

AUTOMATIC CLASSIFYING METHOD FOR WEDGE TIGHTNESS BY SUPPORT VECTOR MACHINE AND ARTIFICIAL NEURAL NETWORK

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Abstract

This study proposed an automatic classifying system for the tightness of a generator's wedge. It consists of 4 processes called data collection, preprocessing, feature extraction, and classification. The aim of this study is to classify and verify the tightness of a generator's wedge for the Electricity Generating Authority of Thailand by using 2 machine learning algorithms called support vector machine (SVM) and artificial neural network (ANN). The linear function and radial basis function (RBF) are selected for the SVM classifier. The evaluation of the SVM classifier is completed by using a 10-fold cross validation technique to give high accuracy and a low number of false negatives (FN). From the simulation results, the efficiencies are above 90% in the time domain and the frequency domain, which are satisfactory for classification. By comparison, the signals extracted in the frequency domain have fewer FN than the time domain. The ANN gives the best performance among the classifiers in the time domain (93.75% for the ANN, 92.34% for the SVM with the linear function, and 91.38% for the SVM with the RBF) and the frequency domain (100% for the ANN, 100% for the SVM with the linear function, and 99.47% for the SVM with the RBF).

Keywords: Wedge tightness signal, support vector machine, artificial neural network, classification

Introduction

Nowadays, the use of electricity is increasing rapidly around the world due to the exponential growths of new technology and of populations. Electricity is involved in all daily activities such as in industries, hospitals, and houses. Therefore, more usage of power plants is needed to support

the demands of users. The information about a generator, such as the tightness of a generator's wedge, is very important to evaluate the safety of the generator. Traditionally, human judgment has been used to determine the wedge performance inside a generator by inspection and evaluation.

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A human can check the wedge tightness by tapping with a hammer, feeling for vibration, listening to the sound with trained ears, and recording the degree of looseness on a chart. A tight wedge has very little vibration and a hard ringing sound. On the other hand, a loose wedge has noticeable vibration and a very hollow sound (Klempner and Kerszenbaum, 2004). This method is very subjective because it depends on the individual judgment of an operator by hearing the sound from the wedge. However, it consumes both time and cost because the rotor in the generator has to be removed and the generator needs to be shut down during the operation. Hence, robots have been used instead of humans to determine the wedge performance, which is cost efficient because the rotor does not need to be removed during the operation. George *et al.* (1996) introduced the testing of the stator wedge tightness in an electrical generator that contains a vibration sensor attached to the stator core lamination and a mounting system for mounting the base assembly to the impact assembly. At first, the robots used for generators in Thailand were imported robots. However, such robots are very expensive and too big for some generators in Thailand. Therefore, the Electricity Generating Authority of Thailand (EGAT) plans to develop its own robot that is both smaller and has a lower cost. The robot also is required to automatically classify the wedge performance of a generator.

The task of a robot can be divided into 2 main functions including the wedge tapping control and the automatic analysis of the wedge tightness system. The wedge tapping control is used to adjust the tapping pattern of the robot to be a single, periodic, or repeating pattern. The wedge tightness signals are analyzed afterwards. There are 4 steps to analyze the wedge tightness signals including data collection, preprocessing, feature extraction, and classification.

Data collection provides the raw data received by the robot to illustrate the wedge inside the generator. Preprocessing refers to improving the raw data's quality, including filtering and noise cancellation. Feature extraction reduces the pattern vector to a lower dimension and keeps the useful information from the derived vector,

called the feature vector. Classification takes the feature vector as an input to define the tightness of the wedge by placing the feature vector into the most appropriate class (Tohka, 2013). Many classification methods have been applied to the system such as the nearest neighbor classifier, wavelet transform, probabilistic classification, and multiclass classification.

The SVM classification is an alternative way for pattern recognition by using the separation on the hyperplane (decision boundary) to distinguish data diversity. The ANN classification is a machine learning algorithm to teach, recognize, and remember different traits. The ANN also has low computation loads, and flexibility for pattern recognition. A computational neuron can produce either a linear or non-linear input which allows the network to learn efficiently. The ANN is configured for a specific application such as pattern recognition or data classification through a learning process. There are many research works using the SVM and ANN for classification such as cardiac auscultation analysis, a screening system to diagnose disease from heart sounds in a digital format (Phatiwuttipat *et al.*, 2011). The SVM and ANN classification methods also are used for analyzing construction materials with ultrasonic waves to find the number of defects, and the results are very accurate (Saechai *et al.*, 2012). The objective of this work is to develop an automatic classification system for determining the tightness of a generator's wedge.

This study is beneficial for identifying the tightness of a generator's wedge in a power plant. A brief description of the SVM and ANN classifiers, the methodology, and the comparison between both the classification results are discussed in the following sections.

Material and Methods

System Configuration

In the experiment, Figure 1 illustrates the robot developed by the National Electronic and Computer Technology Center (NECTEC) that is 180-300 mm wide, 300 mm long, and 20 mm thick. The developed robot is cheaper than the cost

of an imported robot (about 250000 dollars).

The overall robot system is shown in Figure 2. The control box acts like a brain and nervous system and is responsible for controlling and linking all functions into the entire system, including movement of a camera, movement of the robot, and the wedge tapping. The display monitor is used for monitoring each activity in the system including the video camera, the wedge's result, the position of the robot, and the graphical user interface. The joystick is used for controlling the direction of the camera, the

movement of the robot, and the tapping pulse. The robot connects to the control box via a cable. This study focuses on the wedge tightness signal analysis.

The raw data of the wedge tightness signal obtained from the robot goes through the process called "automatic analysis of wedge tightness system" in order to classify the data. The block diagram in Figure 3 illustrates the signal processing part of the wedge tightness signal.

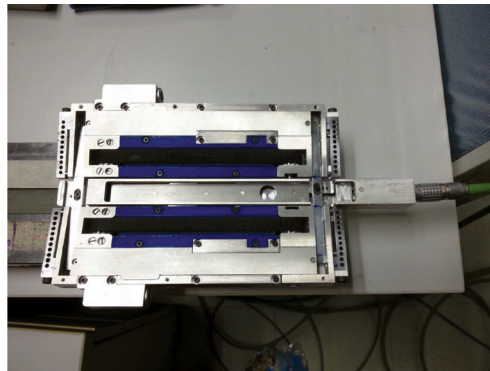


Figure 1. Developed robot for testing

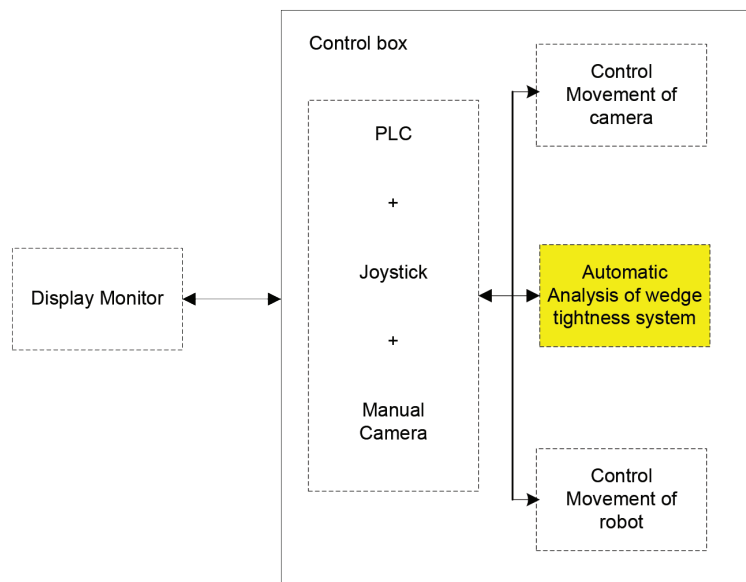


Figure 2. Overall robot system

Data Collection

Data collection comes from the robot tapping on the generator and receiving a reacted signal back. “Signal conditioning” is used in order to focus and make the signals even clearer. A data acquisition system is used to convert analog data samples from the robot into digital numeric values to plot a graph (Figure 4). Figure 4(a) and Figure 5(a) show the tight wedge data signal and the loose wedge signal, respectively. The real

raw data is obtained from the board calibration, which has 20000 sampling points. The robot taps every 100 ms and each sampling point has a time interval of 50 μ s.

In this experiment, there are 240 inputs for each wedge signal (tight and loose). The inputs have been reduced to 2000 sampling points to extract only the significant parts. The 2000 sampling points of the tight wedge signal and loose wedge signal are shown in Figure 4 and Figure 5, respectively.

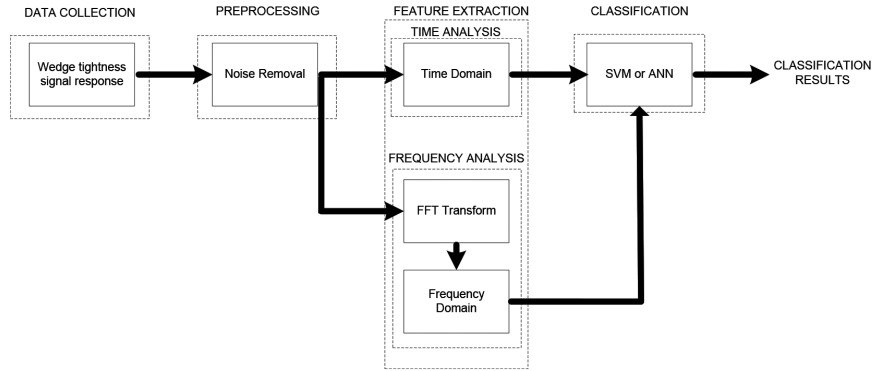


Figure 3. Block diagram of signal processing part

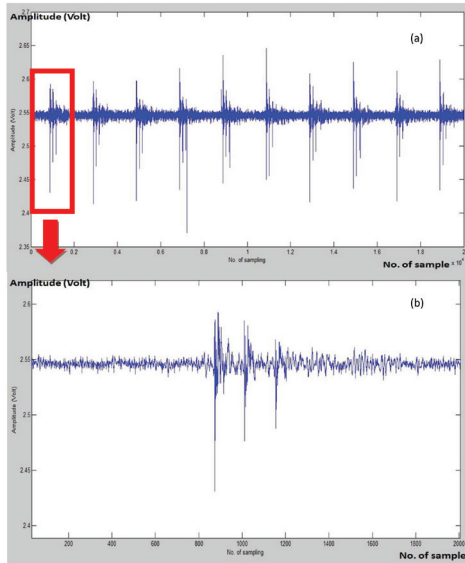


Figure 4. a) The original sampling points of tight wedge signal b) The 2000 sampling points of tight wedge signal

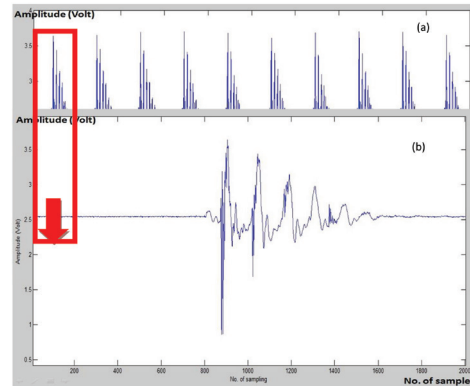


Figure 5. a) The original sampling points of loose wedge signal b) The 2000 sampling points of loose wedge signal

Preprocessing

Preprocessing is used for the preparation of the signal. Preprocessing refers to operations performed on the raw data to improve the quality, such as filtering and noise cancellation. The wedge tightness signal response is reduced by using a threshold to capture the significant part. The threshold is set to 2000 sampling points to remove the unwanted parts of the signal.

Feature Extraction

Feature extraction extracts the significant features from the raw data. A fast Fourier transform (FFT) algorithm is used for feature extraction in the frequency domain. The FFT is a very useful tool for signal analysis to obtain the features for classification (Kim *et al.*, 2012). The FFT is computed in the same way as the discrete Fourier transform (DFT) by letting $x_0, \dots, x_{N-1}$ be complex numbers. The DFT can be defined by the formula as follows:

$$X_k = \sum_{n=0}^{N-1} x_n e^{-i2\pi k \frac{n}{N}}$$

where $k = 0, \dots, N-1$

By contrast, the FFT takes approximately $N \log_2 N$ operations which mean it is faster than

the DFT, which takes approximately N^2 operations. There are 2 methods used in this experiment to obtain the input features of classifiers as follows:-

i) Time domain classifier: 2000 data points in the time domain are used in this experiment, as shown in Figure 6.

ii) Frequency domain classifier: 2000 data points are transformed to the frequency domain by using the FFT, as shown in Figure 7.

Classification

The input sample is separated into 2 classes including 120 tight wedge data signals and 120 loose wedge data signals. The classification methods used in this experiment are the SVM and the ANN.

Support Vector Machine (SVM)

The SVM is one of the important models for pattern recognition and classification. The main concept of the SVM is to transform an input signal into feature space and divide the clear gap between classes with an optimal hyperplane (decision boundary) and maximum margin (support vector) (Avci 2009), as shown in Figure 8 (Chatunapalak *et al.*, 2012). Since most of the data are non-linear and non-separable, a kernel function is used for mapping a non-linear input space into a linear space (higher dimensional feature space) to perform the separation (Ahmad *et al.*, 2004). Figure 9 illustrates how to transform a non-linear data point to a higher dimensional feature space by using the SVM with a kernel function.

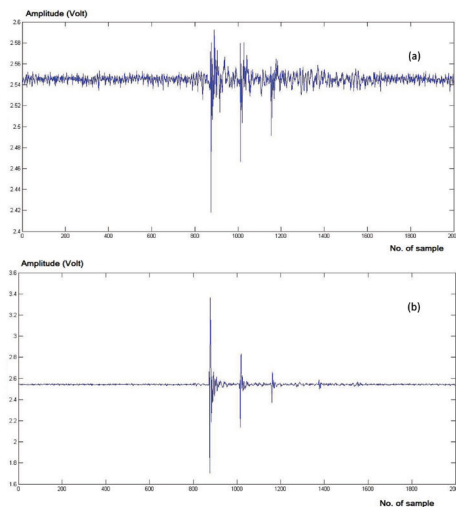


Figure 6. a) Tight wedge signal in the time domain
b) Loose wedge signal in the time domain

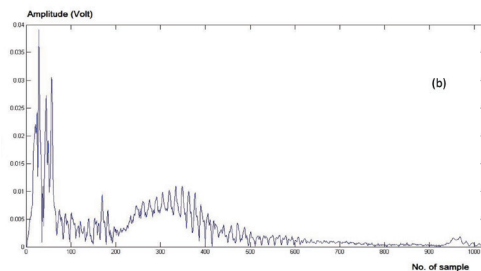


Figure 7. a) Tight wedge signal in the frequency domain
b) Loose wedge signal in the frequency domain

Many kernel functions are used for the SVM classifiers such as the linear, polynomial, RBF, FFT, etc. The kernel parameters in a kernel function must be set properly to maximize the accuracy of the SVM classification. This study selected the linear and RBF kernels for the SVM classification.

The SVM classification trained and evaluated the input samples with a data splitting method. The training and testing samples generally split into 90% and 10% of the input samples for each class, respectively. The input, training, and testing samples are provided in Table 1. The binary classifications of the SVM are implemented for classification. Each data input is prepared in the form of a row vector. Then, all the data inputs are added together to generate a vector of size $v \times u$ where v represents the number of input samples. Each input sample contains columns of features (2000 features), as shown in the formula as follows:

$$\begin{bmatrix} a_{1,1} & \dots & a_{1,u} \\ \vdots & \ddots & \vdots \\ a_{v,1} & \dots & a_{v,u} \end{bmatrix}_{v,u}$$

The output of a wedge tightness signal depends on the data class. The numbers 1 and 0 are set as a target for class 1 and class 2 (tight and loose wedge), respectively. The output vector for binary classification is presented as follows:

$$\text{Class 1} = \begin{bmatrix} 1 \\ 0 \end{bmatrix} \quad \text{Class 2} = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$

The proper kernel function is selected to train the non-linear SVM classifier. The linear and RBF kernels are used to train the classifiers and test the results because the RBF kernel has good classification according to many studies. The RBF kernel gives a high classification performance in this study. Ten-fold cross validation is applied for classification, as shown

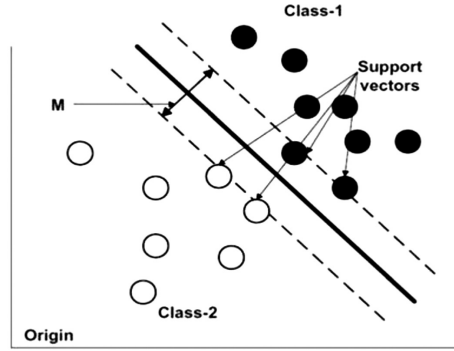


Figure 8. Basic concept of support vector machine

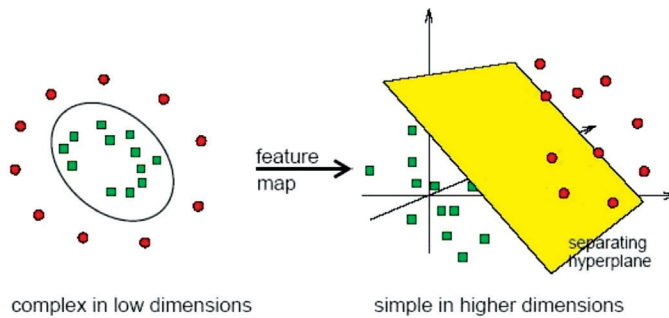


Figure 9. Transformation of non-linear data points to higher dimension linear space

in Figure 10. The datasheets are randomly divided into 10 subsets. Each subset is constructed and trained by using 9 out of 10 (90%) subsets and tested 1 out of 10 (10%) to obtain a cross validation estimate of its error rate. The process is repeated in the same steps for 10 subsets and averaged for classification accuracy from all the data (Delen *et al.*, 2005). The proposed SVM classification used MATLAB for simulations.

Artificial Neural Network (ANN)

An ANN, usually called a neural network, is a good technique for determining pattern recognition. The main concept of an ANN is inspired by the animal nervous systems (brain), which is composed of a large number of highly interconnected processing elements (neurons) working to solve specific problems through a learning process. The learning process of the ANN includes adaptive learning, self-organization, real-time operation, and fault tolerance. The ANN uses the back-propagation model to solve non-linear signals.

The back-propagation model is a feed-forward multi layered ANN that allows a signal to travel 1 way from input to output with no feedback (loops). Figure 11 illustrates the back-propagated model of the ANN. According to Figure 11, the ANN network consists of 3 layers including the input layer, hidden layer, and output layer. The input layer represents the raw data fed into the network as an input, which forwards to the hidden layer. The hidden layer consists of neurons for solving a complex problem by calculation, and forwards the result into the output layer. The output layer takes the results from the hidden layer, performs a calculation, and gives the final result.

The input samples and classes are the same as the SVM. MATLAB is used to train, validate, and test for neural network pattern recognition protocol by selected input and target. Training, validation, and testing are set to 85%, 5%, and 10%, respectively to maximize the accuracy of the ANN classification by providing a large group of training sets. The number of hidden neurons is set to 10 to minimize

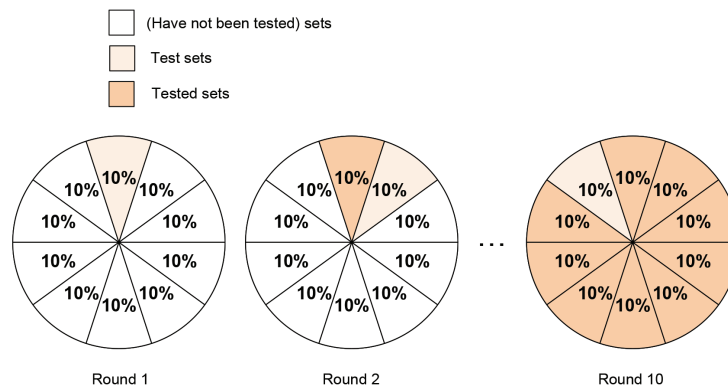


Figure 10. Ten-fold cross-validation procedure

Table 1. Classification results in the time domain

Methods	Kernel Function	TP (%)	FP (%)	FN (%)	TN (%)	PPV (%)	NPV (%)	Sensitivity (%)	Specificity (%)	ACC (%)	Training time (S)
ANN	-	46.25	5	1.25	47.51	90.55	97	98.24	90.52	93.75	2.000
SVM	Linear	48.04	5.71	1.97	44.31	89.4	95.79	96.08	88.59	92.34	7.460
	RBF	48.03	6.66	1.98	43.34	87.84	95.69	96.1	86.67	91.38	3.857

the training time of the ANN classification.

Results and Discussion

Each raw wedge tightness signal is preprocessed and its features extracted to obtain the input features for the classifier. The number of total input samples, training samples, and testing samples are mentioned in a previous section. The trained classifier is evaluated by test samples. The classification accuracies are analyzed by using 2 different types of input features from the data that were obtained in the time domain and frequency domain. The efficiency of each single classification is obtained by a 2×2 confusion matrix. The confusion matrix is a table that shows the performance of the algorithm. An example of a confusion matrix is shown in

Figure 12. The first and second rows represent the data with a target tight wedge and loose wedge, respectively. The first and second columns represent the predictor of a tight wedge and loose wedge, respectively. True positives (TP) are the number of tight wedges which are correctly classified. False positives (FP) are the number of loose wedges which are misclassified from tight wedges. True negatives (TN) are the number of loose wedges which are correctly classified, and false negatives (FN) show the number of tight wedges which are misclassified from loose wedges. Positive predictive value (PPV) and negative predictive value (NPV) are the rates at which the predictor can give a correct classification for the tight wedge and loose wedge, respectively. Sensitivity and specificity are the correctness predictions for the tight wedge and loose wedge,

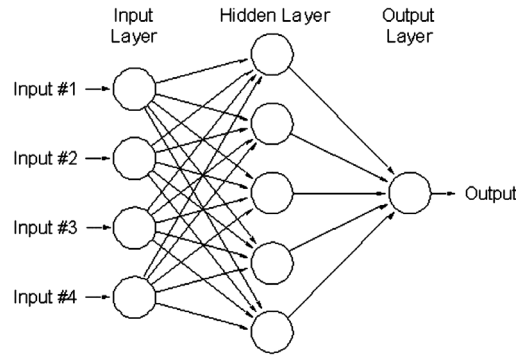


Figure 11. Back-propagation model of artificial neural network

	Condition positive	Condition negative	
Test outcome positive	True Positive (TP)	False Positive (FP)	Positive Predictive Value (PPV) $\frac{TP}{TP+FP}$
Test outcome negative	False Negative (FN)	True Negative (TN)	Negative Predictive Value (NPV) $\frac{TN}{FN+TN}$
	Sensitivity $\frac{TP}{TP+FN}$	Specificity $\frac{TN}{FP+TN}$	Accuracy $\frac{TP+TN}{TP+FP+FN+TN}$

Figure 12. Example of 2×2 confusion matrix

respectively. The accuracy value (ACC) is the average accuracy in the classification tables. All values in the tables are the average classification accuracies of 10 confusion matrices.

Time Domain Analysis

The result of the classification algorithms for the wedge tightness signal in the time domain is shown in Table 1 including the SVM (linear function and RBF) with the kernel functions and ANN classifier.

From Table 1, the value of specificity in the time domain between 2 classes (tight and loose wedge) is classified. The ANN has a correctness prediction in the tight wedge or sensitivity of about 98.24%, which performs better than the SVM in both the linear function (96.08%) and RBF (96.1%). The correctness prediction in the loose wedge or specificity also increases by using the SVM with the RBF (86.67%), the SVM with the linear function (88.59%), and the ANN (90.52%), respectively. In comparison, the SVM with the RBF kernel function has an accuracy of about 91.38% which is worse than that of the SVM with the linear function (92.34%), but has a twice faster average training time than that of the linear function. The training time of the linear function performs slower than the RBF because the data type of the wedge tightness is relatively small. The training time also depends on the group of data. From the results, the ANN classifier provides the best efficiency, compared with both the SVM (linear function and RBF) classifiers in the time domain. However, a false negative is very important for wedge tightness because the misclassification of a loose wedge can cause uncertainty in a generator. Since FN still exist in the time domain (1.25% for the ANN, 1.97% for the SVM with the linear function,

and 1.98% for the SVM with the RBF), frequency domain classification is applied to decrease the number of FN.

Frequency Domain Analysis

The classification result in the frequency domain is shown in Table 2 including the SVM (linear function and RBF) with the kernel functions and ANN classifiers. From Table 2, the number of FN for the SVM with the RBF is 0.08%, which is the worst classification, compared with the other methods. The number of FN in the ANN and SVM with the linear function is reduced to 0%, which is a perfect classification for wedge tightness. The sensitivity and the specificity of the ANN and SVM with the linear function are 100% which means all predictions of the tight wedge and loose wedge are correct. The training time decreases when using the SVM with the linear function (11.182s), the SVM with the RBF (7.095s), and the ANN (2s) methods.

Conclusions

The automatic classification method for wedge tightness by the support vector machine and artificial neural network provides good recognition and classification results in the frequency domain. The classification results show that the ANN classification method has the best performance with the highest accuracy, sensitivity, and specificity with the shortest training time. The results show that the frequency domain signal has more accuracy than the time domain signal. By comparison between the 2 SVM methods, the linear function provides a better solution in terms of accuracy, but consumes more time than the RBF does.

Table 2. Classification results in the frequency domain

Methods	Kernel Function	TP (%)	FP (%)	FN (%)	TN (%)	PPV (%)	NPV (%)	Sensitivity (%)	Specificity (%)	ACC (%)	Training time (S)
ANN	-	56.67	0	0	43.33	100	100	100	100	100	2.000
SVM	Linear	50	0	0	50	100	100	100	100	100	11.182
	RBF	49.92	0.46	0.08	49.55	99.12	99.84	99.84	99.09	99.47	7.095

For further study, binary-classification (tight or loose wedge) from this experiment may not be sufficient to identify a suspected loose wedge in a generator in a real environment. The multi-classification technique can be developed in the future to predict how many degrees of looseness there are in a suspected loose wedge for a generator. For instance, a multi-class support vector machine has been used by an automatic screening method to detect glaucoma for early treatment and preserve eyesight (Vejjanugraha *et al.*, 2013). Moreover, the automatic classifying method for wedge tightness needs a graphical user interface for ease of use and understanding.

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