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Classification Techniques for Control Chart Pattern Recognition: A Case of Metal Frame for Actuator Production

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ABSTRACT

Statistical process control (SPC) plays a significant role in hard-disk drive manufacturing as there is a crucial need to constantly improve of productivity. Control chart is one of the SPC tools that have been widely implemented to identify whether nonrandom pattern caused by assignable cause exists in the production process. Decision rules are usually used for detecting nonrandom patterns on control chart. However, recent research has shown that these rules had tendency of producing false alarm. This is a problem occurred in the case study company, who is a manufacturer of metal frame for actuator. The company is adopting technologically advanced equipment for its quality assurance system and computer software for data analysis and control chart. Currently, the company use decision rules for detecting nonrandom patterns on control chart - for example, if 6 or more consecutive data inputs found to be in an increasing or decreasing order, these data contain trend pattern. In attempt to improve the accuracy of data analysis, this research investigated the application of 3 classification techniques, namely neural network, *k*-nearest neighbor and rule induction, in discretion of nonrandom patterns. By considering the control charts of 3 different product lines, 3 types of nonrandom patterns, which are Trend, Cycle and Shift, are to be observed. Based on the real data inputs, the percentage of accuracy in error detection by each technique of each product line is compared. It is found the accuracy of *k*-nearest neighbor is highest with the percentage of correctly prediction between 96.99 - 98.7%.

Keywords: control chart, pattern recognition, neural network, K-Nearest neighbor, rule induction

1. INTRODUCTION

The hard disk drive producers have constantly relocated theirs major production hub to Thailand. This began in around 1983 when Seagate Technology moved their head-stack assembly out of Singapore due to the relatively low-wage labors and encouraging investment environment of Thailand. Incumbent expanded from then on, including part supplier and other hard disk drive producers [1]. The shift in production trend has resulted in the country's remarkable export volume. The company in this case study - whose name needs to be confidential for protection of trade secret - manufactures metal frame for actuators, an important component of computer's hard-disk, as its major product line. The company's Quality Control Department has stored large amount of quality inspection data. Various techniques have been used to analyze them for instance data mining [2] and statistical process control (SPC)[3]. One of SPC techniques currently adopt is the control chart, where $\bar{x}$ - r and $\bar{x}$ - s control charts along with decision rules for detecting nonrandom patterns are implemented. Rules for example zone tests or run rules have been widely used in industry to detect control chart pattern [4], [5]. However, these rules can yield an excess of false alarms as the patterns are normally distorted by common cause variation of unknown factors in manufacturing process [6].

Many research has used the neural network (NN), which is a computer model that resembles the biological characteristics of human neural network and simulates the function of human brain, for recognition pattern in control chart (for example [7], [8]). This is because NN is capable of learning, adapting, determining and recognizing various patterns. Such NN is capable of recognizing patterns and responding to difficult problems, discerning relationship between complex set of data, and forming a sophisticated mathematical model.

Apart from NN, other classification methods have also been implemented in control chart pattern recognition for example decision tree [9], k-nearest neighbor [10] ,[11]. Yet limited work has been reported in the comparison of those techniques in order to find a suitable technique for control chart pattern recognition. The comparative study helps to identify appropriate technique for control chart pattern recognition which not only applied to the case study company but also has a potential to be applied to other processes. As a result, this work attempts to compare NN with two other classification methods namely k-nearest neighbor and rule induction in terms of their classification accuracy. Actual inspection data from the case study company was used to compare those methods in detecting patterns including Trend, Cycle and Shift.

2. LITERATURE REVIEW

2.1 Neural Network

Artificial neuron or processing element (PE) constitutes the basic component of neural network. The input signals are received through dendrite-like weight connection. Each cord is assigned a connection weight, which resembles the change in magnitude of synapse signal transmission. Each PE attains output by calculating weighted sum (Sj) from $\sum_i a_i w_{ij}$, where a_i is the activation level of unit i, and w_{ij} is the weight from unit i to unit j. Activation function $f(x) = \frac{1}{1+e^{-x}}$ was applied S_j to calculate output of that PE [12].

PE needs to be connected into a network similar to the network of human brain. Although there are many types of connection of PE, multi-layered neural network is the type implemented in this research. Figure 1 shows a multi-layered neural network, which represents a comprehensive connection network. In the beginning of the learning process, connection weight is randomly assigned, starting from small weight values. After a data pair is received from the training data set, the NN adjust the weights to minimize error function. Learning algorithm used in this research is the Back propagation. Number of hidden layer and hidden node can have significant impact on output accuracy. Appropriate number of hidden layer and hidden node are usually set by trial-and-error. Alternatively optimum setting of these parameters can be identified by using design of experiment technique [13], [14].

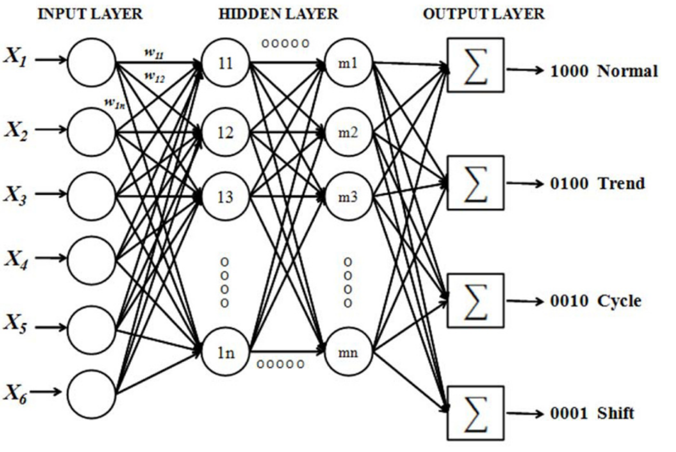

Figure 1. Multi-layered Neural network.

Table 1. Comparing the use of neural network recognition of control chart pattern

Author	Type of network	Pattern for detect	Data use
Pham and Wani [7]	back propagation	Normal , Cyclic, Increasing or decreasing trends, Upward or downward shifts	Experiment
Cheng [8]	back propagation	Trend, Cycle, Systematic variable, Mixture, Sudden Shift	Model
Guh and Tannock [15]	back propagation	Natural, Shift, Trend, Cycle	Model
Guh and Hsieh [16]	back propagation	Normal, Upward Shift, Downward Shift,Upward Trend, Downward Trend, Cycle	Model and Experiment
Perry et al. [17]	back propagation	Trend, Cycle, Systematic variable, Mixture	Model
Al-Assaf [18]	back propagation	Natural, Shift, Trend, Cyclic, Shift &Cyclic, Shift &Trend, Trend &Cyclic	Experiment
Pham and Sahran [19]	Spiking	Normal, Upward Shift, Downward Shift, Upward Trend, Downward Trend, Cycle	Model and Experiment
Guh [20]	back propagation	Natural, Cycle, Increasing Trend, Decreasing Trend, Upward Shift, Downward Shift, Systematic, Mixture	Actual Data

From Table 1, NN is now regarded as an acceptable approach to recognition of control chart pattern. Mostly, back propagation neural network is used, except the research conducted by Pham and Sahran[19], which adopted the Spiking method in error detection of control chart. Their work showed that spiking neural network gives high pattern recognition accuracies. Various of error patterns were investigated in literature, for example, Normal, Trend, Cycle, Shift, Systematic

Variable, and Mixture, yet the most common ones are Normal, Trend, Cycle and Shift. Data used for training of NN include experimental data, simulation data and actual data. Pham and Wani [7] and Al-Assaft [18] used experimental data in training of NN in their research, while Guh and Hsieh [16] and Pham and Sahran [19] applied both experimental data and simulation data in NN training. In contrast, Cheng [8], Guh and Tannock [15] and Perry [17] used only simulation data, whereas Guh [20] used only real data for training of NN. Most research results obtained demonstrated more than 90% accuracy, for example, Pham and Wani[7]'s pattern observation and recognition technique yielded as much as 99% accuracy, whereas Guh and Tannock[15]'s accuracy measurement of control chart pattern by NN found 95% accuracy for Normal pattern and 90% accuracy for Cycle pattern.

2.2 k-Nearest Neighbor Classification

The k-nearest neighbor (kNN) is one of the tools for pattern classification. It utilized the method of 'instance-based learning', in which the training data is memorized and the classification of a new record is done by comparing it to the most similar record. The training samples are described by n attribute and represent a point in and n-dimensional space. A kNN classifier classifies a new record by searching the pattern space for the k training samples that are closest to the unknown record. Euclidean distance is the most common index to define the similarity of the pattern. The Euclidean distance between two input represented in n-dimensional space $X_1 = (x_{11}, x_{12}, \ldots, x_{1n})$ and $X_2 = (x_{21}, x_{22}, \ldots, x_{2n})$ denoted by $d(x_1, x_2) = \sqrt{\sum_{i=1}^{n}(x_{1i} - x_{2i})^2}$

As the kNN relies on distance measurement, all input data should be normalized to prevent inputs with large value from outweighing inputs with lower value. In order to normalize numeric attribute A to v' which has the range between [0,1], Min-max normalization is calculated from , $v' = \frac{v - \min_A}{\max_A - \min_A}$ Where $\min_A$ and $\max_A$ are the minimum and maximum value of attribute A.

The kNN is capable of producing high accuracy model for complex decision. It is one of the most widely used classifier due to its good generalization and easy implementation [21]. However, this method is computationally expensive [22] and calculations time is usually long. Several works have been reported in using kNN for control chart pattern recognition. For instance, He and Wang [10] proposed the adaptive kNN rule called fault detection method using kNN rule (FD-kNN) for fault detection in statistical process monitoring for semiconductor manufacturing process. However, the FD-kNN constructed only from the learning sample without assumption on their distribution so later on, Verdier and Ferreira [11] proposed a new adaptive distance for kNN rule for fault detection in semiconductor manufacturing. The results suggested that this new rule is more reliable than the Euclidean distance as it takes into account the local structure of dependence of the variables.

2.3 Rule Induction

Rule induction is one of the machine learning or artificial intelligence techniques. Rule learners have been adapted from decision tree learning by growing a complex tree, which overfits the data and then utilize pruning algorithm to simplify the tree. Rule induction algorithm implemented in this work is similar to the Repeated Incremental Pruning to Produce Reduction (RIPPER) by Cohen [23] which is the improvement of IREP

(Incremental Reduced Error Pruning) by Fürnkranz and Widmer [24].

RIPPER consists of two phases, growing phase and pruning phase. In growing phase, Starts with empty ruleset, RIPPER iteratively adding rules to the ruleset until all positive examples are covered. Rules are greedily added to ruleset until 100% accuracy is achieved. Every possible value of each attribute is tried and the condition with highest information gain is selected. In the pruning phase, pruning metric $\frac{p}{p+n}$ is used. The algorithm grows and prunes rules until there are no positive examples left or the error rate is greater than 50%.

Industrial application of rule induction for classification purpose has been reported. For example, Markham et al. [25] used a rule induction approach, specifically CART algorithm, to determine the number of kanbans in a just-in-time production system. The results suggested that CART was able to accurately predict the number of kanbans. Arinze et al. [26] used rule induction to improve forecasting accuracy. In their work induced rules were created from time series training data sets to predict the most appropriate forecasting method. Though applications of rule induction in industries have been reported, there was no report on the application of this technique in control chart pattern recognition.

3. RESULTS AND DISCUSSIONS

Research methodology is summarized in Figure 2. Starting with data collection, Actual Bore Hole Diameter measurement data were collected from the quality control department in the case study company. Three types of product were involved in the data collection process but due to the commercial confidentiality, the 3 products thereafter called product X, product Y and product Z. Then patterns were generated for model training and testing. Training data was used for model construction and testing data was used to test the model accuracy. Data for training was simulated separately between Upward-Downward Trend, Upward-Downward Shift, and Cycle pattern. While mixing of patterns were generated for testing purpose. The experimental results are explained as follows:

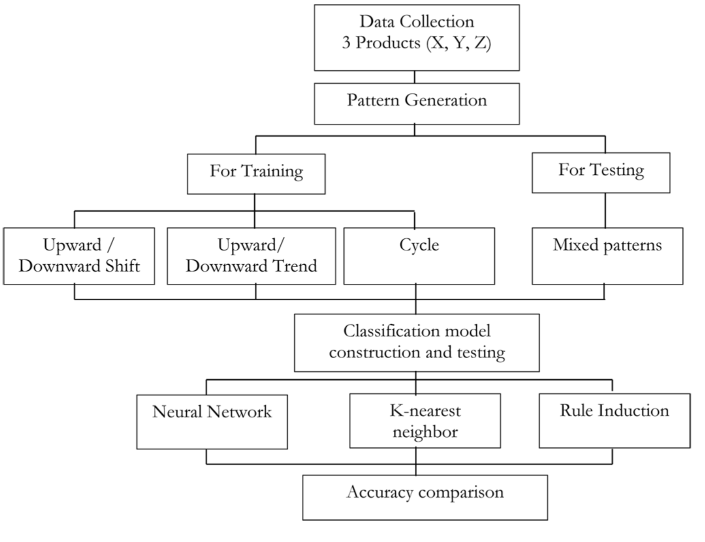

Figure 2. Research Methodology

3.1 Training and Testing Data Preparation

The data collected were prepared by firstly, calculated the average and standard deviation of the data. Then the mean and standard deviation of the actual data were used to simulate training data from the Equation below:

$$x(t) = A(t)+d(t) \tag{1}$$

Whereas $A(t)$ represents the real data obtained from the case-study factory, t is a time variable, $x(t)$ is the data at time t and $d(t)$ represents an error pattern at time t (which equals 0 when error is not detected).

Calculation of $d(t)$ for different error patterns is described as:

- Shift pattern: $d(t) = us$ when u is a variable for position of shift (u= 0 before a shift, u=1 after a shift) and s represents the magnitude of the resulting shift ($-0.2\sigma \leq s \leq +2.5\sigma$).

- Trend pattern: $d(t) = d\,t$ when d is the slope of the trend ($-0.22\sigma \leq d \leq +0.22\sigma$).

- Cycle pattern: $d(t) = a \sin(2\pi t/\Omega)$ when a represents the amplitude of cycle ($1.0\sigma \leq a \leq 2.5\sigma$), and Ω is the period of the cycle.

After data with nonrandom pattern were simulated, A corresponding function graph needs to be plotted (Figure 3), and then its pattern was observed for error. Figure 3 shows different pattern in control chart for training of three techniques; Upward-Downward Trend, Upward-Downward Shift, Cycle and Normal. The X-axis represents the number of each of 36 data entries: the Y-axis represents the length of Bore Hole Diameter.

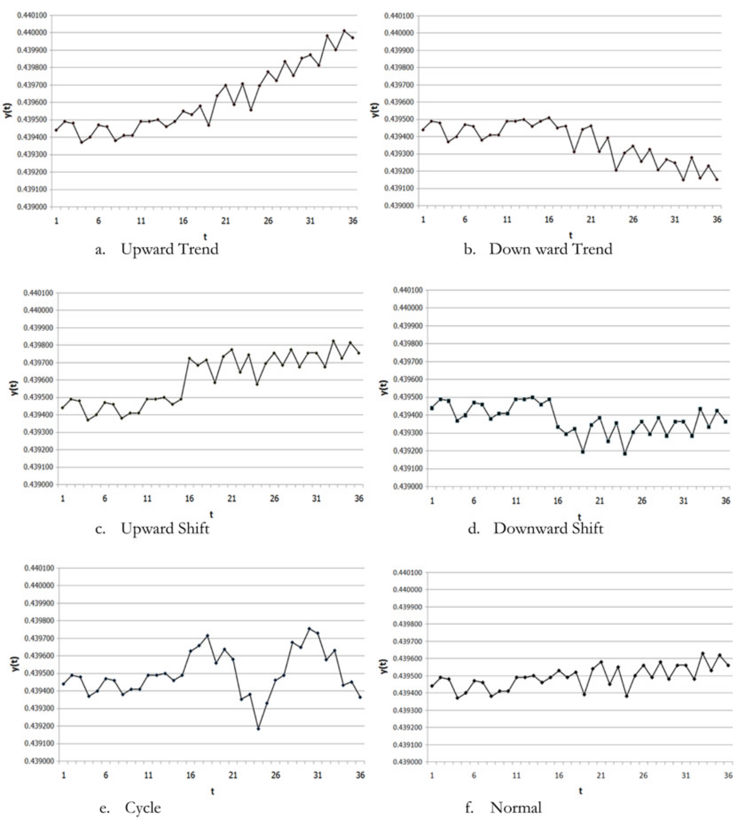

Figure 3. Examples of graphs plotted for different data types of product X used in training of neural network

Another set of data were simulated for testing of model performance. A corresponding function graph (Figure 4) was plotted, and its configuration was analyzed as to whether or not a nonrandom pattern was detected. Figure 4 shows nonrandom data of product X, used for testing of accuracy. The X-axis represents the number of each of 144 data entries: the Y-axis represents the length of Bore Hole Diameter. It is observed that simulation of nonrandom data for testing of three techniques' accuracy is described as Normal, Increasing Trend, Shift, Normal, Cycle, Normal, Shift, Normal and then Decreasing Trend, respectively.

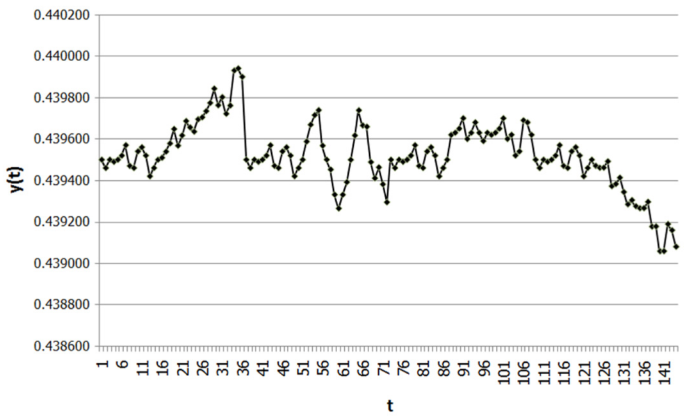

Figure 4. Plotted graphs showing error patterns of product X for testing of accuracy

3.2 Models Construction

Simulation data were used to construct models using three techniques; NN, kNN and Rule Induction.

3.2.1 Models input and outputs

Inputs of artificial intelligence techniques were data of Bore Hole Diameter from control charts. 6, 9 and 12 input data, called "Window Size," are subject to continuous measurement of this experiment. For example, Window Size of 12 refers to a sequence of 12 data entries such as (X_1, X_2, X_3, X_4,..., X_{12}). After the first 12 inputs were investigated, the new data input will queue up after X_{12} term, which subsequently becomes the X_{12} as the first data term (X_1) of the existing series was discarded. The new set of 12-data series continues to be detected for error, as shown in Figure 5. The cycle of error measurement then repeats until all data were investigated.

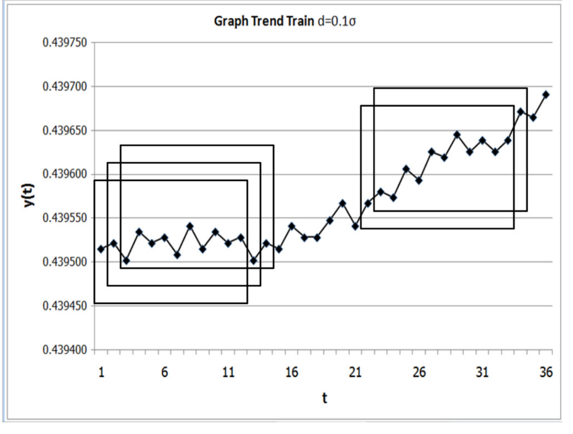

Figure 5. Window size of 12 data entries

Figures 4 shows Window Size of 12 data entries for product X. Each series of 12 historical data were processed at a time. These data entries, in turn, become inputs in Alyuda NeuroIntelligence Program for NN which operates as pattern recognition program for artificial intelligence techniques, and become inputs in Rapid Miner Program which operates as pattern recognition program for k-nearest neighbor and rule induction techniques.

Outputs were 4 types of error formats – Normal, Trend, Cycle and Shift pattern. Outputs of pattern recognition of NN are coded, such as 1000 denotes a Normal pattern; 0100 for Trend; 0010 for Cycle, and 0001 for Shift pattern.

3.2.2 Neural network model

Exhaustive Search was conducted identify number of the hidden layers and hidden nodes. The number of hidden layers was searched between 1-3 hidden layers, given that the lowest possible PE for each layer is 1, and the highest possible PE is 25. Part of the search results is demonstrated in Table 2.

Table 2. Example of appropriate architecture for neural network from alyuda neuroIntelligence program, in case of 6-data series for product X

Architecture	Number of Weights	Fitness	Train Error	Validation Error	Test Error
6-1-4	15	2.270833	0.548004	0.555046	0.559633
6-2-4	26	2.626506	0.610572	0.610092	0.619266
6-3-4	37	3.353846	0.727077	0.720183	0.701835
6-4-4	48	3.963636	0.765912	0.761468	0.747706
6-5-4	59	3.253731	0.734628	0.715596	0.692661
6-6-4	70	3.758621	0.77562	0.747706	0.733945
6-7-4	81	3.57377	0.79288	0.788991	0.720183
6-14-20-4	482	6.290323	0.960432	0.841026	0.841026
6-15-20-4	509	6.964286	0.972422	0.871795	0.85641
6-16-20-4	536	8.125	0.978417	0.866667	0.876923
6-17-20-4	563	10.263158	0.96283	0.85641	0.902564
6-18-20-4	590	5.416667	0.972422	0.871795	0.815385
6-19-20-4	617	8.125	0.977218	0.871795	0.876923
6-20-20-4	644	6.964286	0.991607	0.876923	0.85641
6-7-10-9-4	268	5.069767	0.87918	0.848624	0.802752
6-8-10-9-4	285	3.353846	0.824164	0.770642	0.701835
6-9-10-9-4	302	4.541667	0.924488	0.844037	0.779817
6-10-10-9-4	319	4.36	0.867314	0.825688	0.770642
6-11-10-9-4	336	4.541667	0.891046	0.844037	0.779817
6-12-10-9-4	353	4.844444	0.901834	0.834862	0.793578
6-13-10-9-4	370	4.954545	0.898598	0.816514	0.798165

From Table 2, the number of weights is the number of all weight connection. If number of hidden layers and nodes are increase, the number of weights will consequently increase due to the increasing in number of connections between neurons. As for the Fitness value, the Alyuda NeuroIntelligence Program provides the following explanation – "Fitness is calculated using network error on the test set and unit penalty, Unit penalty is a parameter that specifies a percentage of dataset to use by feature selection algorithm." Train Error refers to the error resulted from data used for the training of NN. Validation Error represents the error resulted from the data used for validation – preventing an 'overfitting' during the training. Test Error is the error occurred after the training process of NN terminates. The Fitness value is used to determine the optimal hidden layer; the higher Fitness value signifies the better hidden layer. Therefore, in considering the optimal hidden layer of product X according to the analysis of 6-data series of Alyuda NeuroIntelligence software, it is found that the optimal hidden layer is the second layer with 6-17-20-4 formation and Fitness value equaling 10.263158, which is the highest among all other hidden layers. The same rule applies to product Y and Z, and their results are presented in Table 3. The four numbers in Table 3 represent number of hidden nodes in the input, first hidden, second hidden, and output layer respectively.

Table 3. Optimal architecture design of neural network for each product type

Type of Product	Number of node in each NN layer		
	Window Size = 6	Window Size = 9	Window Size = 12
X	6-17-20-4	9-13-13-4	12-18-8-4
Y	6-20-9-4	9-20-19-4	12-18-19-4
Z	6-18-16-4	9-19-9-4	12-14-14-4

3.2.3 K-Nearest Neighbor model

The same data set used for NN training is used to construct kNN model. Several parameters has to be set before constructing the model. The number of nearest neighbor, *k,* was set to 1, the measure type was set to be mixed measure using mixed Euclidean distance.

3.2.4 Rule induction model

Rule induction model was developed using Rapid Miner Software with the same data set used to train NN and kNN. Several parameters need to be specified in the learning process. Firstly, Criterion used for selecting numerical split was information gain. Secondly, 'Sample ratio' of training data used for growing and pruning was set to 0.9. Next, 'Pureness' which is the necessary amount of major class in a covered subset in order become pure, was set to 0.9. Finally 'Minimal prune benefit' or the minimum amount of benefit which must be exceeded over unpruned benefit in order to be pruned was set at 0.25.

3.3 Model Accuracy Comparison

Another set of data was simulated for Normal, Trend, Cycle and Shift patterns, in order to assess the accuracy of three techniques. The models accuracy were measured using the following equation

$$\text{Percentage accuracy} = \frac{\text{Number of correctly classified data}}{\text{Number of total data}} \times 100 \quad (2)$$

The historical data used in training of NN – 6-data, 9-data, and 12-data series – is then compared for each product type in order to conclude as to how much historical data is needed to achieve the highest possible accuracy. Models accuracy was summarized in Table 4.

Table 4. Model accuracy of the three classification techniques at three window size.

Product Name	Neural network			K-nearest neighbor			Rule Induction		
	6 input	9 input	12 input	6 input	9 input	12 input	6 input	9 input	12 input
X	79.86	88.24	91.73	96.26	96.03	97.44	84.32	85.59	85.49
Y	82.73	88.24	84.21	96.47	96.99	96.84	85.54	83.01	86.77
Z	87.77	94.85	90.23	98.06	98.38	98.57	84.10	90.66	87.52

From table 4, model accuracy depends largely on window size. This is especially true in NN model where the accuracy alter significantly with window size. For product X, the highest accuracy NN model is at window size of 12 at 91.73%, while kNN achieved the highest at 97.44% at window size of 12 and rule induction at 85.59% at the window size of 9. As a result, kNN model has the highest accuracy. Similar results can be observed in product Y and Z that kNN has the highest accuracy at 96.99% and 98.57% respectively.

4. Conclusions

The main purpose of this research is to explore the application of classification techniques; Neural network, k-Nearest Neighbor and Rule Induction in pattern recognition for detection of nonrandom patterns such as Trend, Cycle and Shift. The Window Size variables set in this experiment are sequences of 6-data, 9-data and 12-data, and 4 types of observable pattern are Normal, Trend, Cycle and Shift. Actual data of 3 products from a case study company was combined with the simulated nonrandom patterns. It is found that the accuracy of the model depends largely on window size and the model with the highest accuracy is the model trained with kNN techniques.

The three techniques used in this research have certain advantages and limitations. NN has the ability to detect complex nonlinear relationships between input and output parameters with less statistical assumption. However, it suffers from its 'black box'-like properties, in which the relationship between input and output parameters cannot easily be explained. NN also prone to over fitting and the training process is slow as numbers of parameters affecting network performance need to be tried in trial and error fashion. kNNs are simple to understand and easy to implement. However, kNN can be slow for large training examples and sensitive to irreverent parameters. Rule induction, unlike NN and kNN, can be used to describe complex data with relatively simple rules that are easy to understand. Limitation of rule is that it does not perform well with noisy data.

The case study has demonstrated that the proposed method can be used with actual data. However, the current system implemented is stand-alone system which is not linked to the company database. To further enhance the performance of the system, it should be linked to the company database so that the detection in online mode is possible.

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