832, United States of America*

Abstract

Predictive maintenance and sound operating industrial equipment are essential for nearly any production plant. The absence of a systematic maintenance program and data-driven mindset in making manufacturing decisions may result in serious safety risks, unexpected equipment damages, and financial strain. Condition monitoring and predictive maintenance management systems are commonly used in tandem with the Internet of Things, linking sensors on machines and transmitting the data through a wireless network to a data-logging center that will allow further analysis and support decision making. The system described in this paper measures vibrations using sensors attached to low voltage motors and then utilizes a two-phase machine learning approach for predictive maintenance. In the first phase, we conducted an analysis to look for any abnormal behavior, and in the second phase, we attempted to determine the type of specific faults that may occur. The proposed predictive maintenance system aims to reduce the fault detection time and assist with diagnosing the type of fault occurring. We utilized and tested three machine learning algorithms to detect abnormal motor behavior: support vector machine, backpropagation neural network, and random forest. For predicting the type of specific motor faults that may occur, we used a support vector machine. This two-phase machine learning approach demonstrated promising results in detecting abnormal behavior in low voltage motors. Therefore, integrating this machine learning component as a part of a predictive maintenance system can result in high confidence about the motor condition, reduce maintenance cost, and enhance the safety of the operators and the machines.

Peer-review under responsibility of the scientific committee of the 3rd International Conference on Industry 4.0 and Smart Manufacturing

Keywords: Predictive maintenance; condition monitoring; machine learning; low voltage industrial motors

* Corresponding author. Tel.: +1-334-844-1420..
E-mail address: kmykoniatis@auburn.edu

Peer-review under responsibility of the scientific committee of the 3rd International Conference on Industry 4.0 and Smart Manufacturing
10.1016/j.procs.2022.01.210

1. Introduction

One of the most common industrial machines that is used in a wide range of applications is the low voltage induction motor. Low voltage motors are the workhorse for many segments of the manufacturing industry. These motors offer a compelling balance of performance, reliability, motor control, and overall system cost. Although induction motors are reliable, possible faults such as bearing defects, rotor broken bar, and misalignment may affect the quality of the product and cause unexpected breakdowns, injuries, or even death to the workers [1]. Therefore, real-time condition monitoring (CM) and predictive maintenance (PdM) are crucial tools that can detect anomalies and predict patterns of possible defects in equipment and production processes and can ultimately prevent failures and avoid these incidents. The most common issues for 100 studied petrochemical plants around the globe were due to mechanical motor failures [2], [3]. Therefore, we tested different machine learning (ML) algorithms to explore PdM techniques to detect, predict and ultimately avoid problems that may occur due to failures of low voltage industrial motors.

In the literature, CM and PdM terms have been used interchangeably (e.g., [4] and [5]), yet this is not the case. The main difference between PdM and CM is the timing. Both monitor the health and condition of manufacturing machines or assets. However, CM focuses on real-time conditions, while PdM is focused more on the early detection of anomalies and defects of machinery. Specifically, CM utilizes modern technologies, such as the Internet of Things, for real-time monitoring of one or more parameters of condition in machinery. Thus, CM usually informs about the current condition of a machine to allow maintenance to be scheduled, or other actions that could potentially prevent a future failure [6]. On the other hand, PdM's main focus is on using techniques and data analysis tools to predict several days in advance possible system defects and anomalies, and prevent unplanned reactive maintenance without incurring costs associated with doing too much preventive maintenance.

According to Yarmoluk and Treumpi [7], CM went through 4 generations. The first generation of CM, also known as C.M 1.0, lasted from the 1980s and earlier. This generation of CM is referred to as "condition-based-reactive maintenance" because CM would alert only when a failure had occurred. Although CM 1.0 was beneficial for alerting about a machine failure, it did not provide sufficient time to plan maintenance. The second generation of CM or CM 2.0 (from the 1990s to the 2000s) significantly improved the detection of anomalies. In addition, magnetic mounted sensors and more measurements on the machines were deployed to reduce energy consumption and collect helpful measurements about the power consumption, motor speed, vibration, and temperature. During CM 3.0 era (the 2010s) smart sensors, processing power, advanced communication and storage systems as well as industrial internet of things (IIoT) technology provided the opportunity to detect potential failures much earlier than the second generation of CM. Finally, CM 4.0 integrates and deploys artificial intelligence and ML techniques. These techniques can provide suggestions for the possible cause of the failure and recommend future maintenance tasks. The remainder of the paper is organized as follows: Section 2 provides a brief background on existing work that has been conducted concerning CM and PdM. Section 3 provides the research methodology that we followed including the data collection process, algorithm implementation, and parameters tuning. Section 4 describes the results from phase 1 and phase 2. Finally, in Section 5 we discuss conclusions and future work.

2. Background

CM is an important aspect of machine maintenance and quality management and provides significant financial advantages. According to Besnard, Nilsson, and Bertling [8], CM can reduce the life cycle cost for a wind turbine by approximately 27%. Moreover, You, Liu, and Meng [9] reported a 32 percent decrease in maintenance costs of ball grid array solder joints using CM. According to [10], using oil CM can help to determine the appropriate interval of oil change in asphalt paving machines. Other benefits of CM include: less machine failure costs, higher productivity, and operation safety [11], less waste, on-time, and exact maintenance operations [12], being able to predict the remaining useful life of machines and equipment [13].

Jagtap, Bewoor, and Kumar [14] introduced an enhanced version of a generalized coordinated CM system. To achieve a better performance in fault detection, they combined several CM techniques such as analysis of vibration, using ultrasonic devices, wear debris analysis. As a case study, they monitored an induced draft fan in a power plant in the west of India. They used their observations to find problems in the input bearing of hydraulic coupling. They concluded that using all these techniques in parallel will help to detect problems in advance. Taghipoor and Mosavi [15] investigated a vibration monitoring system in a gas compression station in Iran. They analyzed the effect of these items on the performance of the CM system: sensors location, the transmission of vibration signals to the control room, number of sensors, data storage, and different methods for vibration data analysis. They improved the CM system by determining the proper number of sensors. They also mentioned that the organization personnel was unfamiliar with such advanced vibration analysis methods.

Mykoniatis [16] developed and implemented a motor management CM system that can use both temperature and vibration data to detect anomalies in low voltage motors. The developed CM system uses predefined limits for vibration and temperature to detect abnormal conditions. When an abnormal condition occurs, the system will send an alert to the supervisor's mobile phone and simultaneously trigger an alarm system. The alarm system remains activated until the supervisor uses his/her RFID batch to stop the alarm. The supervisor can additionally check and access the motor condition remotely using the CM system. In the system, a Fast Fourier Transformation algorithm captures the most dominant vibration frequency. Also, the system includes an RGB LED that shows three conditions with different colors: Green (normal), yellow (warning), and red (alarm). In general, the system has the following functionalities:

- CM using vibration and temperature data
- Logging the vibration and temperature data
- A program for setting abnormal limits for both vibrations and temperatures
- An audiovisual component for showing different states of the system (normal, warning, alarm)
- Sending mobile alerts
- Enforced inspection using RFID technology
- Connection to wireless internet
- A GUI for remote access and checking a motor’s condition

The results of pilot testing for vibration and temperature data showed that the system can successfully identify abnormal behavior in the vibrational frequency or temperature, and then in turn trigger the alarm system. Vibration-based damage detection methods have been used since the late 1970s and 1980s [17]. Vibration measurements using sensors have also been applied to find possible damages in blades of wind turbines (e.g., [18], [19]). The CM of rotating machinery using vibration-based damage detection technology has also been implemented successfully. Carden and Fanning [20] analyzed 250 references and considered nine categories for the different vibration-based methods. They mentioned there is no agreement between authors in the literature about the best method to detect damages in different structures.

The Industrial Internet of Things (IIoT) has made it possible to connect a network of machines embedded with sensors, software, and other technologies for exchanging data with other devices and systems via the internet. IIoT also provides a great opportunity for implementing PdM. For example, Kan and Kumara [4] presented a new approach to use parallel computing and network analysis to facilitate processing the massive amount of data that a large-scale IIoT system provides. They also designed a parallel computing technology that can use several processors to improve the efficiency of the computation process. Moreover, the availability of off-the-shelf IIoT technology ensures remote PdM is financially feasible. For instance, Pesch and Scavelli [5] created a PdM system for active magnetic bearings (AMBs) that works remotely and costs less than 100 USD. They used a Raspberry Pi single-board computer with an MBC500 AMB test rig. The Raspberry Pi can check the position sensors and current sensors of AMBs using an analog to digital convertor.

The application of IIoT for PdM purposes is becoming common in different industries. Dong, Mingyue, and Guoying [21] designed a predictive maintenance system for a coal mine. Their system includes three components: A station to observe equipment state, a center for watching the coal mine, and a remote PdM system. In the remote PdM system, a group of technicians and experts observe the parameters. Based on their observations, they create statements and send those to the monitoring terminal. They used ventilator equipment to test their proposed model. They concluded their system can enhance safety in coal mines. Combining IIoT with innovative approaches such as cloud computing [22], image processing [23], and big data analytics [24] is becoming a standard in the era of industry 4.0.

In more conventional approaches, when a signal passes a specific threshold, an alarm informs users about a potential problem in the physical object. However, a ML approach can help to reduce the time for detecting a fault and assist in diagnosing the type of fault that occurs. ML has additionally been used as an important approach in PdM in different contexts. For instance, Cakir, Guvenc, and Mistikoglu [25] adopted ML models for creating a method to classify bearing damage. They used vibration, sound, rotational speed, current, and temperature for monitoring the conditions of the bearings. For ML, they used support vector machine (SVM), random forest (RF), k-nearest neighbors (KNN), and decision tree (DT) algorithms. They achieved accuracies higher than 99% using all the algorithms. Some other examples of different fields and products that applied ML as a component of their PdM system are heavy equipment engines [26], roads [27], and high voltage circuit breakers [28] to name a few.

ML techniques can also be used for predicting faults in induction motors. Ayding, Karakose, and Akin [29] created a novel artificial immune-based SVM. They used some characteristics of a human immune system to design the SVM kernel and its penalty parameters. They used the proposed algorithm to detect broken rotor bars and faults in a stator short circuit. Their results showed an average performance of 98.85% for detecting faults. They also claimed that their method used less amount of data in comparison with Park vectors' approach. Samanta, Al-Balushi, and Al-Arimi [30] compared artificial neural networks (ANN) and SVM for detecting bearing faults. They used a genetic algorithm for parameter tuning of ANN and SVM. Their results demonstrated that SVM has a superior performance in comparison to ANN. Based on their results, SVM also is more efficient and consumes considerably less amount of time for training. Zhitong, Fang, Chen, and Ewen [31] used SVM to diagnose the fault of rotor broken bars in induction motors. They used Fourier transform to study sample currents. They used the spectrum characteristics as the learning sample. Based on their result, SVM has a good performance for detecting faults.

In this work, we used the vibration data, collected by the Mykoniatis [16] to detect problems in a low voltage motor. At first, we tested different ML algorithms to detect faults (Phase 1). In the next step, we tried to determine what type of faults occur (Phase 2) in a low voltage motor. Our reason for adopting this ML approach is to be able to detect faults quickly and accurately.

3. Methodology

3.1. Data Collection

We used accelerometer sensors to monitor two types of industrial motors. The accelerometer gyroscope sensor (GY521) collects the vibration data to monitor the variations in vibrational frequency. The system has two radio frequency communications modules (XBees S2C) that track the vibration data on the motors. One module serves as an output device between the gyroscope accelerometer sensors. The other module serves as an input device on the computer command station that tracks the vibrational frequency data. The command station allows a central location for logging all the data of each of the motors.

We used two types of low-voltage industrial motors. Motor I is a Marathon Electric motor with 60 horsepower, and Motor II is an Emerson Motor Co. with 40 horsepower. Both motors have the same low voltage (230/460). Fig. 1 presents the remaining characteristics of each of the motors.

For Motor I (class B), we extracted two sets of vibration data from two different places on the motor: motor bearing surface (position 1) and motor body (position 2). Motor II (class F) only contains vibration data from the motor bearing surface. The datasets for class B contain 270 rows and the class F dataset contains 240 rows. All the datasets have 127 columns that contain vibration values from the accelerometer gyroscope sensors. Each dataset also has two more columns named Health_condition and Type_of_fault, resulting in a total of 129 columns.

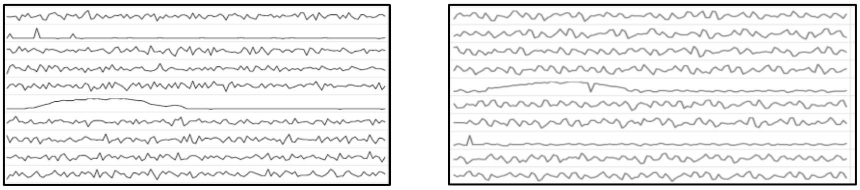
The column Health_condition shows if the row contains data for a normal or a faulty motor. The column Type_of_fault shows the type of problem that occurred to the motor. Hereafter, we will use these abbreviations for each dataset: class B-1 for the dataset that contains vibration data from position 1 of class B motor, class B-2 for the dataset that contains vibration data from position 2 of class B motor, and class F for the dataset that contains class F motor vibration data.

Fig.2 shows the Sparkline of a part of Class F and Class B datasets. In Fig.2-a, the second line and the sixth line show faulty data. In Fig.2-b fifth and seventh lines show defective data. The rest of the lines are representing normal vibrations collected from the motor.

Motor I	
Manufacturer	Marathon Electric
Model	AVH 364TTDC4035AAS
Type	TDC
Class	B
Horsepower (H.P.)	60
Volts (V)	230/460
F.L. (Amps)	142/7.1
Frequency (Hz)	60
Service Factor (SF)	1.15
Speed (RPM)	1775
NEMA Nominal Efficiency (%)	93.6
Nominal Power Factor (%)	84.5

Motor II	
Manufacturer	Emerson Motor Co.
Model	HJ40S2BV-P
Type	CTF1
Class	F
Horsepower (H.P.)	40
Volts (V)	230/460
F.L. (Amps)	46-92
Frequency (Hz)	60
Service Factor (SF)	1.15
Speed (RPM)	1775
NEMA Nominal Efficiency (%)	92.4
Nominal Power Factor (%)	87.4

Fig. 1- Characteristics of motor I (left) and motor II (right)



(a) (b)

Fig. 2 - The Sparkline for a part of class F dataset (a) and class B dataset (b)

3.2. Implementation of Algorithms

As we mentioned in Section 1, we applied a two-phase ML approach. First, we analyzed vibration data to detect abnormal behavior of any kind. Next, we used the same data to detect specific types of faults in the motor, represented in our dataset as the column "Type_of_fault". Our ML approach is inspired by Kusiak and Anoop [18] that used several machine learning algorithms to detect any defect type in wind turbines. More specifically they used neural network (NN), SVM, RF, boosting tree algorithm (BTA), and general chi-square automatic interaction detector (CHAID) algorithms. For the second stage, Kusiak and Anoop [18] used RF because it had the best performance in the first phase. In this paper, we used backpropagation neural network (BPNN), SVM, and RF for the first phase, and SVM in the second phase. These algorithms are selected because they showed plausible results for similar purposes in the literature. In phase 2, we considered three different types of faults: bearing wear, unbalanced mass, and misalignment.

We used R as the programming language to code the different ML approaches. At first, the code reads three different datasets. Then for each algorithm, we split the datasets into testing and training. In the next step, the code uses suitable libraries to implement each algorithm ("e1071" for SVM, "neuralnet" and "BBmisc" for BPNN, and "randomForest" for RF). For all algorithms explored, the code provides confusion matrices for comparison purposes.

For the training and testing sets, we examined two different splits for SVM (33%-67% and 25%-75%). We selected these splits to ensure there is enough data in the train sets and the test sets. We avoid using splits that produce smaller test sets (e.g., 80%-20%) because the test dataset would not include all the different defects that we considered in this work. The splits that have reduced training sets (e.g., 50%-50%) could be also problematic. These splits cause the training set to be too small for the ML algorithms to learn about all the different types of data that we have in our dataset. For BPNN and RF, we randomly selected 33% of the data as a test set and the remaining data as a training set.

3.3. Parameters Tuning

Parameter tuning has an important effect on the accuracy of the ML algorithms. Table 1 shows the parameters that we used for parameter tuning during phase 1.

For the SVM algorithm, we tested Radial and Linear kernels. For Radial kernel, we compared five combinations of cost and gamma ((0.025, 0.5), (4, 0.5), (32, 1), (4, 1.5), (32, 2)). We also used the *tune()* function to try different combinations of cost (2^{-5}, 2^{-4}, 2^{-3}, 2^{-2}, … to 2^{5}) and gamma values (from 0 to 2 increased by 0.1 steps), testing all the possible combinations. Additionally, but now for the Linear kernel, we considered four different values of cost (0.01, 1, 2, 12).

For the BPNN algorithm, we checked a combination of 2, 5, and 8 neurons with three different learning rates (0.002, 0.2, 0.8). The 0.002 learning rate had a superior performance in comparison to others, therefore, for the second round, we compared seven different neurons (12, 16, 20, 24, 28, 32, 64), using 0.002 as the learning rate.

Finally, for RF, we tested four different numbers of trees (500, 1000, 5000, 150000) and six different variables for splitting each node named as *mtry* in RF documentation in R (3, 4, 5, 6, 7, 8).

In phase 2, we used the same combination of parameters for tuning the SVM algorithm. We used accuracy as a measure to select the best parameters for each algorithm and also the best algorithm. The accuracy is computed by the percentage of correctly classified observations.

Table 1. Parameter values for each classification method

Algorithm	Parameter values
SVM	Two splits for test and train sets (33%-67%, 25%-75%) Radial: Cost, Gamma: (0.025, 0.5), (4, 0.5), (32, 1), (4, 1.5), (32, 2), Tuning Linear: Cost: 0.01, 1, 2, 12
BPNN	Number of neurons, learning rate: (2, 5, 8), (0.002, 0.2, 0.8) Number of neurons, learning rate: (12, 16, 20, 24, 28, 32, 64), (0.002)
RF	Number of trees: 500, 1000, 5000, 150000 mtry: (3, 4, 5, 6, 7, 8)

4. Results and discussion

This section includes the results for both phases and the corresponding discussion. In section 4.1 we provide the highest achieved accuracy for each of the classification methods and a summary of the results for phase 1. In section 4.2 we introduce the best classification method for each dataset and a summary of the results for phase 2. Finally, in phase 4.3 we provide a discussion about the results of both phases.

4.1. Phase 1 Results

The results of our SVM modeling approach are illustrated in Table 2. To be concise, the table only shows the best results for each dataset for all the classification methods. As it can be observed in Table 2, the Linear kernel and the cost of 1 demonstrated the highest accuracy for class B-1 and B-2 (100% and 89.06% respectively). The best split for test and train sets was 33% and 67% for class B-1 and 25% and 75% for class B-2, respectively. On the other hand, class F achieved an accuracy of 100% using the Radial kernel with cost equals 0.5 and gamma equals 0.1. The test and train split for the Radial kernel was 33% and 67%, respectively.

Table 3 shows the result for BPNN. For classes B-1 and B-2, the best number of neurons was 5 with a learning rate equals to 0.002. For class F, the best learning rate was the same as classes B-1 and B-2, however, the best number of neurons was 24. The highest accuracies for classes B-1, B-2, and F were 92.94%, 95.29%, and 98.75%, respectively.

Finally, Table 4 presents the results for the RF model. For this algorithm, the best number of variables available for splitting each tree node, which is referred to as the *mtry* parameter, was 5 for all classes. Furthermore, the ideal number of trees was the same for all the classes (500). Class B-1 had the highest accuracy of 91.76%. For classes B-2 and F, the best accuracies were 94.71% and 96.25%. Fig. 3 displays the accuracy of prediction for the test datasets used for classes B-1, B-2, and F for the different machine learning algorithms.

Table 2. SVM parameter tuning result

Dataset	Parameters	Confusion Matrix	Accuracy
Class B-1	Split 33% -67% Linear Kernel Cost = 1	labels.test pred.test Normal Faulty Normal 78 0 Faulty 0 6	100%
Class B-2	Split 25%-75% Linear Kernel Cost = 1	labels.test pred.test Normal Faulty Normal 54 7 Faulty 0 3	89.06%
Class F	Split 33% -67% Radial Kernel Cost = 0.5 Gamma = 0.1	labels.test pred.test Normal Faulty Normal 74 0 Faulty 0 5	100%

Table 3. BPNN parameter tuning result

Dataset	Parameters	Confusion Matrix	Accuracy
Class B-1	Number of Neuron= 5 Learning Rate= 0.002	labels.test pred.test Normal Faulty Normal 75 6 Faulty 0 4	92.94%
Class B-2	Number of Neuron= 5 Learning Rate= 0.002	labels.test pred.test Normal Faulty Normal 75 4 Faulty 0 6	95.29%
Class F	Number of Neuron= 24 Learning Rate= 0.002	labels.test pred.test Normal Faulty Normal 72 1 Faulty 0 7	98.75%

Table 4. RF parameter tuning result

Dataset	Parameters	Confusion Matrix	Accuracy
Class B-1	Number of Trees= 500, mtry = 5	labels.test pred.test Normal Faulty Normal 78 7 Faulty 0 0	91.76%
Class B-2	Number of Trees= 500, mtry = 5	labels.test pred.test Normal Faulty Normal 78 5 Faulty 0 2	94.71%
Class F	Number of Trees= 500, mtry = 5	labels.test pred.test Normal Faulty Normal 74 3 Faulty 0 3	96.25%

As it can be observed, by using the SVM modeling approach we achieved the best performance for class B-1 and class F data with 100% accuracy. However, for class B-2 data, BPNN had the best performance with an accuracy of 95.29%.

4.2. Phase 2 Results

As we observed in phase 1, SVM exhibits the best performance in two of the datasets, and therefore we selected this approach as the classification method for our Phase 2 results. Table 5 shows the classification method results for three classes: B-1, B-2, and F. For class B-1, the accuracy for the second phase was 95.23%. Class B-2 had an accuracy of 90.48%. Lastly, class F had an accuracy of 96.67%, achieving the highest accuracy when compared to the other two classes.

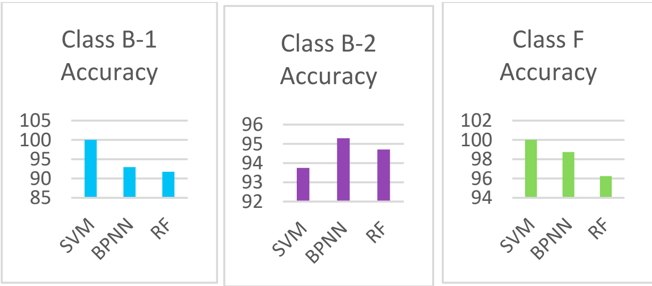


Fig. 3. Comparison of different classification methods for phase I

Table 5. Results for phase 2

Dataset	Parameters	Confusion matrix					Accuracy
		labels.test					
		pred.test	Bearings wear	Mass unbalanced	Misalignment	None	
Class B-1	Split 33% -67%, Linear Kernel, Cost = 1	Bearings wear	1	0	0	0	95.23%
		Mass unbalanced	0	0	1	0	
		Misalignment	2	0	1	0	
		None	0	1	0	78	
		labels.test					
		pred.test	Bearings wear	Mass unbalanced	Misalignment	None	
Class B-2	Split 25%-75%, Linear Kernel, Cost = 1	Bearings wear	1	0	0	0	90.48%
		Mass unbalanced	0	1	0	0	
		Misalignment	0	0	1	0	
		None	0	3	4	54	
		labels.test					
		pred.test	Bearings wear	Mass unbalanced	Misalignment	None	
Class F	Split 25%-75%, Linear Kernel, Cost = 1	Bearings wear	1	0	0	0	96.67%
		Mass unbalanced	0	0	0	0	
		Misalignment	0	0	0	0	
		None	0	0	2	57	

4.3. Discussion

Comparing the results obtained in this study with the results achieved by a data-mining approach that monitors motors of wind turbines [18], for phase I, the latter had an overall accuracy of 95.8% for SVM, 97.6% for NN, and 99.4% for RF, while we attained an accuracy of 100% for SVM, 98.75% for NN, and 96.25% for RF. For phase 2, [18] had an overall accuracy ranging from 78.35% to 98.83% for different runs, compared to a 96.67% accuracy for phase 2 in our work.

We achieved good accuracies for detecting faults and the type of faults by the SVM algorithm. Using SVM for PdM is encouraged by the literature. For instance, Kudelina et al. [32] suggested SVM for PdM because of the high efficiency and accuracy that this algorithm provides. Moreover, Widodo and Yang [33] inspected the application of SVM in different fields for PdM. They concluded SVM is a promising procedure for predicting and diagnosing faults in machines. Also several other works used SVM and achieved high accuracies for detecting faults in different machines and equipment (e.g. [25], [29], [30], [34], [35], [36]). Therefore, we suggest considering SVM as a good candidate for PdM.

It is worth noting that the achieved results for detecting faults in phase 1 show that our methodology can inform the users with relatively high accuracy about potential abnormal conditions that may occur to low voltage industrial motors. A critical advantage of the proposed approach is that it can assist managers to plan and predict when there is a need for maintenance and avoid unnecessary costs. Performing predictive maintenance can help prevent accidents and avoid hazards that can occur because of working with a faulty motor.

As it is evident from the confusion matrices in Table 5, the results of phase 2 are not as promising as phase 1. The best performance was achieved for the time when the motor had no problems. This is because we did not have enough historical data for each type of fault to train the algorithm for detecting the different types of faults. As it is shown in a predictive model using the supervised learning technique [37], small datasets can deteriorate the accuracy of supervised ML algorithms. This ML component could achieve better performance and accuracy if we could collect more historical data for each of the different types of faults. Therefore, using this two-phase ML approach, even with a limited amount of historical data for specific faults, can be useful for differentiating and predicting a normal condition from an abnormal condition with high accuracy. This could help industries that use low voltage industrial motors to become aware of a future fault in a motor and check for possible faults before occurrence.

5. Conclusion and future work

In this paper, we implemented a two-phase ML approach for PdM. In phase 1, we analyzed vibration data to detect any potential abnormal behavior. We applied three ML algorithms such as BPNN, SVM, and RF and compared them in terms of performance accuracy. The SVM model provided the best performance with an accuracy of 100% for two of the datasets analyzed (class B-1, class F), which contained 15% of faulty data. Since SVM exhibited the best performance in phase 1 we decided to use this approach for phase 2 for detecting specific motor faults. Although in the second phase, SVM was able to distinguish normal conditions from abnormal with high accuracy, the results for detecting specific types of faults were not very convincing. This is due to the scarcity of data to represent all the different kinds of faults in a motor. The latter emphasizes the need for historical data based on different types of motor faults (i.e electric imbalance, misalignment, wear, rotor – imbalance, etc.). Another interesting observation is the dramatic changes in the accuracy of the ML algorithms using different parameters, highlighting the importance of appropriate parameter tuning for ML algorithms. The implemented approach showed a strong performance for detecting faulty conditions that can help factories to detect abnormal behavior in low voltage induction motors on time. Integrating the proposed two-phased ML approach within an automated maintenance management system [16] could prevent accidents and stop the system before a problem occurs.

As previously stated, one of the biggest challenges of this work was the lack of data representing each type of fault in a motor. Therefore, as future work, we plan to develop a digital twin of the system [38] to generate simulated data of anomalies (e.g. faulty gears, loose foundations, and rotor broken bar), and use them as an input to the PdM ML component. In addition, we plan to test additional classification methods on the data for the second phase (e.g. logistic regression, BPNN, RF, and decision tree). Finally, throughout this work, only three different kinds of fault were analyzed. Thus, in the future, we would like to expand this work and include additional types of motor faults.

References

[1] R. A. Patel and B. Bhavesh R, "Condition monitoring and fault diagnosis of induction motor using support vector machine," *Electric Power Components and Systems,* pp. 663-692, 2016.

[2] W. Garrison, "One hundred largest losses-A Thirty-year review of property damage losses in the hydrocarbon-chemical industries," in *M&M Protection Consultant*, Chicago, 1988.

[3] P. A. Carson and C. J. Mumford, "An analysis of incidents involving major hazards in the chemical industry," *Journal of Hazardous materials,* pp. 149-165, 1979.

[4] C. Y. H. Kan and S. Kumara, "Parallel computing and network analytics for fast Industrial Internet-of-Things (IIoT) machine information processing and condition monitoring," *Journal of manufacturing systems,* pp. 282-293, 2018.

[5] A. H. Pesch and P. N. Scavelli, "Condition monitoring of active magnetic bearings on the internet of things," in *Actuators*, 2019.

[6] P. Večeř, M. Kreidl and R. Šmíd, "Condition indicators for gearbox condition monitoring systems," *Acta Polytechnica,* p. 6, 2005.

[7] D. Yarmoluk and C. Truempi, "Why move from condition monitoring to predictive maintenance? – Part 1," IBM, 15 March 2019. [Online]. Available: https://www.ibm.com/blogs/internet-of-things/iot-condition-monitoring-part-one/. [Accessed 18 March 2020].

[8] F. Besnard, J. Nilsson and L. Bertling, "On the economic benefits of using condition monitoring systems for maintenance management of wind power systems," in *2010 IEEE 11th International Conference on Probabilistic Methods Applied to Power Systems*, 2010.

[9] M. You, F. Liu and G. Meng, "Benefits from condition monitoring techniques: a case study on maintenance scheduling of ball grid array solder joints," in *the Institution of Mechanical Engineers*, 2011.

[10] V. V. Karanović, M. T. Jocanović, J. M. Wakiru and M. D. Orošnjak, "Benefits of lubricant oil analysis for maintenance decision support: a case study," in *IOP Conference Series: Materials Science and Engineering*, 2018.

[11] X. Tang, X. Wang, R. Cattley, F. Gu and A. D. Ball, "Energy harvesting technologies for achieving self-powered wireless sensor networks in machine condition monitoring: A review," *Sensors,* p. 4113, 2018.

[12] J. M. Wakiru, L. Pintelon, P. N. Muchiri and P. K. Chemweno, "A review on lubricant condition monitoring information analysis for maintenance decision support," *Mechanical systems and signal processing,* pp. 108-132, 2019.

[13] Z. Zhao, B. Liang, X. Wang and W. Lu, "Remaining useful life prediction of aircraft engine based on degradation pattern learning," *Reliability Engineering & System Safety,* vol. 164, pp. 74-83, 2017.

[14] H. P. Jagtap, A. K. Bewoor and R. Kumar, "Failure analysis of induced draft fan used in a thermal power plant using coordinated condition monitoring approach: A case study," *Engineering Failure Analysis,* no. 111, p. 104442, 2020.

[15] M. Taghipour and A. Moosavi, "A look at Gas Turbine Vibration Condition Monitoring in Region 3 of Gas aTransmission Operation," *Journal of Environmental Science, Computer Science and Engineering & Technology,* vol. 9, no. 3, pp. 423-432, 2020.

[16] K. Mykoniatis, "A Real-Time Condition Monitoring and Maintenance Management System for Low Voltage Industrial Motors Using Internet-of-Things," in *International Conference on Industry 4.0 and Smart manufacturing (ISM 2019)*, 2020.

[17] C. R. Farrar and S. W. Dowbling, "Damage detection and evaluation II," in *Modal analysis and testing*, Dordrecht., 1999.

[18] A. Kusiak and V. Anoop, "A data-mining approach to monitoring wind turbines," *IEEE Transactions on Sustainable Energy,* vol. 3, no. 1, pp. 150-157, 2011.

[19] A. Abouhnik and A. Albarbar, "Wind Turbine Blades Condition Assessment based on Vibration Measurements and the Level of and Empirically Decomposed Feature," *Energy Conversion and Management,* pp. 606-613, 2012.

[20] E. P. Carden and P. Fanning, "Vibration based condition monitoring: a review," *Structural health monitoring,* pp. 355-357, 2004.

[21] L. Dong, R. Mingyue and M. Guoying, "Application of internet of things technology on predictive maintenance system of coal equipment," *Procedia engineering,* vol. 174, pp. 885-889, 2017.

[22] P. Qian, D. Zhang, X. Tian, Y. Si and L. Li, "A novel wind turbine condition monitoring method based on cloud computing," *Renewable energy,* pp. 390-398, 2019.

[23] K. Sujatha, B. Deepalakshmi and S. Q. Cao, "Optimal condition monitoring of wind turbines using intelligent image processing and internet of things," *International Journal of Renewable Energy Technology,* pp. 158-180, 2018.

[24] G. Manogaran, R. Varatharajan, D. Lopez, P. M. Kumar, R. Sundarasekar and C. Thota, "A new architecture of Internet of Things and big data ecosystem for secured smart healthcare monitoring and alerting system," *Future Generation Computer Systems,,* pp. 375-387, 2018.

[25] M. Cakir, M. A. Guvenc and S. Mistikoglu, "The experimental application of popular machine learning algorithms on predictive maintenance and the design of IIoT based condition monitoring system," *Computers & Industrial Engineering,* vol. 151, p. 106948, 2021.

[26] A. Joelian, "Engine replacement scheduling optimization using Data Mining," *Journal of Physics Conference Series,* 2020.

[27] N. Silva, J. Soares, V. Shah, M. Y. Santos and H. Rodrigues, "Anomaly detection in roads with a data mining approach," *Procedia computer science,* pp. 415-422, 2017.

[28] P. Dehghanian, Y. Guan and M. Kezunovic, "Real-time life-cycle assessment of high-voltage circuit breakers for maintenance using online condition monitoring data," *IEEE Transactions on Industry Applications,* pp. 1135-1146, 2018.

[29] I. Aydin, M. Karakose and E. Akin, "Artificial immune based support vector machine algorithm for fault diagnosis of induction motors," in *International Aegean Conference on Electrical Machines and Power Electronics*, 2007.

[30] B. Samanta, K. Al-Balushi and S. Al-Araimi, "Artificial neural networks and support vector machines with genetic algorithm for bearing fault detection," *Engineering applications of artificial intelligence,* pp. 657-665, 2003.

[31] C. Zhitong, J. Fang, H. Chen, G. He and R. Ewen, "Support vector machine used to diagnose the fault of rotor broken bars of induction motors," in *Sixth International Conference on Electrical Machines and Systems*, 2003.

[32] K. Kudelina, T. Vaimann, B. Asad, A. Rassõlkin, A. Kallaste, and G. Demidova, "Trends and Challenges in Intelligent Condition Monitoring of Electrical Machines Using Machine Learning," *Appl. Sci.*, vol. 11, no. 6, Art. no. 6, Jan. 2021, doi: 10.3390/app11062761.

[33] A. Widodo and B.-S. Yang, "Support vector machine in machine condition monitoring and fault diagnosis," *Mech. Syst. Signal Process.*, vol. 21, no. 6, pp. 2560–2574, Aug. 2007, doi: 10.1016/j.ymssp.2006.12.007.

[34] J. Guo, A. Li, and R. Zhang, "Tool condition monitoring in milling process using multifractal detrended fluctuation analysis and support vector machine," *Int. J. Adv. Manuf. Technol.*, vol. 110, no. 5, pp. 1445–1456, Sep. 2020, doi: 10.1007/s00170-020-05931-5.

[35] Y. Sun, Y. Cao, G. Xie, and T. Wen, "Condition Monitoring for Railway Point Machines Based on Sound Analysis and Support Vector Machine," *Chin. J. Electron.*, vol. 29, no. 4, pp. 786–792, Jul. 2020, doi: 10.1049/cje.2020.06.007.

[36] S. K. Jalali, H. Ghandi, and M. Motamedi, "Intelligent Condition Monitoring of Ball Bearings Faults by Combination of Genetic Algorithm and Support Vector Machines," *J. Nondestruct. Eval.*, vol. 39, no. 1, p. 25, Feb. 2020, doi: 10.1007/s10921-020-0665-7.

[37] A. R. Ajiboye, R. Abdullah-Arshah, Q. Hongwu and H. Isah-Kebbe, "Evaluating the effect of dataset size on predictive model using supervised learning technique," *International Journal of Software Engineering & Computer Sciences*, vol. 1, pp. 75-84, 2015.

[38] K. Mykoniatis, and G. A Harris, "A digital twin emulator of a modular production system using a data-driven hybrid modeling and simulation approach," *Journal of Intelligent Manufacturing*, vol. 1-13, 2021