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Research Article

Identify and Classify Vibration Signal for Steam Turbine Based on Neural Sleep Fuzzy System

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Abstract: Vibration in a steam turbine-generator is one of the many default problems, similar to thrust, crack and low or high speeds, all of which causes damage to the steam turbine if leaves unprotected. It leads to accidents and damages, when overcome the limit of alarm or danger zones. The protection of steam turbine generators from danger leads to reduced maintenances and augmented stability of power generation. The main proposal of this study is to identify and classify vibrations in alarm and shutdown zones, it is also intended to produce a smooth signal that can be used to adjust control value, which influences the vibration value during the start-up and power generation. We compared the series and parallel-connected Neural Network (NN) that is related to time and error to identify vibration acceleration signals and flow by sleep fuzzy sugeno system, which are designed and simulated in MATLAB. The results showed that parallel-connected NN is superior to its series-connected counterpart with vibration signals, where the Neural-Sleep-Fuzzy system and the NSFS robust system produces zero voltages when it lacks vibrations, more so after receiving a linear signal to influence nonlinear signals of vibration. This study concluded that the Artificial Intelligent (AI) system with sleep fuzzy sugeno system can be implementing to classify the fault of optimal vibration signal limitation and check the suitable treatment for this fault. Also, the analysis of results can conclude that using parallel NN is faster and more accurate compared to series NN connection.

Keywords: Neural-fuzzy, neural network, steam turbine, vibration

INTRODUCTION

A steam turbine is an intricate control system in a power plant used for adjusting power. Its control is based on an adjusted control valve within the required range (Chan *et al*., 2014). Vibration is a behavior related to a rotating machine, which is turned from factors such as multi-mass, multi-flexible shaft, centrifugal masses and the elasticity of a shaft (Broy and Sourkounis, 2014). The vibration signal has nonlinear characteristics. Vibrations on steam turbine are based on dominant components of the shaft's rotating speed and the harmonics of rotating speed (Yanbing *et al*., 2011).

A vibration signal has been collected from a sensor in the time domain and is transferred to frequency domain for it to be used with steam turbines in predicting faults that depended on Fast Fourier Transformer (FFT) technique**.** It seems that this technique analyzes a vibration signal to predict and display the faults of a turbine-generator system (Wentao *et al*., 2014; Yin *et al*., 2013). These signals can be employed with intelligent systems, such as NN or Fuzzy System (FS) (Marichal *et al*., 2010). NN with statistical methods can be used to classify, identify and show a system's health. Moreover, it is diagnosis of the fault for electric machines (Su *et al*., 2011). Fuzzy with an expert system can be used for the same purpose as well. These methods have been utilized with a vibration velocity in RMS form as an indicator of the health of a machine (McKee *et al*., 2015, 2011). FS was continued with two techniques utilizing fuzzy applications such as Takagi-Sugeno-Kang (TSK) and Mamdani Fuzzy Inference System (FIS) (Xie *et al*., 2010; Kangarani Farahani and Mehralian, 2013; Marichal *et al*., 2010); with each of them consisting of three parts;

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fuzzification, fuzzy rules and defuzzifiction bulk. Moreover, TSK is more suitable than the Mamdani system in nonlinear applications (Xie *et al*., 2010). An example of implementations of T-S fuzzy is its utilization in improving the dynamics of nonlinearity processing related to drum-type in steam turbine (Jia and Liu, 2014).

Artificial Neural Network (ANN): is a technique related to nonlinear enforcement that is vastly used in industries, science and businesses for prediction, clustering, identification and classification of signals and data. Moreover, the limitation of accuracy is designed based on the designer experiment and precision with an operation system. Furthermore, these networks are operating on schedule, as a supervised network and unsupervised or non-teaching network (Kangarani Farahani and Mehralian, 2013). Neuron-fuzzy is the combination between fuzzy and neural technique, producing a hybrid method called "neuron-fuzzy" system (Marichal *et al*., 2010; Xie *et al*., 2010; Abraham, 2003). Indeed, a neural fuzzy system is one type from AI, which is wisely applied with conventional and unorthodox ideas. Moreover, employing AI with different sciences predicts error, reduces noise and augments decision accuracy. The aim of this study is to simulation the fault diagnosis of the vibration signal in ST based on NSFS, moreover, NSFS output is modified to proportional with the vibration fault level which is system throughput can feed to control system.

LITERATURE REVIEW

In recent years, many investigators utilized intelligent networks such as NN in different implementations because it is more proper with the sciences. (Zhang *et al*., 2008) introduced the probability of neural networks PNN to identify and classify the vibrations of turbine rotors. The PNN inputs were a singular spectrum, power of the spectrum and spectrum of wavelet energy. This type of network showed that the accuracy for the classification of training was 100% while for the hidden it was 80% (Zhang *et al*., 2008). Another researcher used PNN algorithm to classify the fault of the machine during happen.

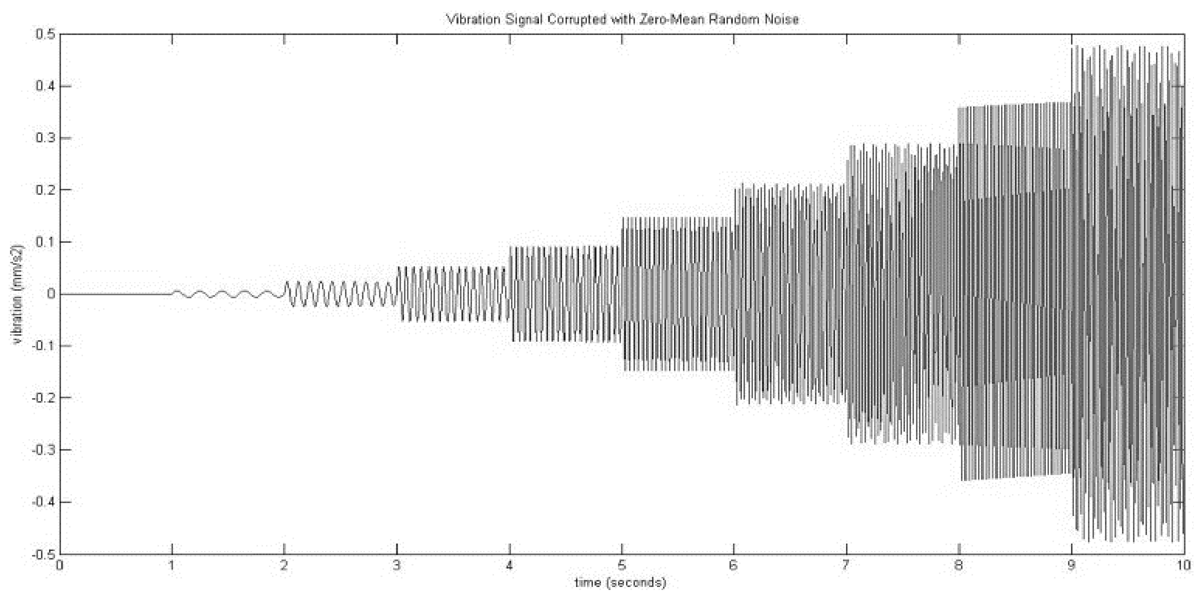
Thereafter, researchers demonstrated a mix of two intelligent methods, leading to increased accuracy of a system and unaugmenting of the error of the fault decision. They use the Adaptive Neural Fuzzy Inference System (ANFIS). Nguyen *et al*. (2015) summarized and realized a new algorithm based on a change in setting the value of membership, depending on the error results with clustering and building ANFIS. They have divided the work with three main steps; first, the data embodying rule for building clustering technique. Thereafter, ANFIS was implemented and eventually, the error value is tested if it is under the operation limitations, otherwise, fuzzy settings will be changed based on clustering (Nguyen *et al*., 2015). Al Mashhadany (2012) has presented the use of ANFIS for identification and control, which is based on the identity and control of the complex movement of robots (Al Mashhadany, 2012). Al Mashhadany (2013) used hybrid systems based on ANFIS to increase the qualification of the controllers' signal. He reduced the over shoot signal and the time it needs to get setup (Al Mashhadany, 2013). (Kazemian and Yusuf, 2014) have concentered on predicting tests of the membranes related to medicine (Kazemian and Yusuf, 2014). (Panda and Patro, 2013) designed a new controller system that is related to the temperature of dry gas. However, work increases the efficiency operations for boilers. Eventually, the investigators installed a new controller system in the power plant (Panda and Patro, 2013). Farhan *et al*. (2013) have compared three models of artificial intelligent network to predict gold prices. These models are the traditional neural networks, where NN with an output acted as the input to the same network and hybrid method neural- fuzzy network. The results showed that neural with FIS sugeno is better. Moreover, these results are designed based on the wavelet technique (KangaraniFarahani and Mehralian, 2013).

Accuracy and flexibility are two important factors, where the intention of the majority of the work in using neural with fuzzy as its AI system increases the facility of the network while adding some intelligent ideas for the purpose of making high precision decisions in controlling a system. Symbols utilizing AI can be shown with Rosa *et al*. (2013), where they have managed to approach the hybrid artificial method based on fusing neural and fuzzy systems. They have used non-uniform activation and sigmoidal functions. This hybrid method was utilized to predict the non-stationary signal for time series to molding and predictions (Rosa *et al*., 2013). Rong (2012) presented the fuzzy-neural method to control for an –n-link robot. They showed that the T-S fuzzy was adequate in obtaining the stability of a system from mamdani method with nonlinear signals. It seems that they used the Gaussians radial function of neural network and Gaussian function of the membership function MF of the fuzzy, which pushed the system through control to be more stable and reduce errors that might be present in the decisions. Moreover, the fuzzy-neural system is adaptive and modified based on the system parameters and experience of the designer (Rong, 2012). (Xie *et al*., 2010) designed a new technique that is related to the combination between fuzzy and neural techniques. However, the new method does not need the multiplication units that were used with traditional hybrid networks. Moreover, the new proposal is simpler than the traditional method in hardware enforcement (Xie *et al*., 2010). Fei *et al*. (2014) displayed a new technique by designing a multi-branch of NN and other methods based on the signals, causing the vibration of the steam turbine. The three types of networks are the back propagation network, wavelet network and radial basis network, all of which are connected in parallel. Data inputs to these networks are imbalance, misalignment rotor and oil whip. They showed that the technique improves vibration fault diagnosis in the steam turbines (Fei *et al*., 2014). (McKee *et al*., 2015) presented a procedure of detecting the vibration cavitation, which is based on the analysis vibration signal band and analysis statistical metrics. ISO 10816 is used with this study. Thereafter, the signal in the frequency domain has been classified and analyzed based on ISO 10816 (McKee *et al*., 2015).

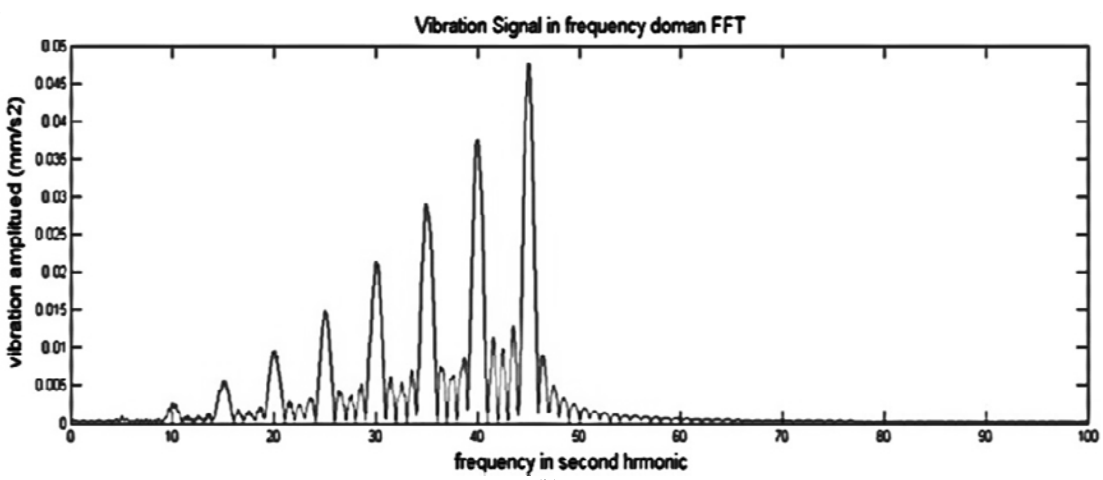
Eventually, Marichal *et al*. (2010) designed the hybrid method to detect the bearing vibration fault. On the surface and inure bearing, this method seemed conventional, but there is a slight alteration, where they utilized the concept of the category's frequency and used several stages from a neural fuzzy system to detect the vibration in the bearing, which is based on the divided the frequency range of the FFT signal to equate categories. Eventually, they applied the vibration signal to the first stage of the neuro-fuzzy technique, while the output of the first stage has been inputted into the second stage for detecting another type of bearing's vibration (Marichal *et al*., 2010).

ARCHITECTURES OF IDENTIFY THE VIBRATION BASED ON THE A NEURAL-FUZZY

This section will be concerned with the vibration signal modulated, neural network parameter, fuzzy design system and integrated intelligent system.



(a)



(b)

Fig. 1: (a): Vibration signal in time domain; (b): vibration signal result from FF network NN

Vibration signal modulated: Lately, many researches are concerned with cataloging and catching signals of a vibration that are related to machines having rotor parts based on intelligent methods. Moreover, researchers began to employ hybrid techniques for enhanced fault observation precision and augmenting the reliability of the controlling systems (Nopiah *et al*., 2015; Xiao *et al*., 2013; Londhe *et al*., 2014). In fact, the first step involves a vibration acceleration data being simulated for a steam turbine, as illustrated in Fig. 1a. The signals of a vibration were transferred to a frequency domain based on the FFT technique; thus, the vibration amplitude is based on the frequency of the machine. Figure 1b shows the FFT signal after being modulated (Marichal *et al*., 2010; McKee *et al*., 2015). Moreover, a vibration was simulated to show the frequency to be in the range between 0-100Hz and the machine operates in 3000rpm. Then, results display data as harmonic frequencies of 1X and 2X. Furthermore, a vibration appears in the 1X, but not in 2X. It seems that the FFT result is responding to the vibration for monitoring and analysis, but is unsuitable for signal control. However, we were processing the output of the FFT technique via an intelligent system to identify and classify a vibration during alarms. ISO 18062-2 has classified a vibration of the steam turbine-generator to three zones, which are AB, BC, CD (McKee *et al*., 2012, 2015). Actually, this approach was discussed and centered on the vibration in the BC zone, which is related to the alarm zone.

$$a = -A \sin \omega t$$

where,

- a : Acceleration vibration in time domain
- a : Acceleration amplitude
- ω : 2πf
- f : Frequency
- yxx : Output of vibration data after modulated

The output of the FFT method was multiplied by different values to generate multiple vibration levels and a vector called Z, which is utilized as an input to the neural network:

$$Z = [y11\ y22\ y33\ y44]$$

y11, y22, y33, y44 are the different response to the vibration signal being employed to test the simulation of the intelligent system response.

Neural systems (Back propagation algorithm): NN was divided into two types: supervision and unsupervised network. Each type has many algorithms for applications. A back propagation algorithm with multi-perception layers is a common type; this NN is related to the supervision. Similarly, that type of the network has a single hidden layer feed forward and the output of the neurons in the hidden layer will be inputted to the neurons in the next layer. However, the neuron is multiplied by weights, which added a bias to every input sample or vector (Zurada, 1992; KangaraniFarahani and Mehralian, 2013). This algorithm can be utilized for identify the fault resulted from the vibration on in bearing and extracted feature of these signals (Wulandhari *et al*., 2014).

The error back propagation algorithm utilized in this study was related to two layers. Primarily, it is the hidden layer consisting of 30 neurons. The second layer is the output layer containing four neurons. Indeed, this algorithm is based on the propagation error of the output to correct a weight and the bias is related to the first and second layers. This type of neural network can be described as a supervisor network. Furthermore, an algorithm corrects the weight and bias of the network layers based on six steps, which can be summarized as (Zurada, 1992; KangaraniFarahani and Mehralian, 2013; Elhefnawi and Mysara, 2012); first, the output of the FFT technique was applied as an input to the NN. The output of a neuron in the hidden layer will be a summation of the inputs, multiplied by the weight, which was added to the bias related to the inputs. Thus, the result was applied to the neuron's function, which is called the second step. The third step is similar, but is applied to the output layer. Step four involves the detection of errors. These steps are called the forward steps. Thereafter, error is propagated to correct the weight and bias of the output layer. Eventually, the error was propagated to change the weight and the bias of the hidden layer. The final two steps seem to propagate backward (Elhefnawi and Mysara, 2012). Eventually, we used two models of the NN. Four inputs were deployed with four outputs in the form of a parallel network, as illustrated in Fig. 2a. On the other hand, the input of one neuron and the output of one neuron are represented as a series of multistage network from NN connected in series to identify all of the situations of a vibration in steam turbine. The NN series connection is illustrated in Fig. 2b, which is the result of a parallel-connected NN shown in Fig. 3. Figure 4 represent the mean square error of these results. We compared the parallel-and series-connected NN based on the error and time needed to identify a vibration signal, as illustrated in Table 1, proving that parallel-connected NN is superior to series-connected NN. The main property of the parallel NN in the learning part was shown below:

Fuzzy system: Fuzzy system is massively utilized in control and makes decisions for different industrial problems (Isaza *et al*., 2014; Yue *et al*., 2014; Farouk and Sheng, 2012). Predominantly, "Takagi Sugeno Kang (TSK)" is named the sugeno and mamdani

Table 1: Comparison result to series and parallel network

NN	Average time of training	Average error for max train	NO. of train
Series	0.4195s	2.8×10e-3	100
Parallel	0.3161s	2.3×10e-3	100

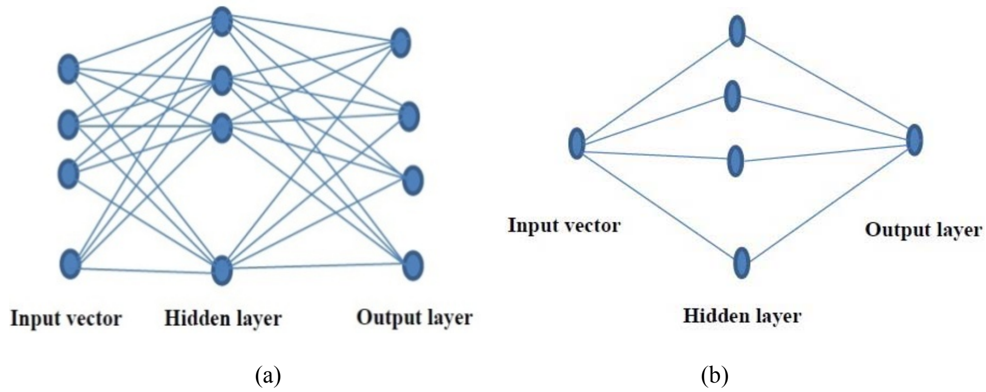


Fig. 2: (a): Parallel input and output; (b): single input and output uses with series NN

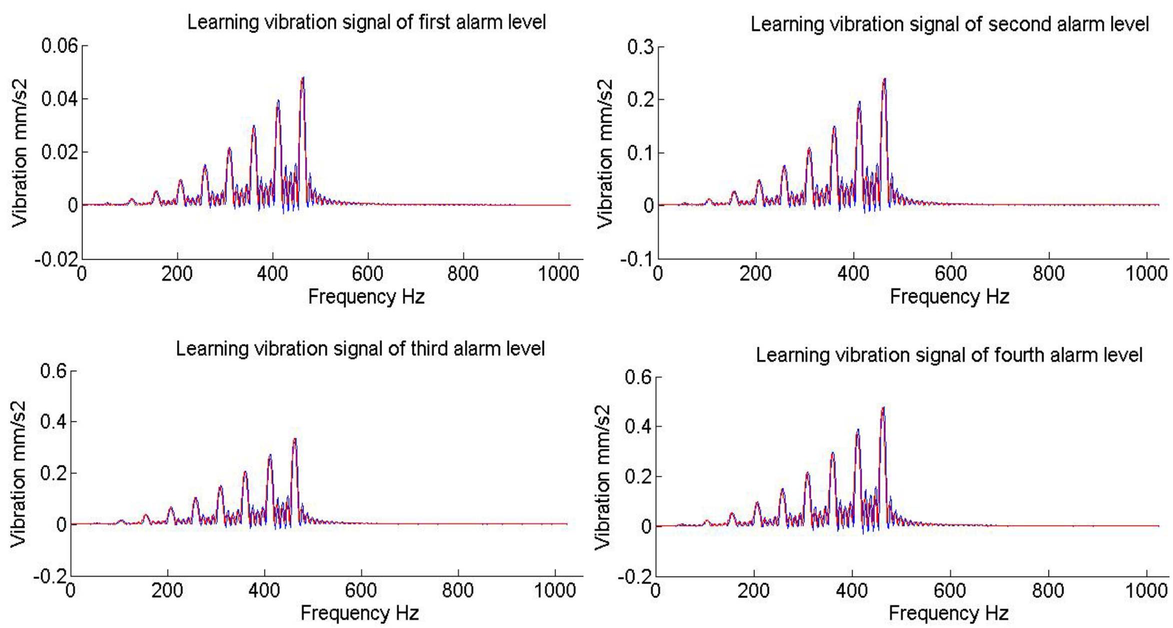


Fig. 3: Show for learning NN the first, second, third and fourth vibration's saturation

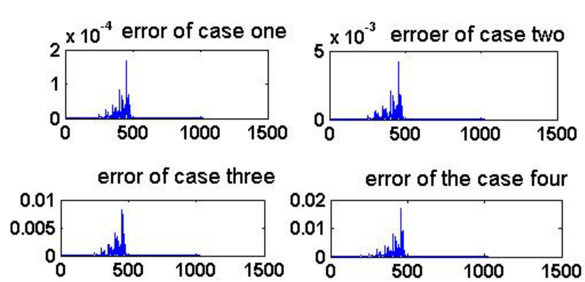


Fig. 4: Delicate of mean square error of four saturations for learning NN

technique and is mostly used with a fuzzy system (Gama *et al*., 2008; Pani and Mohanta, 2014). This approach generates constant voltage based on vibration situations, which is mixed with leading demands of the steam turbine-generator for control. Then, we need the technique to transfer or settle the nonlinear signal to produce linear data for the new expert system. Many investigators mentioned that the sugeno system is more convenient for nonlinear behavior applications. Moreover, the hybrid designs are related to mixing fuzzy with other techniques for the purpose of improving control systems, which showed that sugeno is better than mamdani, due to its higher reliability and flexibility with regards to a nonlinear system (Du *et al*., 2013; Pani and Mohanta, 2014; Boukabou and Mansouri, 2012). Sugeno membership function of this study, designed as the three input membership function, were the vibration signals resulting from the neural,

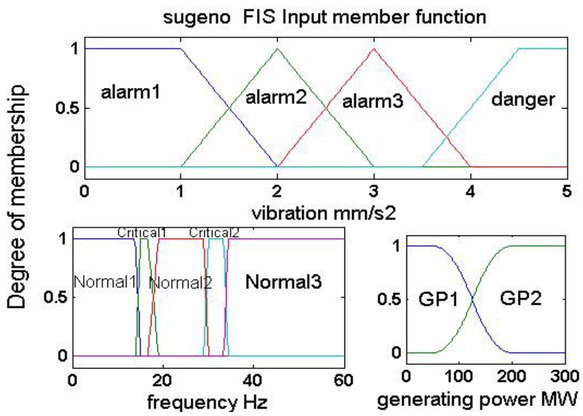


Fig. 5: Sugeno input member ship function

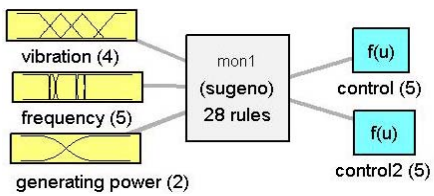


Fig. 6: Sugeno fuzzy inference system with 28 rules

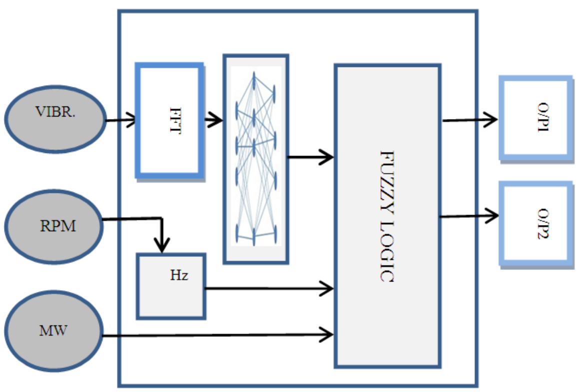


Fig. 7: Represented structure of the NSFS with output and input

while the frequency represent the speed of turbine and generation of power signals being simulated, as shown in Fig. 5. The output membership functions were selecting as constant values. Moreover, the outputs MFs are related to the control via start up and power generation. Eventually, the sugeno FIS system is depicted in Fig. 6. The parameter was utilized in the technique described below:

FIS	Suge no
Number of rules	28
Number of input MFs	1×3
Number of output MFs	1×2
And method	Prod
Or method	Max
Implication	Min
Defuzzifiction	wtaver

Novel design for neural-sleep-fuzzy system: NSFS combined two different techniques into one application in order to improve the behavior of a protection, control and make a decision within a complex system. Indeed, the design approached a contrastive technique from ANFIS, as it employs the neural output to a fuzzy system to improve the decision and output signal's linearity. NN was learning based on the back propagation algorithm to identify the vibration signal of steam turbine-generator in the alarm and the shutdown zones. Thereafter, NN stopped learning and saved the weight and bias of these situations, while the error values are acceptable for four situations related to three cases in the alarm zone and one case in the shutdown zone. The aforementioned cases are related to the offline operation. FFT applied NN to identify the input signal and the results for this part will be zero for diversified signal, where the output is the one related to similar situations, which were saved in NN on offline training. However, the important thing for this part is that the output of NN was changed to linear signal when a nonlinear vibration signal was submitted. Indeed, the previous part has identified and classified vibration signals, which were applied on the NN, while the output of the NN will be inputted to a fuzzy system. Fuzzy system was design as three inputs and two output MFs. The three input MFs are first, one is the output of the NN, which is influenced by the input vibration signal. Second, the MF is the data used to generate power and eventually tries to correlate MF to the harmonic frequency that is related to the turbine's speed. A fuzzy system utilized 28 rules to make certain for decision where the generation of voltage to control the vibration in the steam turbine. Actually, due to the interest in two situations for controlling vibration being related to start up and power generation, the fuzzy is designed with two output MFs. However, the first once is utilized through startup situation, while the second output adjusts the control valve during power generation. From previous analysis, it was made clear that NN decides on machine vibration. Moreover, NN converted the nonlinear signal to linear data. In addition, fuzzy system will be taking into account the influence of other signals such as frequency and power generation deciding on voltage control over steam turbines. This design is shown in the Fig. 7 as the block diagram to all steps on the work. Moreover, it is depicted detail situation in Fig. 8 as flowchart.

SIMULATION RESULT AND DISCUSSION OF THE NURAL-SPEEP-FUZZY

A nonlinear vibration signal was employed to NN, containing 1025 samples. The time needed to classify these vibrations is 0.3077s and is related to paralleling network design. Table 1 illustrates the time and error produced based on the parallel and series-connected

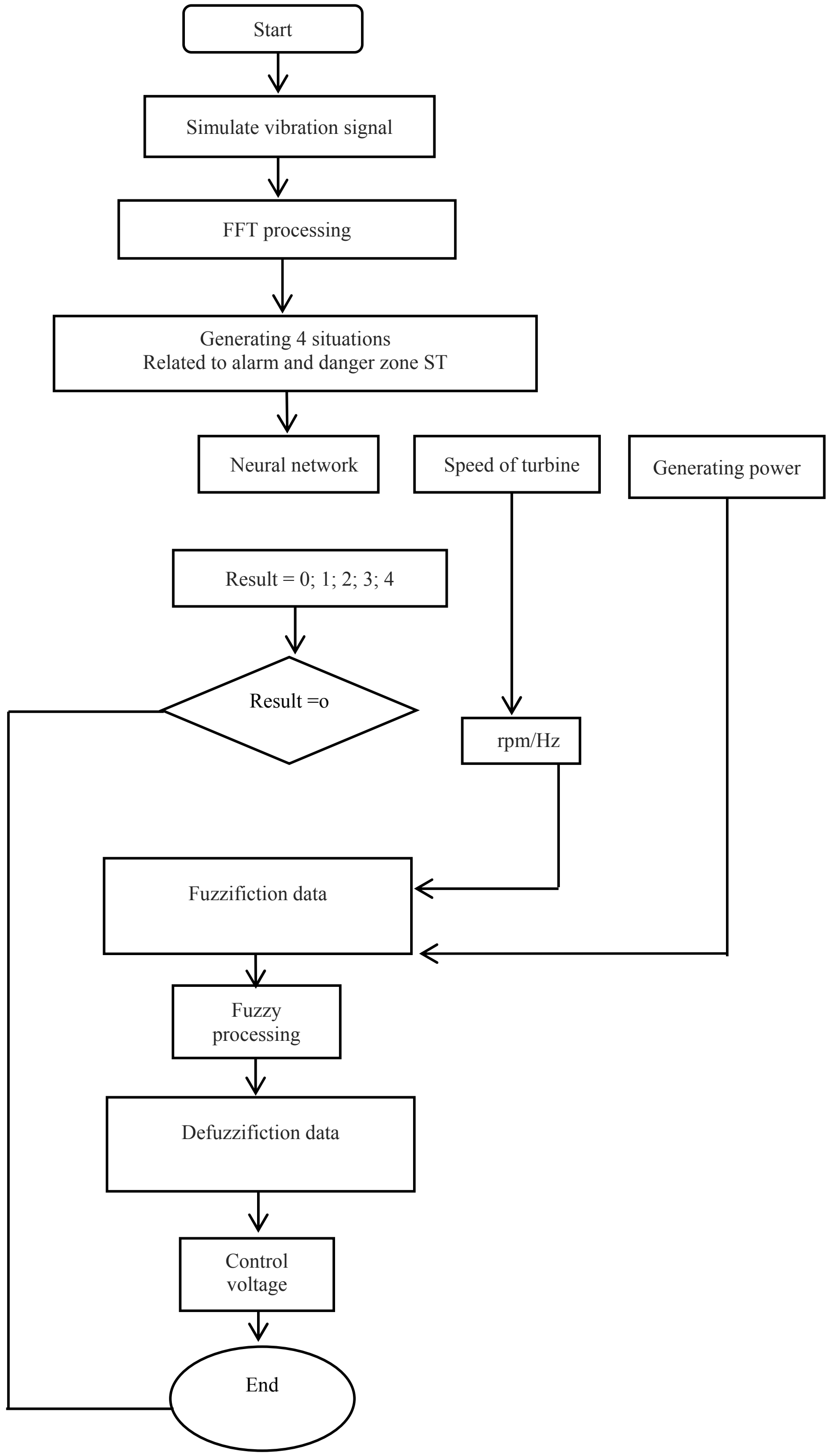
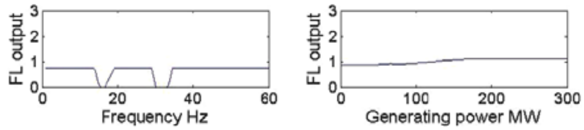
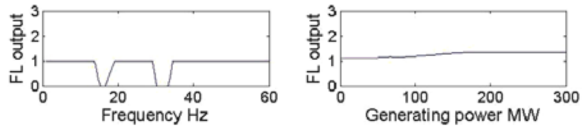


Fig. 8: Flowchart novel structure of neural sleep fuzzy Sugeno system

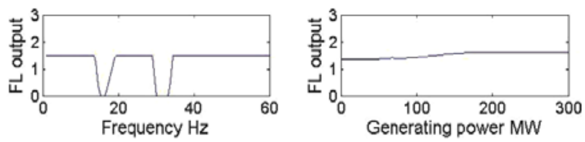
NN. However, Table 1 showed the parallel-connected NN being better than series connected NN for this application, as running time and error are important in completing the other steps of this work. It seems that the main intention of this study is to produce a suitable signal to influence the level of nonlinear signal to be used with steam turbine-generator to control vibrations. These signals are generated from NSFS in Fig. 9, which proportional with the vibration values in Fig. 1, when the first time generation signal linear represented the



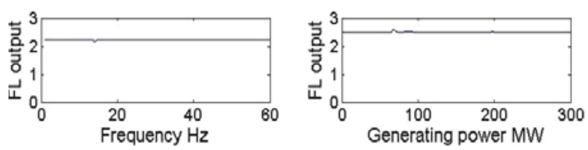
(a) Output effected via alarm 1



(b) Output effected via alarm 2



(c) Output effected via alarm 3



(d) Output effected via alarm 4

Fig. 9: Showed output of NSFS related to four different values of vibration separately a. Resulted from alarm one b. resulted from alarm two c. resulted from alarm three d. resulted from alarm four

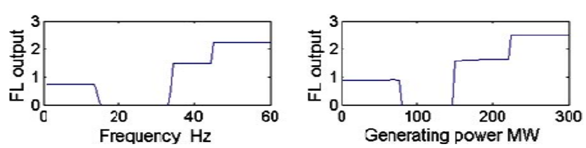


Fig. 10: Showed output of NSFS of four alarm level to start-up and generation power cases

effects of the vibration convenient for feeding to control system. Moreover, it is important that we classify a vibration signal into three categories based on a vibration data in the alarm zone. Thus, the NN was used to classify the simulated signal of a vibration in the alarm and shutdown zones and produce linear data. Fuzzy sugeno system was added to NN to increase signal linearity for controlling steam turbine. Moreover, fuzzy was given the flexibility of adding additional conditions, with new input parameters for augmenting the accuracy of a decision. The additional inputs were a frequency of a machine and generating power, as they take the influence of these signal-enhanced accuracy decisions. Then, the hybrid system will identify the categories and smooth nonlinear signals. The steady signal with more signal processing can be used with steam turbine control to accomplish the main objective to turbine protection. Eventually, the results of the simulation based on MATLAB program are shown in Fig. 10, where it is related to a distinct situation of a vibration. Figure 9 depicts a vibration when increased with different values in the frequency domain.

CONCLUSION

From the Satisfactory results are obtained and its analysis can be concluded the following facts:

- The Comparison of the results between series-and parallel-connected NN are concentrated on running time and the error of training NN. It was shown that parallel-connected NN is better than series connected NN in the identification and classification of vibration signals.
- The output of the NSFS system was a linear signal, which influences nonlinear signals when comparing Fig. 1 and 9. This signal is convenient for mixing with a control system if some steps are added to improve the behaviors of this output data.
- Indeed, the successful identification of vibration levels minimizes the maintenances of steam turbine. This identification can be used with a data-acquisition system to classify the vibration signal of machines online. Moreover, NSFS has facilities that are related to the ability to be utilized with another system based on the change to the setting of values of the input and output membership function for the Sugeno system.

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