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Predictive Maintenance of Vertical Lift Storage Motor Based on Machine Learning

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Abstract: Predictive maintenance is one of the key subjects for Industrial 4.0. The purpose of predictive maintenance is to reduce unplanned downtime, to increase productivity and to reduce production costs. In the repetitive procedures of manufacturing & production, raw materials are put into or picked out from storage warehouse and in some cases are replaced with labour-intensive operations using machineries and equipment. The high-efficiency motor is the core of the automatic storage warehouse. The personnel who supervise the equipment need to check if a machine has any malfunction? Any downtime for maintenance is the waste of production time.

This research integrates the ANN model of machine learning (ML) to build an intelligent predictive maintenance system for the motor of vertical lift storage. Results of the proposed method are presented which show that our method has the ability to reduce waste, costs, and thus improve efficiency of supply chain.

Keywords: Predictive maintenance system; industrial 4.0; machine learning; artificial neural network (ANN).

1. Introduction

With the rise of Industrial 4.0 as proposed in Germany [1] the number of manufacturers towards industrial 4.0 keep increasing. Zhou et al. [1] proposed the method of transition from Industry 3.0 to Industry 4.0, while Germany developed the implementation plan for Industrial 4.0. The main points of the plan can be summarized with building a network and studying two major themes, i.e., smart factories and intelligent production. Gokalp et al. [2] argues that companies can easily integrate data mining and machine learning in their business process for monitoring and improving. Lin et al. [3] argued that, however, many small and medium-sized enterprises (SMEs) in various countries are having trouble pushing the computerization and automation in their plants, not to mention the Industrial 4.0. This is because most SMEs still use traditional machines without sensors and, hence, cannot collect data from machines or from production lines. Therefore, these SMEs are having trouble to catch up the trend of Industrial 4.0.

The past studies related to Industrial 4.0 focused more on manufacturing equipment and less on construction of real-time predictive maintenance systems, let alone the application of automatic storage warehouse for raw materials. Therefore, this research proposes the process by utilizing Machine Learning (ML) to develop real-time storage motor predictive maintenance system for SME factory.

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The organization of this paper is as follows. Section 2 is the literature review including automatic storage warehouse, Artificial Neural Network (ANN). Section 3 explains how to use neural network to construct the motor prediction model for automatic storage warehouse. The last section is to summarize and to explain the outcome & performance after applying the proposed model.

2. Literature Review

This study will review and explain the following topics: (1) automatic vertical lift storage and (2) Artificial Neural Network (ANN).

2.1. Automatic Vertical Lift Storage

A traditional manufacturing company usually will have many raw materials that require costly manpower for storage, picking, managing storage space. To achieve better performance, usually a company will adopt the automatic warehouse storage system to streamline the logistic and is integrated in the production process [4]. This kind of automatic warehouse storage system can extract the largest storage capacity with the smallest footprint. Moreover, the system can manage and integrate inventory by adding a layer of higher security for raw material management.

This kind of automatic warehouse system can maximize the usable height of storage operations and increases warehouse efficiency. Patil1 et al. [4] mentioned that Vertical Material Handling Lift can reduce cycle time and is cost optimized. Once the operator requests the item and places the shelf under the retrieval area, within a few seconds, the motor will locate the right position at the correct ergonomic height for collection. Advantages of automatic storage of warehouses include: (1) effective use of storage space, (2) efficient improvement of storage, (3) savings and labour-saving of warehouse operations, and (4) improvement of management standards.

An example of automatic storage warehouse is as shown in Figure 1. An efficient raw material supply based on the vertical lift storage plays an important role in modern factory. Since the manufacturing environment varies depending on the operation, therefore, repeated procedures from dedicated production lines allow the same product produced with 24 hours a day and 7 days a week (also called 24/7). In many cases, it can replace labour-intensive operations by using machinery and equipment. The more production processes are repeated, the more effective automation can achieve.

The core for the automatic storage warehouse is the high-performance motor as shown in Figure 2(a). The motor can run through the vertical lift chain to drive the automatic storage disk as shown in Figure 2(b). The person who supervises this equipment needs regularly checking the motor. If the motor needs repair or, in the worst case, has malfunction, then the downtime of the machine can lead to the waste of production time. Therefore, this research intended to provide a solid method to predict the repair time for motor maintenance by using a machine learning method. Our approach can automatically prevent the unpredicted downtime and, hence, increase the efficiency of manufacturing operation.

2.2. Artificial Neural Network (ANN)

Machine Learning (ML) is a kind of computer system or algorithm that can perform a specific task such as prediction or recognition without using explicit instructions [5, 6]. Usually training data, samples, or patterns are prepared as input for the system to learn. Output data can be obtained by using the learning algorithm. One of the most famous learning algorithm/model of ML is Artificial Neural Networks (ANN).

Figure 1. Vertical lift storage.

Figure 2. (a). High efficiency motor for vertical lift storage.
(b). Drive Storage Saver Operation.

ANNs are information-processing systems that contain element, i.e., neuron, and the processes network model. The network transfer connection through interconnection links. These links have associated weights, which multiplied by the input signal (net input). Output signal(s) obtain by applying an activation function for net investment. A simple neuron of a neural network (see Figure 3) may have two inputs (x_1,x_2) and one output neuron (y), where weights in between input and output neurons are denoted by w_1 and w_2. Given a single layer network with a single layer weighted interconnection as shown in Figure 3, the various inputs of the network are represented by the mathematical symbol x_i. Each of these inputs is multiplied by the connection weights. These weights are represented by w_{ij}. A simplest case of ANN is a computation process that simply summarizes the input value times the connected weights and then processed by a transfer function. The output y is derived from the net value of Equation (1). Rameshkumar et al. [7] mentioned that this process is suitable for large-scale physical implementation.

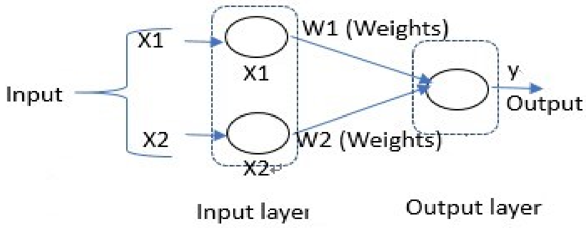

Figure 3. A simple artificial neural network.

An Artificial Neural Network (ANN) is a network model that is highly utilized to solve nonlinear problems. Its application fields are very extensive as introduced in Caslino et al. [5], Lin et al. [3] and Kumru [8]. The major features of a neural network are massive parallel processing, nonlinear output, and the ability to predict by using the multi-layer structures. The most basic component of a neural network is a processing element (PE). The output of each PE is connected to the PE of the next layer. The input value of the next PE comes from the output of each PE in the previous layer. The formula for the output value of the processing unit and the input value is generally expressed as a function of the sum of the input value times the linked weights minus the bias as Equation (1):

$$\boldsymbol{A} = f(net_j) = f(\sum_i w_{ij}x_i - \theta_j) \tag{1}$$

where the variables in equation (1) are:

$\boldsymbol{A}$ = the output of the processing element (PE) of a neuron,
x_i = input data,
net_j = integration function,
θ_j = the bias value of the PE j
w_{ij} = weight(s) between two layer of PEs
$\boldsymbol{f}$ = transfer function.

The so-called *weight* is the data linking between processing units, and the symbol w_{ij} is the intensity of the influence between *i-th* processing unit (current layer) and *j-th* processing unit (next layer). The integration function is the sum of input values from all processing units by multiplying the linkage weights, and the output values are obtained through the conversion or transfer function. The transfer function mainly corresponds to the output value to the function interval of the S-type. One of the most commonly used transfer function is sigmoid function (equation (2)) and the other one is hyperbolic tangent function (equation (3)). The formulas of these two functions are as follows:

$$f(net) = \frac{1}{1 + exp^{-net}} \tag{2}$$

(Sigmoid fc.)

The output of the sigmoid function is between 0.0 and 1.0, and the input/output curve of the sigmoid function is steep. Therefore, when the net signal is close to zero, the output value is close the 1/2. When the net value is large, the output value is close to one.

$$f(net) = \frac{exp^{net} - exp^{-net}}{exp^{net} + exp^{-net}} \tag{3}$$

(Hyperbolic Tangent fc.)

The output shape of hyperbolic tangent function is also a line with S-shape. It is symmetric if corresponds to the origin, and the corresponding interval is between -1.0 and 1.0. This type of function is better for applications that expect positive and negative output values.

Among many neural network models, BPN has proved to be a well-studied model in solving complex nonlinear problems as had mentioned in Rameshkumar et al. [7]. If a problem domain that is difficult to be modelled using mathematic formula, then, BPN (Back Propagation Network) will be a good method for these problems [6, 7]. This research intended to handle the real-time prediction problem for the motor-maintenance prediction, which is a complex nonlinear problem. Therefore, this research applied BPN model, one of the Machine Learning method, to predict the motor maintenance time for vertical lift storage.

3. Case study

Automatic storage warehouse is an important part of the rapid development of modern logistics system. It has many advantages such as saving land, improving warehouse automation level and management level, improving management and operation's personnel quality, reducing storage and transportation loss, and improving logistics efficiency. The high-performance motor, which runs through the chain to drive the automatic storage tray, is the core of the automatic storage warehouse. When the loading of raw material increases, the motor current will also increase. When lowering the material plate, the motor current will also decrease. To obtain the current variation log, we added the current sensor as shown in Figure 4(a) to extract the current data from the vertical lift motor. And the load current is plotted as shown in Figure 4(b).

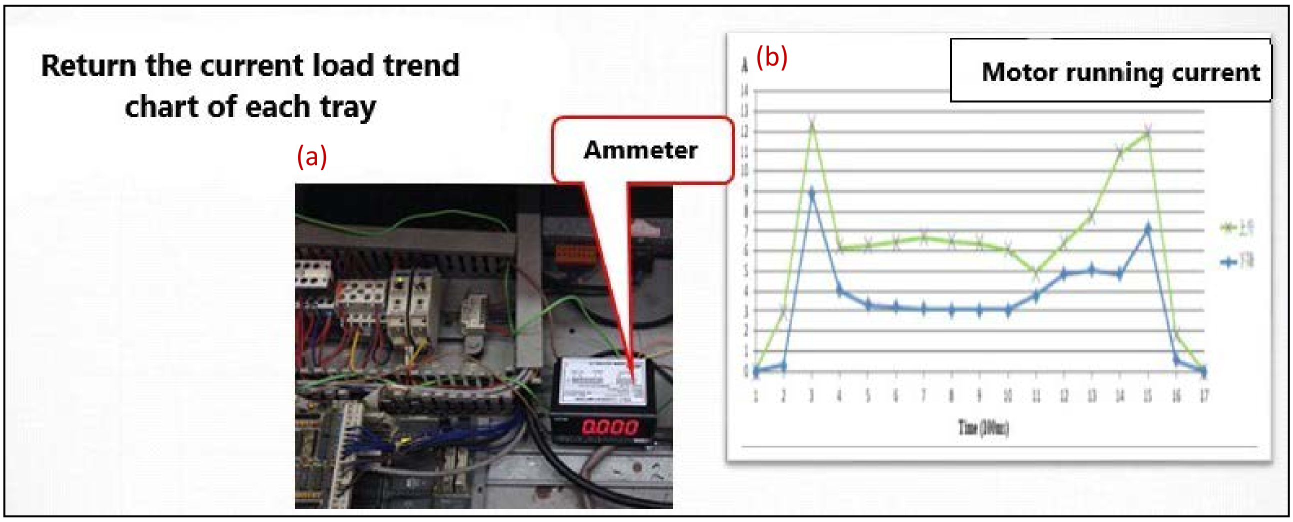

Figure 4. (a) Setup a current sensor on the motor of vertical lift (left).
(b) Current plot (right).

It is considered at the beginning that the load current of the motor may be affected by the weights of material when collected from the storage warehouse and put into the tray. Fortunately, after we examine the real world data of load current with various weights, it appears that the load current is not affected by the different material or by the various weights. As have shown in Figure 4(b), we noticed that the motor rise (the upper line of Figure 4(b)) and the motor fall (the lower line of Figure 4(b)) are all in the same pace regardless of any kind of weights. Therefore, this research uses the load current data directly for constructing the predictive model.

Table 1. Sensor log from the motor of vertical lift (partial data).

No	Current(A)	Voltage(V)	Temperature (℃)	Time	Machine ID	Machine Type
5982293	1.847	0	0	2018/1/18 14:52:54	Stg101	STORG
5982294	6.439	0	0	2018/1/18 14:52:54	Stg101	STORG
5982295	3.422	0	0	2018/1/18 14:52:54	Stg101	STORG
5982296	3.206	0	0	2018/1/18 14:52:54	Stg101	STORG
5982297	3.551	0	0	2018/1/18 14:52:54	Stg101	STORG
5982298	4.103	0	0	2018/1/18 14:52:54	Stg101	STORG
5982299	4.68	0	0	2018/1/18 14:52:54	Stg101	STORG
5982300	4.511	0	0	2018/1/18 14:52:54	Stg101	STORG
5982301	7.136	0	0	2018/1/18 14:52:54	Stg101	STORG
5982302	0.34	0	0	2018/1/18 14:52:54	Stg101	STORG
5982303	0	0	0	2018/1/18 14:52:54	Stg101	STORG
5982462	8.215	0	0	2018/1/18 14:54:02	Stg101	STORG
5982463	8.859	0	0	2018/1/18 14:54:02	Stg101	STORG
:	:		:	:	:	:

Procedure for establishing an automatic storage warehouse motor is as follows.

3.1. Pre-processing and transposition of data

The current values of motor are transferred into log file with 7 tuples, i.e., *No.*, *current*, *Voltage*, *Temperature*, *Time*, *Machine ID*, and *Machine type* as shown in Table 1. These data are recorded in every 300 milliseconds.

The data observation is analysed and it is found that every 10 strokes can be treated as one record to determine the rise or fall of the motor.

$$\begin{aligned}&\textit{If } \textstyle\sum_{i=1}^{i=10} (a_i/10) > 4\\ &\text{then motor rises, set } cls=\text{“}1\text{”}\\ &\text{otherwise motor falls, set } cls=\text{“}0\text{”}\end{aligned} \tag{4}$$

These log files are encoded into records where each record contains 10 current values and one class type (“*cls*”) where *cls* represents the rising motion or falling motion of the motor. Equation (4) is used to define the *cls* label. The “*cls*” is set to 1 as the average value above 4 which representing the rise of the motor, otherwise, “*cls*” set to 0. Record *R* is represented as: $R=\{a_1, a_2, \ldots, a_{10}, cls\}$ as shown in Table 2. These records are then sent to the BPN neural networks for pattern learning.

Table 2. Transfer the sensor log data into training data.

no	a_1	a_2	a_3	a_4	a_5	a_6	a_7	a_8	a_9	a_{10}	*cls*
120	1.847	6.439	3.422	3.206	3.551	4.103	4.68	4.511	7.136	0.34	**0**
121	8.215	8.859	5.503	5.63	5.158	6.451	10.628	11.152	0.728	0	**1**
:	:	:	:	:	:	:	:	:	:	:	:

3.2. Establishment of Predictive Process

Establishing an automatic storage warehouse motor is taken as an example to build the automatic predictive maintenance system. An ammeter is added to collect the rising and falling current of the motor. When the tray is raised, the motor is subjected to be loaded, so the current value must be increased. The motor loading is reduced when disk lowering, and thus the current value is reduced. In this research we collected the current value as Table 1 and transferred these data into records as Table 2, where a_1~a_{10} is used as input of the predictive model, and the target value is *cls*, i.e., the prediction result (1: rise & 0: fall). We used BPN of Artificial Neural Network (ANN) as to learn the current pattern and to predicted results.

In our case study, R language is used to implement the neural network model. The neural network model is designed with 3 input layers, 3 hidden layers with 3 nodes each, and 1 output layer. The learning rate of this model is set as 0.01 and the threshold values are set as 0.001 at the beginning.

(a) Training subset: 99 records of input/target pairs are used for BPN (Back Propagation Network) as training. At this stage, synaptic weights are repeatedly updated to reduce errors between experimental output and respective goals.

(b) Validation process: 12 inputs/targets are used for model validation. To avoid over-learning, a basic trend that identifies the subset of training data is used. If the error begins to increase when compared to the verification subset, the training will stop. In order to minimize the overfitting problem, the training phase is stopped when the Mean Square Error (MSE)$\leqslant$0.01.

Here we use the energy function or so called loss function to verify the model performance. If a vector of *j* predictions generated from a sample of *j* data points on all variables where *T* is the vector of observed values of the variable being predicted and *A* is the actual value, then the within-sample MSE of the predictor is computed using the following equation:

$$E = (\frac{1}{2})\sum_j (T_j - A_j)^2 \tag{5}$$

(c) Test process: 12 input/target pairs of data are provided to test the trained predictive model. Errors are evaluated in order to update the threshold and synaptic weights. After these training patterns have learned, verified, and tested, another 100 records of the sensing data are automatically extracted every half day from the motor action. We defined that when 60% of the data patterns is predicted as abnormal, the equipment inspection or replacement should be performed as soon as possible. The notification and the prediction analysis will be displayed in the war room as shown in Figure 5. The structure and weights of the trained neural network is as shown in Figure 6. The Prediction results are transferred into text file and are saved (see Figure 7) for future analysis.

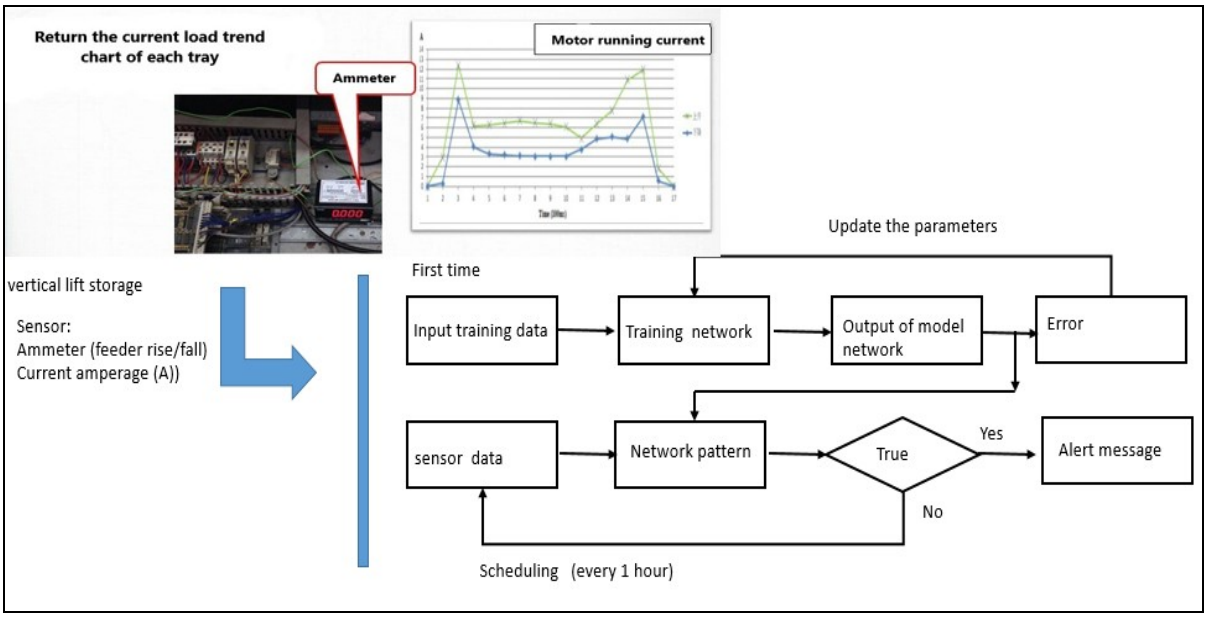

Figure 5. Prediction follows the current value of vertical lift motor.

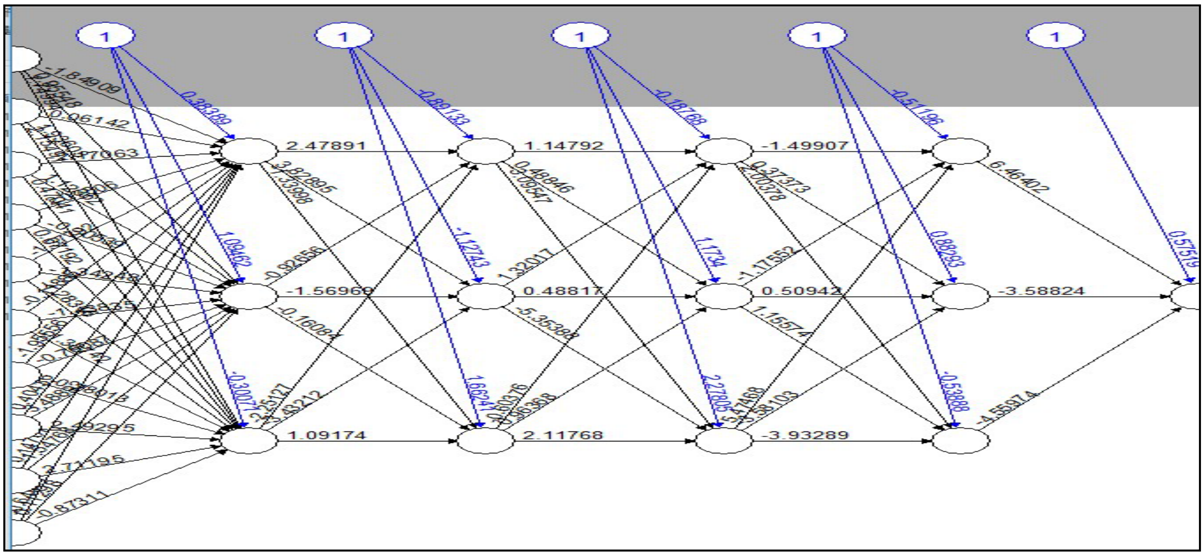

Figure 6. The structure & weights of the trained neural network model.

3.3. Summary

We have demonstrated that a machine learning method via BPN neural network model can be useful for predictive maintenance of vertical lift storage motor. To extract the data from motor, we added the ammeter to collect the current data and to detect if the motor is rising or falling. Total 123 records are used in this research for training, validating, and testing so that the predictive model is built. The current values are transferred as a_1~a_{10} and is used as input of the predictive model and "*cls*" is used as the target value. The results of our proposed model are as shown in Table 3, where the correction rate under training and testing is 99% and 91%, respectively.

Table 3 shows that it is feasible to apply the machine learning method to predict the timing of when should the vertical lift motor be replaced. This model can also be applied to handle other types of motor operation. What we suggest is that a warehouse can derive 500 current values twice a day for predictive maintenance model training. The application scenario of motor replacement is when the health indicator of the motor shows above 60% of the abnormal results (see the right arrow in Figure 8), derived from the trained BPN model. In this case, early equipment inspection and replacement should be conducted to avoid the motor failure. In this way, a SME can reduce the unnecessary waste or cost of motor failure and, hence, can improve the efficiency of operation and production.

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"X" "a1" "a2" "a3" "a4" "a5" "a6" "a7" "a8" "a9" "a10" "a11" "Intspec_pred" "spec_pred"
1 0.167 5.797 3.387 3.32 3.365 3.014 2.989 2.976 2.98 2.972 0 0 0.00236496117879197
2 6.969 9.343 5.675 5.221 10.044 12.597 4.224 4.126 0 0.03 1 1 0.995547076585698
3 1.453 1.389 5.741 3.244 3.691 4.654 4.291 4.564 0.049 0 0 0 0.00246556283213975
4 2.465 5.655 5.645 5.444 5.466 8.948 12.181 9.095 0.136 0 1 1 0.997377795361405
5 5.878 6.098 6.174 6.003 5.75 4.652 6.437 10.148 12.05 2.809 1 1 0.997846446588394
6 1.352 12.871 5.721 5.07 4.719 6.093 10.429 12.724 2.756 0.026 1 1 0.997829426752016
7 0.626 9.634 3.881 3.24 3.133 3.105 2.893 2.906 2.94 2.941 0 0 0.00330245175980429
8 0.068 8.451 6.702 5.924 6.036 5.828 5.904 5.79 4.995 5.114 1 1 0.997345116679873
9 6.484 6.211 3.318 3.253 3.272 3.31 3.231 4.132 4.495 4.408 0 0 0.00585785448962452
10 0.203 9.708 3.948 3.241 3.155 3.15 2.893 2.887 2.885 2.883 0 0 0.00324769699230835
11 5.633 5.883 5.937 5.99 5.798 5.706 5.583 5.498 5.459 4.758 1 1 0.997264267372239
12 0.044 5.133 4.024 3.267 3.857 4.08 4.375 4.086 7.18 0.287 0 0 0.00234145708510876
13 0.45 12.512 6.204 5.573 5.553 5.068 7.782 11.835 12.448 0.773 1 1 0.997828251621227
14 8.191 7.657 5.568 5.695 5.046 7.123 11.374 13.015 2.977 0 1 1 0.99784706365929
15 6.822 6.056 3.306 3.245 3.762 4.244 4.615 4.325 2.156 0.025 0 0 0.0111743599729257
16 5.217 5.651 3.309 3.249 3.768 4.17 4.807 4.207 5.288 0.041 0 0 0.0164531321595368
17 1.09 5.726 3.344 3.227 3.699 4.737 4.474 6.878 0.135 0 0 0 0.0032946123175573
18 1.449 11.051 5.722 5.565 5.499 9.062 12.31 5.351 0.05 3.524 1 1 0.997353218587516
19 11.098 5.649 5.737 5.439 5.578 9.503 12.159 5.89 0.046 5.507 1 1 0.997368477659371
20 4.829 9.399 5.299 5.408 5.731 5.313 4.469 5.789 9.89 12.879 1 1 0.997432654916835
21 0.114 6.469 3.941 3.285 3.153 2.914 2.981 3.004 3.014 3.702 0 0 0.00261186356617814
22 5.7 5.217 7.237 7.171 11.259 0.889 0.145 8.003 1.231 0 1 1 0.997645782918715
23 8.459 8.086 4.612 6.321 10.393 4.798 0.03 10.06 0.035 0 1 1 0.997789864910988
24 5.662 3.554 3.273 2.974 4.573 4.817 4.706 4.913 0.066 0 0 0 0.00262021414183042
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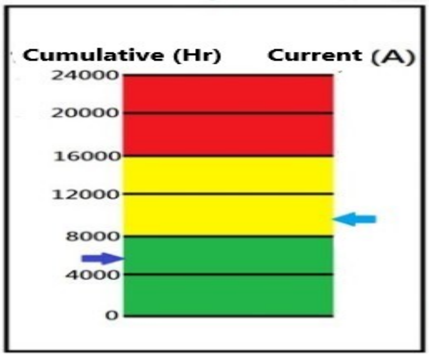
Figure 7. The prediction results derived from the model are transferred into text file.

Table 3. Correction rates of the predictive model.

Item	ANN-BPN
correction rate for Training	99%
correction rate for Testing	91%



Red Color : failure warning
Yellow Color : inspection warning
Green Color : in good condition
Left arrow → : accumulated working hours of the motor
Right arrow ← : predictive warning position

Figure 8. Health Indicator of vertical lift storage motor.

4. Conclusion

The traditional vertical lift storage operation is that the personnel who supervises the equipment needs to inspect the equipment regularly. If the machine needs to be repaired and it happens that it is difficult to repair, in this case, any downtime will result in wasted production time. This study proposes an automated predictive maintenance system that integrates machine learning (ML) in a Small Median Enterprise (SME) production factory. The proposed model is applied to predict the problem before the motor is damaged which will cause unexpected downtime and extra cost.

The proposed method is applied in a vertical lift storage warehouse which is belongs to a SME. We use the current of the motor in the vertical lift storage and use the rise or fall of the loading tray to collect the data. By adding current meter sensor, we are able to convert the motor current values into a sensor log file, and transferred into 10-column current values and a motor rise or fall characteristic value. By using the machine learning algorithm, the motor prediction model of the automatic storage warehouse is established.

The correction rate of the proposed model is above 91%, no matter in training period or testing period. Based on the results of this research, we suggest that machine learning is well applicable to learn the factory maintenance problem and, hence, is helpful for prediction. This research suggests that motor health-index Kanban (in the war room) can be constructed by using supervised learning to derive the prediction results. Notification of the inspection or maintenance can be done in early stage. By using the proposed model, we are able to avoid un-intended failures, therefore, the unexpected wastes, the cost of downtime, and the improvement of supply chain can then be continuously upgraded for SMEs.

Acknowledgment

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