Time Series Analysis for Fail Spare Part Prediction: Case of ATM Maintenance

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***Abstract*—Prediction of failed spare parts is an interesting issue in inventory management. Our work applied predictive analytic to forecast future amount of failed spare parts. This research used maintenance time series data from year 2013 to 2016 to train and test data for a prediction model. In the preprocessing step, we looked into new features based on historical data set. Then, we added the day of week feature into the example of the data set. The day of week feature had an impact to spare parts prediction model. Moving average and windowing methods were used in the preprocessing phase before sending through the prediction model. Artificial neural network and support vector machine for regression were applied to predict the amount of failed spare parts. The experiments demonstrated the average accuracy of failed spare part prediction. The result represented that the support vector machine for regression showed the best accuracy at 88.24%. SVR yielded the highest prediction accuracy at 92.7%.**

***Index Terms*—Time Series; Prediction; Spare Part**

I. Introduction

Nowadays, devices with applications are used to conduct business in the industrial sector. When hardware is used frequently and repeatedly, it would lead to malfunction. The failure may be caused by the expiration of parts. Thus, in real business, hardware need to be maintained or the malfunction parts need to be replaced [1].

There are three levels of maintenance, which are:

1. Corrective maintenance: When the hardware is broken or unable to operate, maintenance services need to be in place to fix the issue.
2. Preventive maintenance: Maintenance services are planned to clean and check the hardware periodically to ensure the availability of hardware prior to any failure as prevention.
3. Predictive maintenance: Some causes of failure are known issue or they are predictable, such as the license expiration, product end of life [2].

If we can predict the failure of parts or symptoms in advance, we can forecast the optimized number of spare parts and service engineer is able to fix the problems appropriately and effectively.

Currently, the maintenance department received incident logs on average about 3,000 cases per day. From 2013-2016, they received transaction logs around 100,000 cases. The large amount of incident cases of automated teller machine (ATM) is considered as a big problem to the maintenance department. Incident log data are a time series data that record maintenance data several times in a day.

In the past, the number of spare parts was calculated from the previous amount of failure recorded in the ATM logs. We are aware that this is not a good methodology. Hence, in our research, we focused on using time series data from incident logs. We proposed the time series model to forecast a symptom that will occur in the future.

This paper is organized as follows. In Section II the related work of spare part prediction technique is presented. In Section III, we describe the framework of the proposed method. In section IV, the experiment and result are presented. Finally, in Section V, the conclusion of this paper is discussed.

II. Related Work

Moving average was used as an estimation of coefficient constant model. This model adopted a method to compute average at any time of data and add some weights to the data [3].

A simple moving average method, which is a classical method to estimate trend or cycle of time series data is adopted. The moving average of order m has the following formula:

$$T_t = \frac{1}{m}\sum_{j=-k}^{k} y_{t+j} \tag{1}$$

where m is an order of moving average and $m=2k+1$, k is a time period of t for the estimated average of trend-cycle. The average eliminates some of the randomness in the data and remains smooth trend-cycle component.

Weighted moving average was moving average that calculates with a weight function. Weight moving average can be written as:

$$T_t = \sum_{j=-k}^{k} a_j y_{t+j} \tag{2}$$

where $k = (m-1)/2$, t was a time period of the estimate of trend-cycle, a_j was a weight factor. A sum of weight was one [4].

This research used many techniques to forecast demand and to reduce inventory level in retail sale [5]. It also used a conventional method, such as the moving average, naive theory, and exponential smoothing to predict the demand for electronic spare parts and the other technique to compare the performance [6].

Artificial neural network (ANN) is also called as the multi-layer perceptron. ANN consists of the connected group of the artificial neuron. The structure of artificial neural network includes the input layer, hidden layer, and the output layer. The back propagation neural network consists of two parts, including the propagation and weight update. The second part will adjust the weight of each connection and reduce the error rate value. It will be repeatedly processed until the satisfied result can be determined. After many training cycles, the error rate value should be minimal [7].

The research used evolution strategies for ANN model to predict the order of the module of SLMA module. This research presented that the evolution strategies have a chance to alter the method to train the ANN model and gain the optimal weights [8].

In [9], they tried to predict the failure rate in water supply system. They used artificial neural network to predict the failure rate of house connections and distribution pipes. The performance of the artificial neural network was accepted [9].

The paper in [10] used the back propagation neural network (BPNN) with adaptive differential evolution for time series prediction. They considered initial weights and thresholds in the BPNN model. The research defined a proper initial parameter. The result presented higher accuracy than the other models, such as ARIMA model [10].

In [11], the researchers compared two network traffic activities prediction models. The first model was the back propagation neural network and the other was the genetic algorithm based on BPNN. The result illustrated that the genetic algorithm based on BPNN has higher prediction accuracy than the conventional BPNN model [11].

The research reported in [12] used the artificial neural network to predict a part demand of an auto aftermarket. They used mapping relationship with external factor and the part demands. Then, they compared with time series based prediction and neural network was acceptable [12].

Their work [13] aimed to predict production quantity in foundry manufacturing. They compared the prediction performance by two prediction techniques based on foundry manufacturing data set. The first technique supported the vector machine and the other supported the neural network. The result presented that the neural network performed better than other methods [13].

The supported vector machine for regression (SVR) is a high-performance method for recognition and regression problem. The data was mapped to high dimension feature space. The non-linear problem of low dimension was transformed to a linear problem of high dimension. The function was represented using a linear function in the feature space.

$$f(x) = \omega \cdot \varphi(x) + b \tag{3}$$

The optimization problem was written as a formula below:

$$\frac{1}{2} \| \omega \|^2 + C \sum_{i}^{n} (\xi_i + \xi_i') \tag{4}$$

$$\begin{gathered} s.t.\,((\omega \cdot \varphi(x_i) + b) - y_i \leq \varepsilon + \xi_i, i = 1,2,\dots,n. \\ y_i - ((\omega \cdot \varphi(x_i) + b) \leq \varepsilon + \xi_i, i = 1,2,\dots,n. \\ \xi_i' \geq 0, i = 1,2,\dots,n. \end{gathered}$$

Based on the dual problem and Lagrange function, the following is achieved:

$$\begin{gathered} \frac{1}{2} \sum_{i,j=1}^{n} (a_i' - a_i)(a_j' - a_j) K(x_i, x_j) \\ + \varepsilon \sum_{i=1}^{n} (a_i' + a_i) - \sum_{i=1}^{n} y_i (a_i' - a_i) \\ s.t. \sum_{i=1}^{n} (\alpha_i^* - \alpha_i) = 0, \\ 0 \leq \alpha_i^{(*)} \leq C, i = 1,2,\dots,n \end{gathered} \tag{5}$$

where $K(x_i,x_j)$ is the kernel function and the result depends on C and the kernel function.

The research approach in [14] was to predict the failure rate from SVM regression by Fuzzified SVR-PSO model. They used two parameters for modification of parameter optimization of SVR to overcome the problem. Then, they used pipe failure data set to test the prediction model. The result showed significantly high comprehensibility generalization capability [14].

The paper in [15], documented the researchers used support vector regression (SVR) model to forecast in time series data. They applied the genetic algorithm and tabu search to the optimized parameter of seasonal support vector regression model. Then, they compared between the auto regressive integrated moving average (SARIMA) and SVR. This research satisfied the used SSVR model for forecasting seasonal time series data and captured the seasonal data pattern [15].

The paper [16] predicted a demand for electronic spare parts by many techniques. A convention method and the new method was used to forecast, such as the support vector machine for regression and artificial neural network. The result presented a weekly forecasting and the model did not have good predictive capability. Time period for the model was selected individually for the electronic part [6].

The research [16] predicted a demand for distribution network spare parts and inventory quota. This research used support vector machine for regression that uses historical data, such as repair schedule, failure rate, and operating environment. The result presented SVM model with high accuracy and effective solution [16].

The research [17] used artificial neural network (ANN) and support vector regression (SVR) technique for the prediction of Pipe Burst Rate. They used maximum and average of hydraulic pressure as input attributes of the prediction model. Finally, they considered from two real world data set. The result showed that SVR perform better than ANN [17].

III. PROPOSED METHODOLOGY

Figure 1 shows the proposed methodology. The data collection is the first step in the proposed method. The data consist of one hundred thousand records from ATM maintenance department incident logs combined with ATM asset data. Incident log data were summed by day to 1800 records with two attributes that consist of date and amount of ATM failure parts.

Data cleaning and transformation were used for cleaning noisy data. Incident log data contain preventive maintenance data and corrective maintenance data. We filtered out the preventive maintenance from the data set and remainder were the corrective maintenance log from ATM fail issue.

Incident log stores failure symptom with text field. We cleaned the data by collecting significance word from the failure symptom field, then summed the amount of the failure symptom in one day.

Data exploration was used to find the trend and seasonality. The cleaned maintenance of log data were explored by graph and they represented the difference between working day and non-working day (Saturday and Sunday). We then removed the non-working day data that have small number of maintenance data. The data show the significance of the day in a week in a seasonal form. We added an attribute from the day of a week to the maintenance time series data.

We used the moving average to the data set and set a windowing to define the time period, such as 5 days and 7 days which was weighted by Hann function. This resulted in the moving average as the center of the time period.

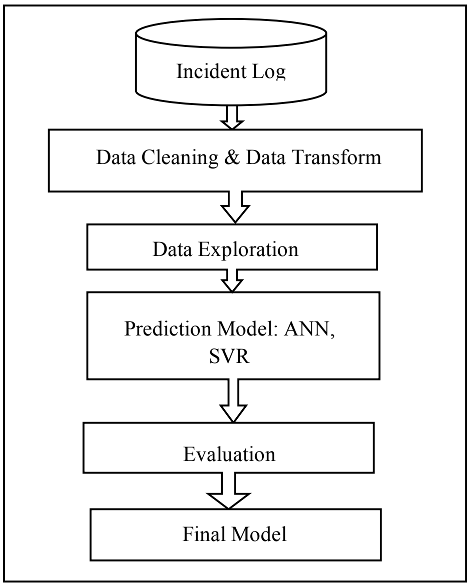

Figure 1: The proposed methodology

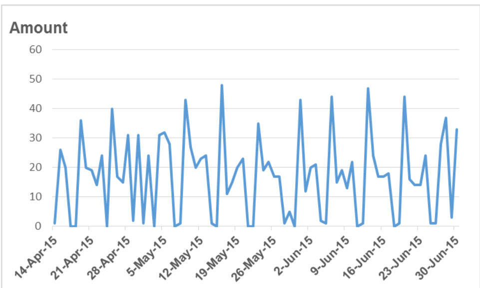

Figure 2: Seasonal Component of the maintenance log data

The prediction model is the support vector machine for the regression and artificial neural network that are used to predict the amount of symptom failure. The support vector machine for regression (SVR) uses polynomial kernel. The evaluation uses sliding windows validation for time series data prediction. Then, we have to select the finalized model from the result of the evaluation process.

IV. Experimental Result

This experiment uses Dell Inspiron 13, Intel Core i7 Quad core Processor, 2.6GHz 8 GB RAM with Windows 10, RapidMiner version 7.1. The goal of our research is to predict the amount of failure symptoms and compare the performance between the neural network and the support vector machine in the spare part inventory forecasting.

The experiment data were the incident logs from January 2013 to March 2016. Then, we generated a new data set from the log file. The historical transaction data were grouped by date and symptoms of failure.

The date is set as id feature and the symptoms of failure is set as a label.

Table 1
Attributes of example set from incident log data

No.	Name
1	Product Name
2	Date
3	Contact Name
4	Account Name
5	Case No
6	Serial No
7	Description
8	Model
9	Problem Detail
10	Status
11	Solved Detail

The data were cleaned by finding word(s) in the failure text defined as the symptoms of failure. Then, we transformed and replaced the data. We generated new data set by grouping them according to the date data.

Table 2
Selected failure part from incident log data

No.	Name
1	Expense
2	Reader
3	Communication
4	Ups
5	Printer
6	Log
7	Boot
8	Power supply
9	Vacuum
10	Box

Table 3
Example of summarize failure symptoms

Date	UTR	Harddisk	CCTV
2013-01-18	22.0	.0	3.0
2013-01-20	.0	.0	.0
2013-01-21	23.0	.0	6.0
2013-01-22	7.0	2.0	6.0
2013-01-23	9.0	.0	.0
2013-01-24	4.0	2.0	1.0

We generated the data set by creating two new features. The new features are the number of day in a week and the number of month. Then, we separated the data set into two groups: training data set between the year 2013 - year 2015 and testing data set in year 2016.

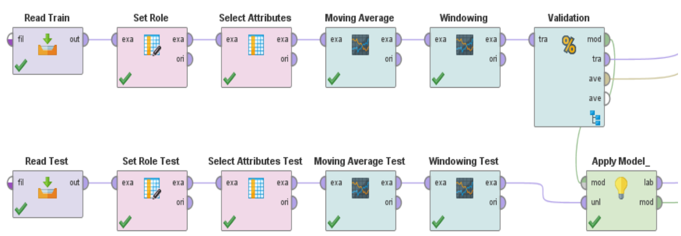

Figure 3: Process in Rapidminer

The parameters of ANN in rapidminer include 500 training cycles with a learning rate of 0.3 and a momentum of 0.2. The number of neurons are calculated as follow:

$$((\text{amount of features} + \text{amount of classes}) / 2) + 1)$$

The training phase inlcudes:

1. Reading the training data set from the excel file.
2. Selecting ID attributes and label attributes from the date and the amount of failure symptoms consequently.
3. Detecting and replacing outliers.
4. Applying moving average to the data set to smoothen the data.
5. Applying windowing to the data set with setup windows such as 5, setting step size to 1 and horizon to 1.
6. Using validation process to validate the model with machine learning and generate final model

The testing phase is described as follows:

Step 1 to step 5 is similar to the training process. The output data set generated from the testing data set will be sent to apply the model operator. We used SVR and Neural network to test the model from the training phase.

Table 4
Accuracy of prediction

	ANN	SVR
Expense	0.919	0.927
Reader	0.879	0.888
Communication	0.903	0.919
UPS	0.877	0.891
Printer	0.877	0.891
Log	0.874	0.874
Boot	0.918	0.91
Power Supply	0.808	0.821
Vacuum	0.814	0.856
Box	0.838	0.847
Average	0.8707	0.8824

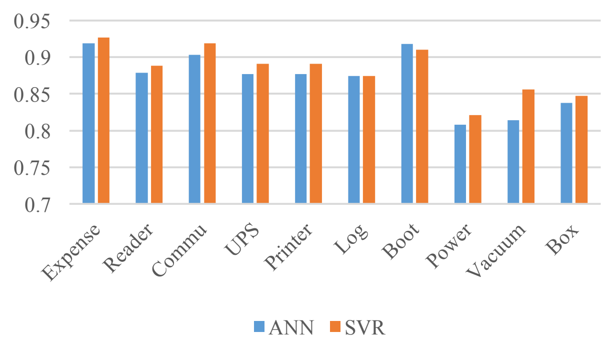

Figure 4: Accuracy of prediction

V. Conclusions

This paper predicted the amount of spare part by artificial neural network and support vector machine for regression from incident log data. From the experimental results, we compared the results from SVR and ANN method. Support vector machine for regression had a higher average prediction accuracy than the artificial neural network in the research model at 88.24%. Support vector machine for regression generated the highest prediction accuracy rate of 92.7% with the expense part. The results indicated that the support vector machine for regression is a satisfied method for predicting the amount of failed spare part with high prediction accuracy and time consuming issue. For further research, spare part failure coincide can be used to improve ATM predictive maintenance with the association rule technique.

Acknowledgments

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