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Development of a Predictive Maintenance System Using Machine Learning Technique

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Abstract

With the growth of the manufacturing industry, any unexpected failure of industrial equipment or machine breakdown can result in severe financial loss for the business. This is why it is critical to have a strategy for early detection and prediction for the failures. Predictive Maintenance encompasses all operational techniques and actions necessary to maintain machine availability and prevent downtime. The purpose of this article is to implement the machine-learning algorithm to develop a predictive maintenance and condition-based maintenance (CBM) systems. A real-world application of existing machine learning techniques for predictive maintenance was proposed and implemented using an artificial neural network (ANN). The results indicated that all predicted failures were correctly classified, with an overall accuracy of 99.9 percent.

Keywords
Predictive Maintenance, Machine Learning, Condition-Based Maintenance, Artificial Neural Network, Optimization, Water Pump System.

1. Introduction
Maintenance is a set of activities that are used to control and maintain and control a system to achieve the required tasks. Maintenance tasks are divided into preventive and corrective categories Baek (2007). Figure 1 further illustrates this classification.

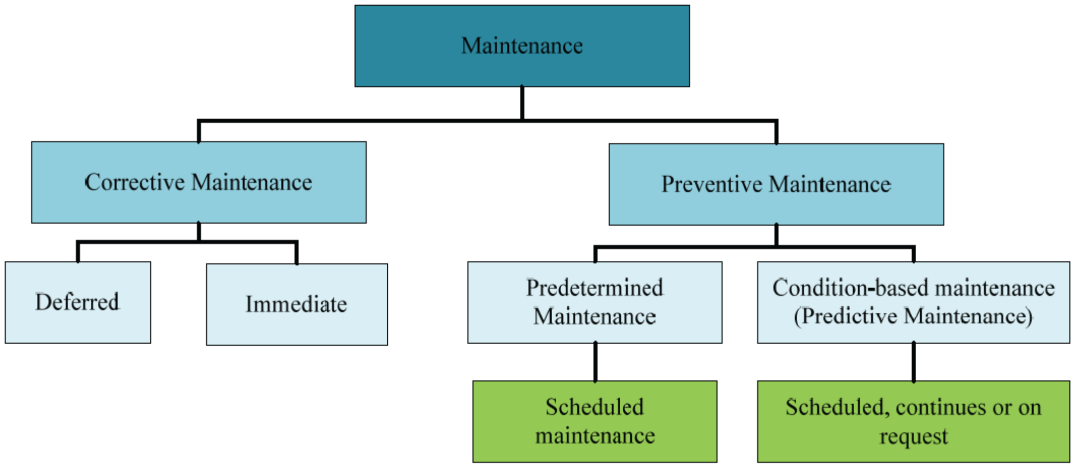


Figure 1. Maintenance classifications

Preventive maintenance is planned maintenance (time-line plan) and performed based on a defined schedule. Therefore, preventive maintenance is established to maintain the machines in a good condition. Consequently, will avoid the occurrence of many sudden breakdowns. Preventive maintenance does not totally eliminate the probability of unplanned repair and the need of corrective maintenance, although the plan implements the required maintenance in order to minimize the probability of the breakdowns (Marseguerra, Zio et al. (2002), Ahuja and Khamba (2008), Yang, Li et al. (2010), Lewandowski and Scholz-Reiter (2013)). Corrective maintenance is a policy that takes place when there is machine failure. It is unplanned and intends to restore a machine to its functional state and to resume production. In Condition Based Maintenance (CBM), activities are performed in response to a specific condition. A major feature of CBM is its ability for predicting failures (Rochdi, Driss et al. (1999), Sarker and Haque (2000)). Physical conditions are determined using sensors or other means (e.g. vibration, or temperature) of monitoring (Mirghani (2001), Al-Najjar and Alsyouf (2003), Al-Najjar and Alsyouf (2004), Tan and Raghavan (2008)). Once the machine reaches one or more predetermined condition levels, maintenance is performed to restore the machine to the desired level. CBM is considered as preventive not corrective, as it is performed based on certain critical signals prior to any failure (Chiang and Yuan (2001), Alsyouf (2006), Ahuja and Khamba (2008)). Figure 2 summarizes the strengths and the weaknesses associated with each method.

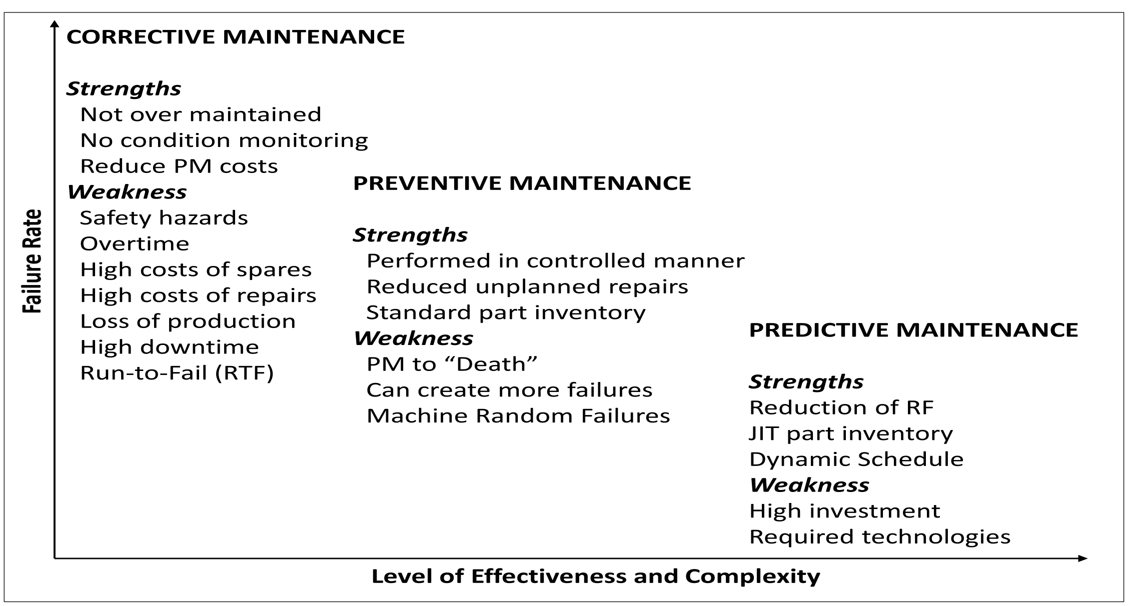


Figure 2. Strengths and weakness of different maintenance policies

The process of maintenance performance evaluation is mainly depended on the availability of data required (Vineyard, Amoako-Gyampah et al. (2000), Savsar (2006)). Most common maintenance performance indicators are for measuring efficiency and cost. Efficiency is measured with respect to the total production time, downtime, and number of breakdowns. The total maintenance cost is used for the analysis of its economic value (Kutucuoglu, Hamali et al. (2001), Komonen (2002), Parida (2007), Kans 2008). To determine the maintenance cost, manager collects information such as expected useful life of equipment, cost of preventive maintenance and its impact on expected life, frequency of required repairs, cost of unplanned repairs, corrective maintenance, and cost of replacing equipment Tarakci, Tang et al. (2009). The industry is mainly driven by performances, downtime reduction and sustainability (Wang and Lee (2001), Grall, Bérenguer et al. (2002), Nakagawa and Mizutani (2009), Smadi and Kamrani (2011)). Maintenance is a vital function for maintaining resources for producing quality products (Sherwin 2000, Yu and Zhao (2005), Li, Wu et al. 2014). Very few studies have been focused on how this interaction is used for the implementation of CBM systems. Most of the works are related to quality control or total quality management tools with no direct link to actual product's quality (Swanson (2003), Han and Yang (2006), Parida and Kumar (2006), Simeu-Abazi and Bouredji (2006)). The proposed strategy has the potential to be implemented in all types and sizes of manufacturing plants and operations. Plant floor information systems can be used as media for collecting data and processing information. According to literature, most maintenance management research works have been focused on developing optimization models, maintenance techniques, maintenance scheduling, performance measurements analysis, information system, plans and policies, and not on the how the function of quality be utilizing for PM. The objective of this study, is to propose a new data mining based on a new classification method for extracting required quality data for predicting machine failures and PM planning prior to machine failures. The rest of this study will discuss the previous researches in the literature in section 2, and the model and results will be discussed in the third section. Final this research will be concluded in the fourth section.

2. Literature Review

Maintenance is established increase machines availability (Ramakumar, Dhillon et al. 2000, Sammouri, Côme et al. (2013)). Condition Based Maintenance (CBM) is performed in response to a specific machine condition. Once the machine reaches one or more predetermined condition levels, maintenance is performed to restore the machine to the desired level. CBM is considered as preventive not corrective maintenance, as it is performed based on certain critical signals prior to any failure Ahuja and Khamba (2008). Other maintenance policies are considered as philosophies because of their comprehensive perspective. These philosophies are Reliability Cantered Maintenance (RCM), and Total Productive Maintenance (TPM) Murthy, Atrens et al. (2002). Mathematical optimization models are used to trade off (balance) the benefit versus cost of maintenance to help in evaluation of maintenance policies with respect to cost-effectiveness, maintenance and inspection frequency, and scheduling with respect to constraints Fernandez, Labib et al. (2003). Scheduling in maintenance is similar to any other scheduling task. It synchronizes different activities in the organization with maintenance to achieve maintenance goals and objectives. Scheduling of maintenance has been studied in the literature as an optimization problem. This problem becomes complicated problems as the system becomes more complex Karim, Candell et al. (2009). The integration of quality and maintenances is in the interest of literature researches. Mehdi, Nidhal and Anis Mehdi, Nidhal et al. (2010) presented a joint model of quality control and preventive maintenance that take into account of the existing of non-conforming units in the production system. Panagiotidou and Tagaras Panagiotidou and Tagaras (2007) investigate the production process to optimize the preventive maintenance with two quality states;: an in control state and may shift to out-of-control state before a failure occurs, or a scheduled preventive maintenance takes place. Ben-Daya and Duffuaa Ben-Daya and Duffuaa (1995) proposed two approaches for linking and modeling the relationship between maintenance and quality. One is depending on imperfect maintenance in which is influence the occurrence of the failure machine. Whereas another one depend on Taguchi's approach. Duffuaa and Ben-Daya Duffuaa and Ben-Daya (1995) investigated maintenance management with the usage of the seven quality tools. Statistical process control is expected to improve maintenance quality and address the quality problems. This entails high product quality and efficient maintenance activities. Maintenance scheduling is one factor of a successful maintenance job. It synchronizes machines, tools, humans, materials and production for effective and high performance maintenance and production at the same time Chen and Liao (2005). Dieulle, et al. Dieulle, Bérenguer et al. (2003) developed a probabilistic method based on the semi sequential property in CBM for scheduling. Oke and Charles-Owaba Oke and Charles-Owaba (2006) tested the sensitivity of a maintenance scheduling model. Raza and Al-Turki Raza and Al-Turki (2007) compared the effectiveness of two meta-heuristics algorithms in solving maintenance scheduling problems. Matsuoka and Muraki Matsuoka and Muraki (2007) developed an optimization model for short term maintenance scheduling of a utility system using a mathematical program with network constrains. In recent years, information technology has grown rapidly. New technologies have emerged leading companies to shift from traditional maintenance to what is known as e-maintenance. The definition of e-maintenance addresses information technology and web-based applications in a context of e-technologies to enable maintenance activities as a proactive decision process and other supporting activities as monitoring, diagnosing, and prognosis. This enables development of new maintenance strategies, improving in maintenance tools and exploring new maintenance activities Wang and Sheu (2003). E-maintenance provides the opportunity of remote maintenance, integration of business processes, more efficient monitoring and easier documentation (2008). Candell, Karim and Soderholm Candell, Karim et al. (2009) presented results of an aerospace industry project; in which e-maintenance framework is introduced using central components in the integration of maintenance, information and communication technology perspectives. Candell, Karim and Soderholm Candell, Karim et al. (2009) believed that an e-maintenance platform has an impact on dependability, safety, and life support costs of critical systems; which means that an e-maintenance platform that is designed and implemented from a service oriented perspective focuses on business process and improves the overall system effectiveness. Karim, Candell and Soderholm Karim, Candell et al. (2009) described the aspects of content sharing within e-maintenance merging maintenance and information and communication technology. Han and Yang Han and Yang (2006) uses information techniques to establish a new e-maintenance system. Data mining was known as knowledge management or knowledge engineering. However, recently, it has an increasing interest in artificial intelligence area. Fayyad, et al Fayyad, Piatetsky-Shapiro et al. (1996) defined data mining as a step in the Knowledge Discovery in Databases (KDD) process, in which it uses different techiques of computations, with suitable computational efficiency cosiderations, introduce a special enumeration of trends or patterns over the data. Adriaans and Zantinge Adriaans and Zantinge (1996) define the data mining as the process of recognizing unknown patterns or trends. Moreover, Fayyad and Stolorz Fayyad and Stolorz (1997) stated that data can be found in two dimensions, these are fields and cases in each field. Yevich Bischoff and Alexander (1997) stated that “data mining is asking a processing engine to show answers to questions we do not know how to ask”. Also data mining can be described as an iterative search Vaz Jr, de QF Araújo et al. (2009). During the excustion process, new knowledge and new hypothesis should be stated to improve the quality and data content. Afrooz Purarjomandlangrudi, et al. Purarjomandlangrudi, Ghapanchi et al. (2014) used anomaly detection (AD) learning algorithm that can detect anomalies that are in early phases. Markus Ullrich, et al. Ullrich, ten Hagen et al. (2013), proposed a data mining model that decrease maintenance visits. Bo Yang, et al. Yang, Li et al. (2010) proposed a data-driven software reliability model (DDSRM) considering the process of recognizing the failures as time dependent. However, unlike previous DDSRMs, this model does not take into account the correlation between a software failure and the most recent failures. Goknur Seyma Cakir Çakir, Houtum et al. (2011) presented a failure prediction decision support model for predictive maintenance of a critical machine component by using the condition monitoring data. In order to identify upcoming failures, several data mining techniques were tested and among them best technique was determined. Eckart Uhlmann, et al. Ullrich, ten Hagen et al. (2013) used data mining and visualization for condition based maintenance. In the proposed approach, reoccurring patterns are recognized which helps decision makers in determining evolving technical problems and taking proper counter measures. X. Z. Wang, et al. Wang, Chen et al. (1997) addresses application of probabilistic networks in order to recognize failures of process units by using data mining approach and extracting knowledge from the databases. Meanwhile, in order to extract data from data sets Carlos A., et al. Vaz Jr, de QF Araújo et al. (2009) proposed a model depending on principal component analysis (PCA), hierarchical classifiers and prototypes methods. Wissam Sammouri, et al. Sammouri, Côme et al. (2013) proposed a methodology to recognize significant co-occurrences between pairs of events of a real floating train data. A knowledge induction model based on C4.5 decision tree algorithm is developed by Cebrail Ciflikli, et al. Çiflikli and Kahya-Özyirmidokuz (2010) in order to detect the failure of the process in a carpet manufacturing firm in Turkey. J. Sun, et al. Sun, Wang et al. (2014) tried to identify high-danger zones in water supply networks by studying reasons of rupture in the water supply networks and showed that data mining of spatial pipe network through changing different initial parameters can be very useful in spatial cluster analysis of bursting pipes. Haruko Iwata, et al. Iwata, Tsumoto et al. (2013) employed temporal data mining process (similarity-based visualization approach) for maintenance and construction of clinical pathway. Li Ran, et al. Li, Wu et al. (2014) measured resistance, capacity, and life cycle of lithium iron phosphate batteries of products using test data collected from life cycle tests. Jinglun Zhou, et al. Zhou, Liu et al. (2010) developed a new reliability estimation method for some special areas such as military and aerospace which is based on small sample and data mining of failure-physics. Bastos, P., et al. Bastos, Lopes et al. (2012) presented a new conceptual framework to develop a predictive maintenance system which is characterized by autonomy in data collecting and the utilization of data-mined knowledge in order to discover failure patterns with the aim of early detection of faults in machines Bastos, Lopes et al. (2012). A more comprehensive survey is listed in Smadi and Kamrani (2011). Data mining has a lot of applications in health management maintenance Xu, Sun et al. (2016).

Klingert et al. Klingert, Roeder et al. (2017) applied data mining approach to determine aspects of typical mechanical machine setups which affect bonding quality and equipment health in mass production. Rezing et al. Rezig, Achour et al. (2018) developed a data mining model to predict sequential maintenance activities. Kovalev et al. Kovalev, Shanin et al. (2018) proposed an information system approach implemented in predictive maintenance of infrastructure depending on data mining for fault. Accorsi et al. Accorsi, Manzini et al. (2017) proposed a data analytics approaches in the field of maintenance engineering. Moreover, neural network has commonly been used in maintenance problems. Bangalore et al. Bangalore, Letzgus et al. (2017) applied neural network algorithm in wind turbines, to the monitor the gearbox. Chen et al. Chen, Deng et al. (2017) introduces various deep neural network models to determine the fault condition of rolling bearing Xia et al. Xia, Li et al. (2017) introduces a neural network model for fault detection of rotating machinery. Zhou et al. Zhu, Chen et al. (2018) proposed deep feature learning model that estimate bearing remaining useful life. Neural network is integrated along with statistical methods to estimate the remaining useful life of components (Ali, Chebel-Morello et al. (2015), Babu, Zhao et al. (2016), Rivas, Fraile et al. (2019)). Many other applications of neural network in fault detection were found in the literature (Ali, Fnaiech et al. (2015), Bangalore and Tjernberg (2015), Chen, Li et al. (2015), Tayarani-Bathaie and Khorasani (2015)). In general neural network also used to optimized the preventive maintenance activities Rosli, Ibrahim et al. (2019).

3. Methodology

Water pump system is a very famous system that is used to moving water from an area to another. A complex water pump system is used normally in different places, including but not limited to, manufacturing plants. Failure in such systems may result in a huge impact to a point that it might be a life threaten situation. Therefore, the discussed problem in this paper is about the failure of this complex system.

The objective of this study is to predict the failure of the complex system using a machine learning algorithm based on CBM strategy. Additionally, it also includes how the function of quality can be utilized for preventive maintenance (PM) that would result on reducing the failure of the complex water pump system. More information about the data will be discussed in the next section.

3.1. Data Collection

Dataset is the most essential part of any machine learning work, and it helps solving complex problems as long as there is a sufficient amount of useful data used accurately and intelligently. This study's dataset is 51 sensors reading for a complex pumping system collected from April 1, 2018, to August 31, 2018. The sensor reading was taken every minute. The total dataset size is 220319 for the 51 sensors, where these sensors may measure different parameters, including but not limited to, pressure, temperature, flow rate, … etc. Data cleaning was performed in the Matlab software, in which missing data was deleted.

3.2. Machine Learning for Predictive Maintenance

Machine learning uses programmed algorithms that can collect and analyze data to a mathematical model as input. Multiple datasets are the main source of data used to build the model. In model creation, three data sets are normally used in different stages. The model is initially fit on a training dataset which is an example set used to fit the model parameters (e.g. weights of connections between neurons in artificial neural networks). Using a supervised learning method, the model is trained on the training dataset (e.g. gradient descent or stochastic gradient descent). Sequentially, the fitted model for the observations predicts the responses in a second dataset. This is known as the validation dataset, and it allows for an objective assessment of a model's fit on the training dataset while tuning the model's hyperparameters (e.g. the number of hidden units in a neural network). Validation datasets also support in regularization as they provide early stopping: stop training when the validation dataset error increases since this is a sign of overfitting to the training dataset. This simple procedure is actually quite complex in practice since validation dataset errors may vary during training, producing multiple local minima. This is why many ad-hoc rules were created to decide when overfitting has truly begun. Finally, the test dataset is a set of data that is utilized to provide an objective assessment of a final model fit on the training dataset. Figure 3 shows the machine learning pipeline architecture.

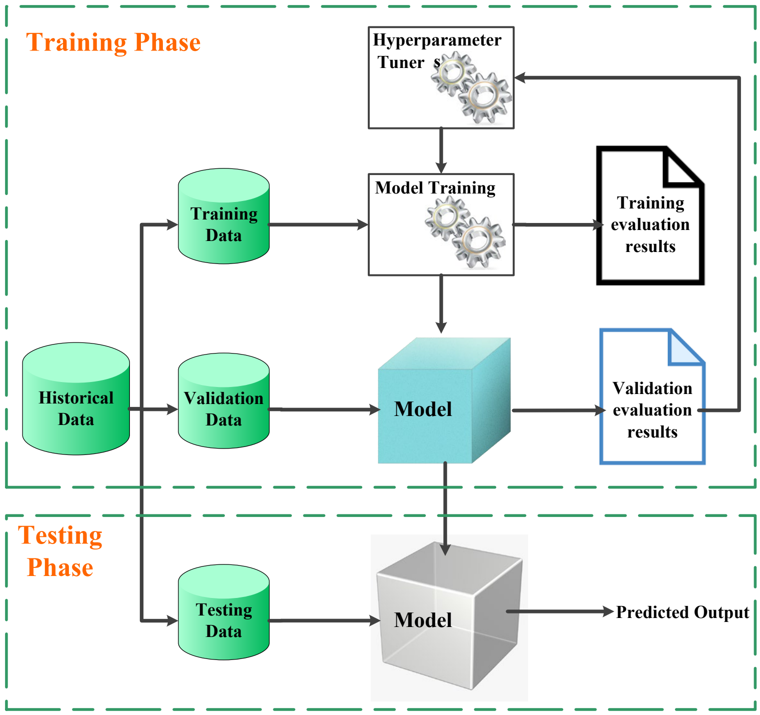


Figure 3. Machine Learning pipeline architecture

In this study, two scenarios will be proposed:

- The first scenario uses raw data input directly into the machine learning algorithm (i.e Artificial neural network (ANN)).
- The second scenario is conducted by applying dimensionality reduction technique such as principle component analysis (PCA) before the data is passed into ANN. The main use of the PCA is to reduce model complexity and avoid overfitting.

The main reason of using these two scenarios is to test if there is an effect on the performance of the ANN model when dimension reduction isn't and is considered.

4. Results and Discussion

4.1 First cenario (predictive maintenance using ANN)

The ANN is an algorithm that predicts whether or not the failure has occurred. Each sensor reading can be expressed as a $1 \times N$ vector **x** which is an input vector to the ANN. The ANN elements modeled by a bias, set of weight coefficients, and an activation function-called *neuron*. The ANN includes three neuron layers: the input layer, one or more hidden layers, and an output layer, as shown in

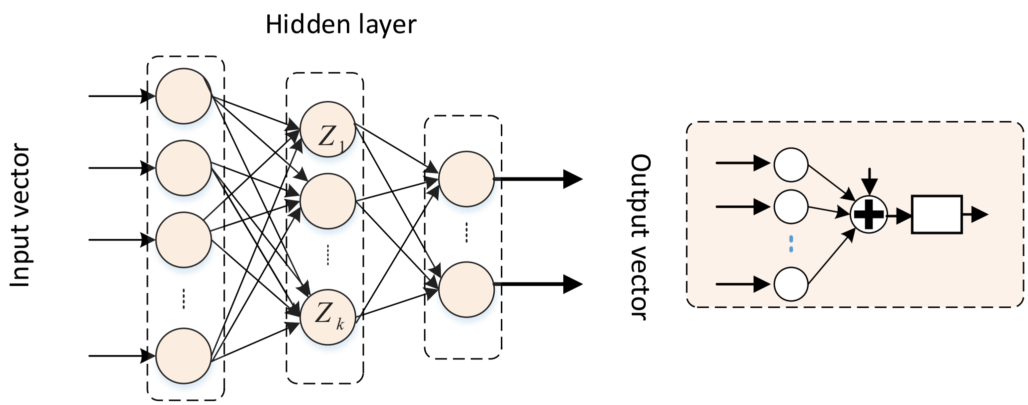


Figure 4. After acceping input vector **x**, the input layer transfers the vector samples to all hidden layer neurons (i.e. 100 neurons in this work). The network weights support in connection between the layers. The computation that occurs in the k^{th} neuron is calculated as

$$z_k = F\left(\sum_{i=0}^{N} w_{ik} x_i + b_k\right), \tag{1}$$

where $F(.)$ is the activation function, b_k is the bias of neuron k, and w_{ik} i= (1, 2...N) is the weighted connection at neuron k. The sigmoid activation function is given by

$$F(\alpha) = \frac{1}{1-e^{-\alpha}} \tag{2}$$

The ANN output can be conveyed as

$$y_h = F\left(\sum_{j=0}^{k} w_{jh} z_j\right), \tag{3}$$

where y_h is the h^{th} network output, $h \in (1, 2 \ldots M)$, $M = 2$ in our case. Each input vector **x** corresponds to a binary $1\times M$ vector **t** (i.e. target vector). The target vector has only one non-zero element the machine status is specified by its position. The cross-entropy loss function (L) is used to calculate the error between the vectors **y** and **t**, which is given by:

$$L = -\sum_{i=1}^{m} y_i \log(t_i) \tag{4}$$

During the training phase, the loss (L) is back-propagated to optimize the network weights and bias. The scaled conjugate gradient algorithm is considered as an optimization algorithm. The training phase stops when L reaches a specified margin (i.e. 1×10^{-6}). In the testing phase, the machine status (failure occurs or not) is determined by argmax(**y**).

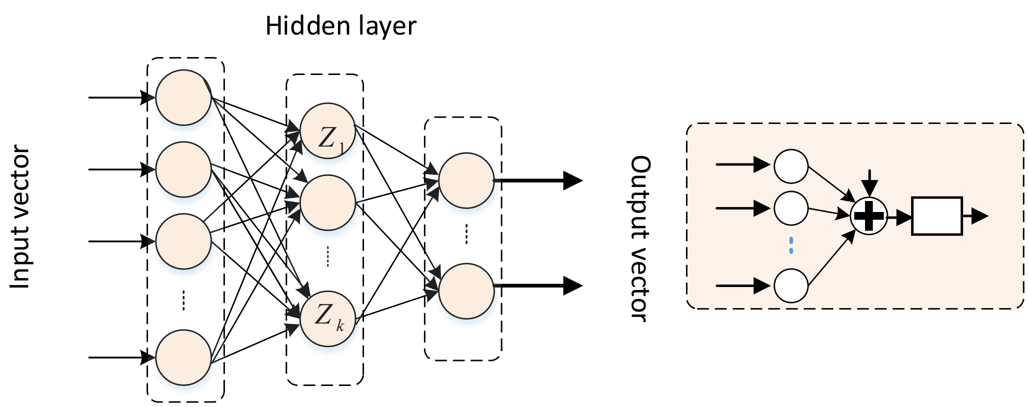


Figure 4. ANN architecture

4.2 Second scenario (predictive maintenance using PCA in conjunction with ANN)

Principle component analysis (PCA) is a standard statistical technique used to reduce dataset dimensionality by extracting the essential features which allows for a much more compact dataset representation. PCA strength for data analysis is due to its proficient computational mechanism. We can represent the training dataset S by one big matrix $\mathbf{X} = [x_1, x_1, \ldots, x_M]$ of size $N \times M$. The mean data vector $\mathbf{\Omega}$ of matrix **X** is defined as

$$\Omega = \frac{1}{M}\sum_{i=1}^{M} x_i \tag{5}$$

Subtracting Ω from each column of the matrix **X**, we obtain a zero-mean data matrix $\mathbf{D} = [d_1, d_1, ..., d_M]$. The covariance matrix **C** of **D** is given as

$$\mathbf{C} = \frac{1}{M}\sum_{i=1}^{M} d_i d_i^T \qquad (6)$$

The matrix size of **C** is $N \times N$ and therefore, it can have up to N eigenvectors and eigenvalues. Let v_i and λ_i be the i^{th} eigenvector and eigenvalue of **C**, respectively; then by using

$$\mathbf{C}v_i = \lambda_i v_i \text{ for } i = 1, 2, .., N \qquad (7)$$

we can determine N eigenvectors, also called principal components (PCs), of **C**. The computed eigenvectors are ranked according to their eigenvalues and amongst them K (where $K \ll$ N) eigenvectors corresponding to the K largest eigenvalues are selected while the rest are discarded. The eigenvectors matrix $\mathbf{V} = [v_1, v_1, ..., v_K]$ represent the projection of PCA space.

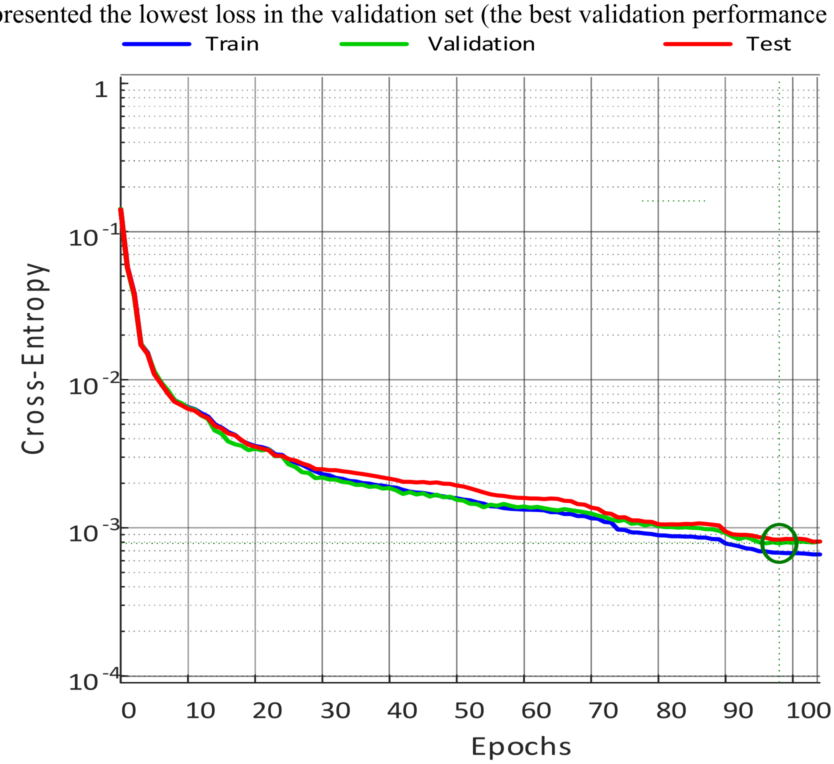
The training dataset is projected on the lower dimensional PCA space as

$$\mathbf{S} = \mathbf{V}^T\mathbf{D} \qquad (8)$$

Likewise, in the testing dataset case, we calculate the mean and then subtract it from this mean. Afterwards, we drop and project it on the lower dimensional PCA. In next section, we will discuss these scenarios in detail.

5.3 Simulation results and discussions

In this section, we will discuss the two proposed scenarios for predictive maintenance. This ANN was trained on 70% randomly selected data from the total dataset and split into 60% for training and 10% for validation. Model parameters were selected from epoch 98 which presented the lowest loss in the validation set (the best validation performance is



0.00078501 at epoch 98) as shown in

Figure **5**. The rest of dataset, which is the remaining 30%, was used for testing. The overall results for the failures prediction are summarized in Table 1 and Table 2. It is clear from the table that all the failure predictions have been well classified with an overall accuracy of 99.9%. There was a 100% accuracy for the case of no failures occurring and 99.6% for the case of failures occurring.

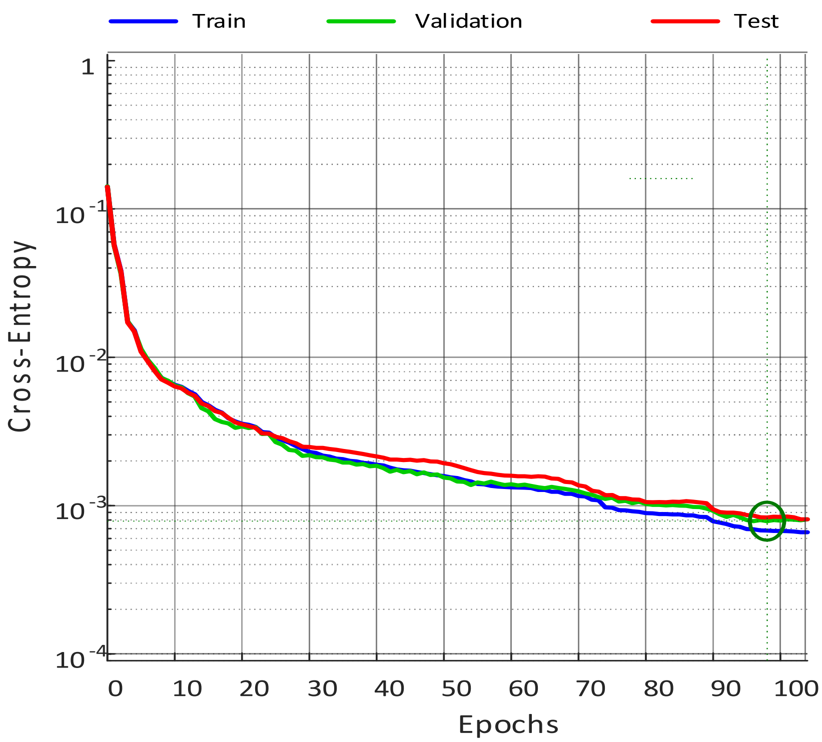


Figure 5. Cross entropy loss during the training phase

Table 1: Confusion matrix of predicted failures

0	99.9	0.4
1	0.1	99.6
	0	1

These feature vectors can then be used ANN classifier input. The use of extremely reduced size feature vectors, obtained using PCA, makes the feature vector matching process computationally efficient, which is an advantage especially for real-time applications purposes.

Figure 6 shows the eigenvalues for a few PCs in descending order. It is evident from the figure that the eigenvalues rapidly converge to zero. Figure 7 shows the value of accuracy of prediction failures as a function of the number of PCs selected *K*. It is clear from the figure that the value of accuracy is above 96% for just eight PCs (out of a total of 51 PCs). This implies that it is reasonable to use only a few PCs for the synthesis of feature vectors and discard the remaining without losing much information.

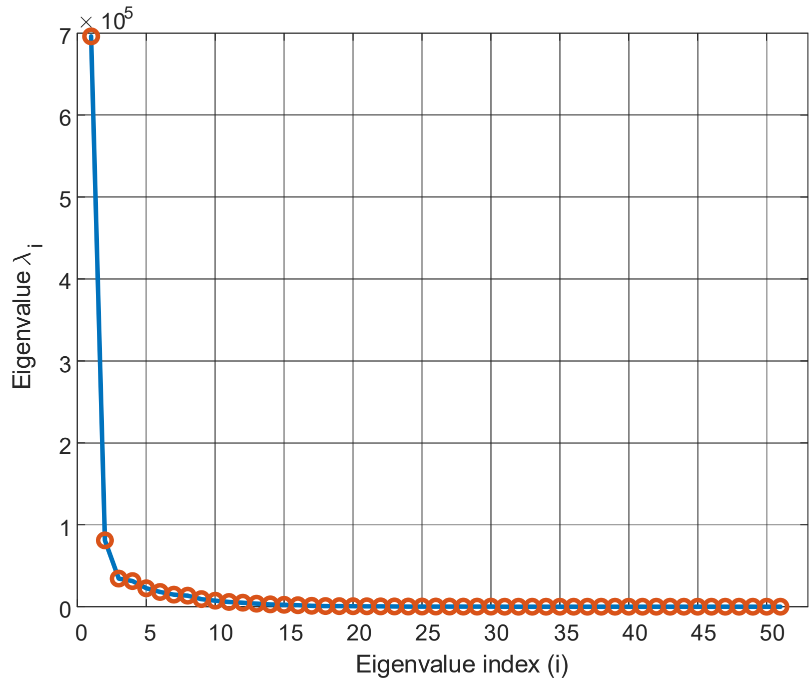


Figure 6. Eigenvalues λi for a few PCs in descending order

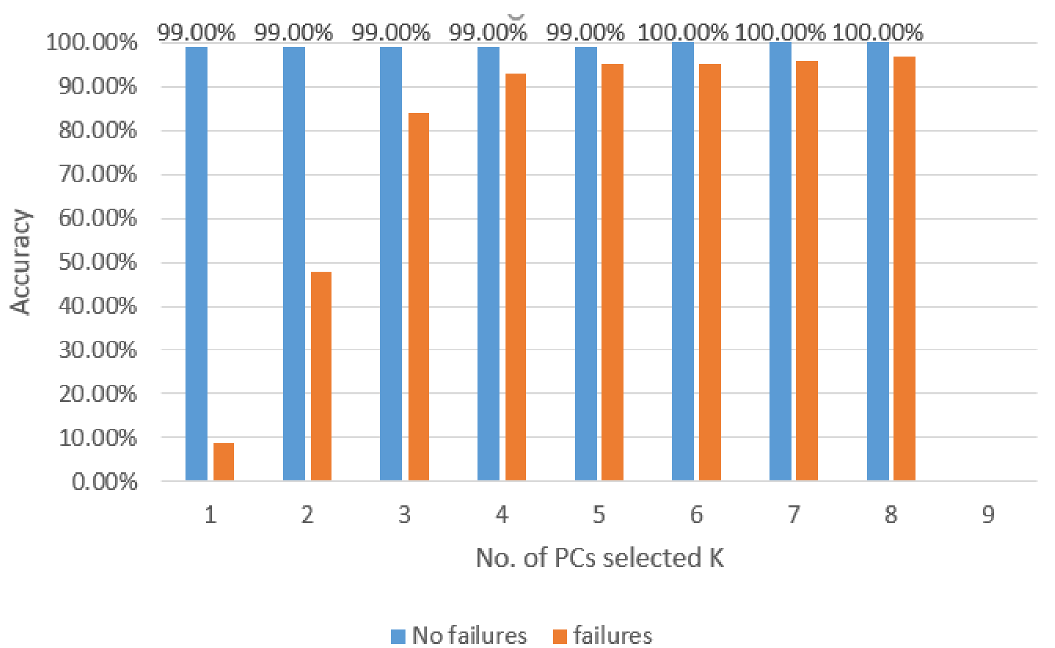


Figure 7. classification accuracy as function of the number of PCs selected

Table 2: Confusion matrix of predicted failures

	0	1
0	99	91
1	1	9

	0	1
0	99	52
1	1	48

	0	1
0	99	16
1	1	84

	0	1
0	99	93
1	0	7

	0	1
0	99	5
1	1	95

	0	1
0	100	5
1	0	95

	0	1
0	100	4
1	0	96

	0	1
0	100	3
1	0	97

5. Conclusion

Predictive maintenance has been established to maintain machines and consequently help to avoid the occurrence of sudden breakdowns. In this study, a machine-learning algorithm, artificial neural network (ANN), was used for a real application of existing machine learning techniques for a predictive maintenance model of a complex water pump system. With the use of a data set and the ANN, two scenarios were proposed. The first scenario included raw data that inputs directly into the ANN and the second scenario is based on applying dimensionality reduction technique such as principle component analysis (PCA) before passing data into the ANN. Results showed that all the failure predictions were well classified with an overall accuracy of 99.9%. The proposed strategy has the potential to be implemented in all types and sizes of manufacturing plants and operations

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