DESIGN OF A PROPOSED NEURAL NETWORK FOR SOUND QUALITY ANALYSIS OF DIFFERENT TYPES FOR CAR SYSTEMS

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Abstract - Nowadays, in spite of advanced technology, there are still some sound problems on modern cars because of mechanical parts, oil lubrications, and electric motors. Due to these unwanted problems, it is necessary to design intelligent predictors such as artificial neural networks. In this investigation, a procedure of testing and evaluation on the sound quality of two types of cars are proposed and sound quality is analyzed through the cars road running test on the providing ground, which is carried out with varying running speed. To improve and predict the results of experimental approach analysis, a proposed neural network predictor is also designed to model of the system for possible experimental applications. The proposed neural network is a feedforward type network, which consists of multi hidden layers. Three different training algorithms are used for training the network. As basic factors for sound quality, only objective factors a considered such as loudness, sharpness, speech intelligibility, sound pressure level. The correlation between sound pressure level and other factors are discussed from a point of view of running speed dependency. Results of both computer simulations and experiments show that the neural predictor algorithm gives good results at accommodating different cases and provides superior prediction on two cars's sound analysis.

Keywords: Neural Network, Sound Pressure, Noise, Sharpness.

1. Introduction

Nowadays, very high sound disturbances are becoming the major concern of acoustic problem in cars during working. Many investigations work and studies about these problems have been investigated, but the requirement of improving sound quality of passenger cars are increasing [1, 2]. In order to improve the sound quality in passenger cars, many noise sources must be considered and human feeling to the noise also be taken into account.

Reducing noise & vibration has long been an aim for the development engineer, and in many cases, levels have been reduced so that many products report very similar results. It's now becoming clear that it's not just level that counts, but also the quality of the sound from the machine. Is it rough? Does it sound tinny? Does it rattle? These issues have been identified by the automotive industry years ago, and now the sound of a car is as important as the trim level, or even performance. Driving a car is a combination of sensations, of which the sound quality is becoming more important. Although many acoustic problems on the cars have been solved, more efforts are required in the field of sound quality. It should be said that the mind of sound quality is not actually applied to the passenger vehicles interior noise. For the acoustics of automotive, especially in passenger vehicles, the sound quality of interior noise could be appointed as a major factor for classifying quality of productions.

Statistical treatments have been applied to sound quality analysis, and many researches of identifications on the sound quality factors using intelligent engineering technology have been tried [1]. Because the most of acoustic problems for automotive accoutered after the design and manufacturing stages as a result, in many cases absorbing and insulting sound after the trial error method is widely applied. It could be an actual approach in effect. But the sound quality problem may not be overcome by the absorbing and insulting. It may have a possibility to include more serious and sensitive factor in structural consideration. Especially in the case of sound quality, more correct prediction and analysis must be required, and more careful research was indeed on the troubleshooting [2].

Sound quality analyses are used in many different fields such as bearing fault detection [3], decision aid in piano purchasing processes [4], multiple motor and bearing fault detection [5], early fault detection in cars [6], motor misfire detection [7], asynchronous motor fault detection [8] and CNC machine tool fault detection [9].

Sound analysis is of great importance in areas such as the automotive industry and electrical systems. In-vehicle sound quality control requires more attention than simply controlling physical acoustic quantities. Recent research has been directed towards improving in-vehicle sound quality through new theories, methods and techniques [10]. Liu et al. proposed a new kernel-based system for sound quality prediction in electric powertrains [11]. The experimental results show that the proposed method gives better results than traditional methods such as Support Vector Machine (SVM). With the developing technology, it is necessary to analyse the causal relationship between the mechanical and electrical noise characteristics of the engine and sound quality in vehicles. For this purpose, Kim et al. proposed a methodology to analyse the relationship between noise frequency components of engines used in automobile interior parts and sound quality [12]. Greco et al. have developed a new matlab toolbox for quantitative sound analysis [13]. Boucher et al. investigated the impact of helicopter noise on people by analysing metrics such as sharpness, particularly loudness, impulsiveness, tonality, roughness, and fluctuation strength on sound quality [14]. In addition to these studies, research has also been carried out on the analysis of tyre sound quality in vehicles [15-16].

Neural networks (NNs) are used in many different sound quality analysis applications such as Sound quality prediction of vehicle interior noise [17], nocturnal sleep sounds classification with NN [18], NN for assessing tone perception in electric powertrain noise, vibration and harshness [19], Sound quality analysis of cars using hybrid neural networks [20], and intelligent classification of automotive horn sound quality [21].

In this paper, a feedforward type NN approach for testing and evaluation of sound quality for passenger vehicles is presented, in order to predict and improve in early design stage.

On the other hand, interior noises of cars are measured under the road running condition on the proving ground, varying it's travelling speed. Only objective factors of sound quality are analysed using a NN predictor.

This paper is organised in the following manner NN and proposed NN structure is explained in Section 2. In Section 3, experimental testing and evaluation of two cars is described. To verify the methodology, experimental and simulation results are provided in Section 4. A brief conclusion is outlined in Section 5.

2. Neural Networks

A NN usually involves a large number of processors operating in parallel and arranged in tiers. The schematic representation of the feedforward NN is given in Figure 1. The first layer receives the raw input information, analogous to optic nerves in human visual processing. Each successive layer receives the output from the layer preceding it, rather than from the raw input, in the same way neurons further from the optic nerve receive signals from those closer to it. The last layer produces the output of the system. Each processing node has its own small sphere of knowledge, including what it has seen and any rules it is originally programmed with or developed for itself. The layers are highly interconnected, which means each node in layer n will be connected to many nodes in layer n-1 (its inputs) and in layer n+1, which provides input for those nodes. There may be one or multiple nodes in the output layer, from which the answer it produces can be read.

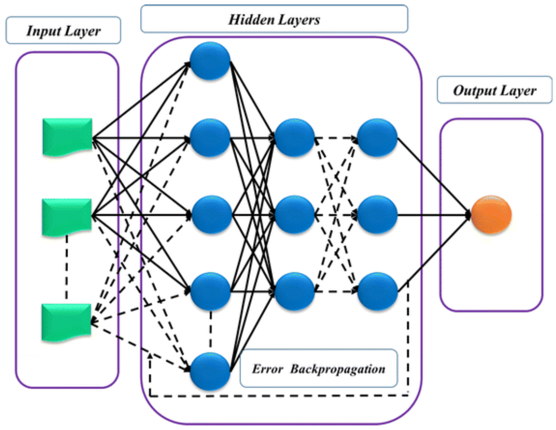

Figure 1: Feedforward Neural Network

NNs are notable for being adaptive, which means they modify themselves as they learn from initial training and subsequent runs provide more information about the world. The most basic learning model is centered on weighting the input streams, which is how each node weights the importance of input from each of its predecessors. Inputs that contribute to getting right answers are weighted higher.

3. Testing and Evaluation System

The testing and evaluation systems for improving interior noise of vehicle are represented in Figure 2. The interior noise must be carefully measured, because the noise is easy to be affected by surrounding conditions, such as road, wind, climate, etc. In general, it can be recommended that the interior noise should be measured the same as the passenger feeling. After recording the signal, the sound indicates are analysed and by the generating system, the subjective evaluation is processed. In this paper, the only objective sound quality is discussed. In Table 1, the detailed measuring and evaluation system's elements are given. The vehicles running test is carried out under the condition of world standard on the straight course at constant speed. In order to watch the effect of running speed., the speed is accelerated up to 120 km/h from 60 km/h by 10 km/h, the measurement is active during 10 seconds at each speed. At the case of automation transmission vehicle, the vehicle runs at the 'D' position under the over drive off' condition.

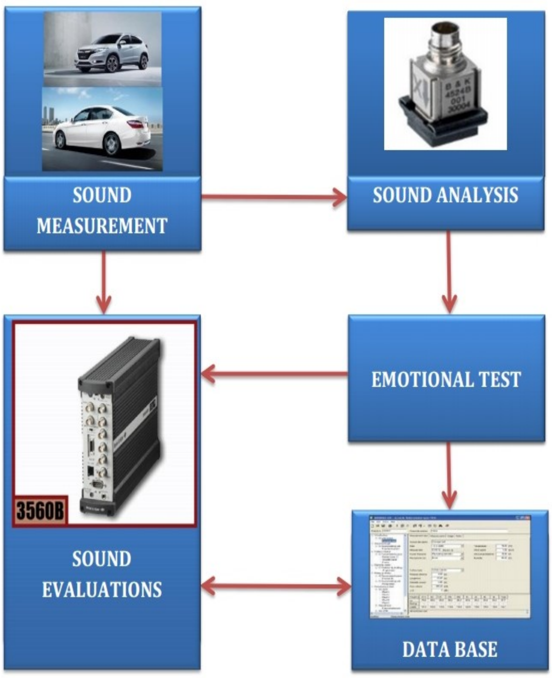

Figure 2: Schematic representation of the system for sound quality testing and evaluation

Table 1. Details of elements for measurement and analysis system

Recording Section	Editing Section	Playback Section
Sound Quality Head and Torso Simulator 4100	PC with Windows NT Sound Card ZE 0770	Power Amplifier ZE 0769
DAT Recorder SONY PC 204Ax WQ 1121	DAT Recorder SONY PC 204Ax WQ 1121	Headphones HT 0012
Conditioning Amplifier 2672	Direct Connection wires	
Positioning Frame UA1324 (Optional)	Sound Quality Software 7998 Zwicker Loudness option BZ5265	
DAT Tape		
Sound Level Calibrator 4231		

NNs are originally developed as tools for the exploration and reproduction of human information processing tasks such as speech, vision, olfaction, touch, knowledge processing and motor control. Today, most research is directed towards the development of neural networks for applications such as data compression, optimization, pattern matching, system modeling, identification, function approximation, and control [22, 23].

4. Feedforward Neural Network

NNs structure similar to the human brain. NNs exhibit nonlinear dynamic behavior and have generalization capabilities. Thanks to these features, NNs can offer flexible solutions to nonlinear problems. In supervised learning, an input and a target output vector are given to the NN during training, and the weight values in the NN are updated and changed accordingly. Thus, the learning process takes place. Feedforward NNs are also a type of supervised learning. Proposed NN can be represented in a general diagrammatic form as illustrated in Figure 3. This diagram depicts the two hidden layers as comprising a nonlinear part. Additionally, this structure uses the backpropagation algorithm to minimize errors [24].

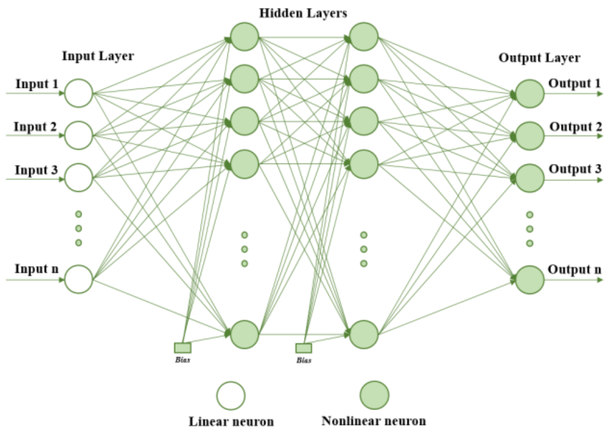

Figure 3: Schematic Representation of the proposed NN predictor

The weights between input and hidden layers are updated as Equation 1 in feedforward NN.

$$\Delta\ W_{ij}(t) = -\eta \frac{\partial E_2(t)}{\partial W_{ij}} + \alpha \Delta W_{ij}(t-1) \qquad (1)$$

The weights between the hidden and output layers are updated as Equation 2.

$$\Delta\ W_{jn}(t) = -\eta \frac{\partial E_1(t)}{\partial W_{jn}} + \alpha \Delta W_{jn}(t-1) \qquad (2)$$

Where α is the momentum term and η is the learning rate. $E_2(t)$ is the propagation error between hidden and input layers. $E_1(t)$ is the error between experimental and neural network output signals [25,26].

The momentum term α ensures that the weight change value is added to the next change at a certain rate so that the network does not get stuck at a local optimum point during learning. It can also be said that the momentum term α enables the memory of past information during learning process. α takes values between 0 and 1. Bias value represents the activation threshold of the neuron. The learning rate η expresses how much error is taken into account. η can take values between 0 and 1. A large η value causes large changes in error values, making convergence difficult. Choosing the η value too small increases the training time significantly.

Different algorithms can be used for training in NNs. It is very difficult to know which training algorithm will be the fastest for a given problem. This depends on many factors such as the number of data points in the training set, the complexity of the problem, the number of weights in the network, etc. Activation functions determine how the outputs produced in the total function of neurons should change. Nonlinear transfer functions are generally used in NNs. Hyperbolic tangent sigmoid transfer function (tansig) is used in this study.

The sum of squares of the difference between the output of the actual system and the output of the model is hence the first metric used to assess the success of the model. This metric is referred to as Mean Squared Error (MSE). MSE is calculated with the formula given in Equation 3.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\varepsilon_i^2 = \frac{1}{n}\sum_{i=1}^{n}(x_i - y_i)^2 \quad (3)$$

Another metric is the R^2, which is a statistical indicator of how much of the variance in a dependent variable in a regression model is explained by an independent variable. R^2 is calculated with the formula given in Equation 4.

$$R^2 = \frac{1-\sum_{i=1}^{N}(x_i-y_i)^2}{\sum_{i=1}^{N}(x_i^2)} \quad (4)$$

In this study, the values α and η, are fixed. This means only the weights of the feedforward connections needed to be adjusted and thus it is possible to employ the standard feedforward algorithm to train the NN.

5. Results and Discussions

In this section, the sound quality parameters affected by the variation of travelling speed of vehicle are analysed using NN. Firstly, the NN is trained on Intel Core i5-4460 CPU 3.20 GHz PC with random location. Network structure and training parameters of the network is given in Table 2. The training algorithms used in the study, MSE and R^2 error values are given in Table 3. As can be seen from Table 3, the lowest MSE for both cars (A, B) is obtained with the Fletcher-Powell Conjugate Gradient training algorithm. In Figure 3, the frequency analysis result of sound pressure level is represented with NN predictor while the vehicle speed is increasing. The vehicle speeds are used as inputs to the network, sound pressures are used as outputs of the network. Therefore, the network has 1 input and 4 outputs. The results indicates that neural predictor is following desired results of two cars. At the low speed range, the noise is almost governed by engine load. This phenomenon generally happens through the travelling speed of car increases up to high speed. The noise generated by engine could be pointed out as major effect to interior noise of passenger's car. By increasing the travelling speed, the sound pressure level of high frequency component is increased. It could be guessed that wind should have a role to increase the interior noise level.

In Figure 4, sound pressure levels of two cars are compared with each other. The sound pressure level of A car is lower that of B car or almost equal, varying to its travelling speed. As can be seen from the Figure 4, sound pressure has similar characteristics for both vehicles. The proposed neural predictor has superior performance in following the desired results of two car's sound pressure levels.

Table 2. Network structure and training parameters

Input Numbers (n_i)	Hidden Layer 1-2 (n_1, n_2)	Output Numbers (n_0)	Activation Function	Learning Rate
1	8, 8	3	tansig	0.001

In Table 2; n_i: input numbers, n_1: number of neuron in hidden layer 1, n_2: number of neuron in hidden layer 2, n_0: output numbers, tansig: Hyperbolic tangent sigmoid transfer function.

Table 3. MSE and R^2 error values

Case	Algorithm Type	Car	MSE	R^2
1	Levenberg-Marquardt	A	0.03388	0.9994
2	Fletcher-Powell Conjugate Gradient	A	0.00121	0.9990
3	Polak-Ribiere Conjugate Gradient	A	0.03864	0.9950
4	Levenberg-Marquardt	B	0.04163	0.998
5	Fletcher-Powell Conjugate Gradient	B	0.00911	0.9999
6	Polak-Ribiere Conjugate Gradient	B	0.17791	0.9995

The relation between sound pressure levels and loudness, as a factor of sound quality is represented and predicted with neural approach in Figure 5 for two cars. For two cars, the relation has almost the same linearity. This trend means that the loudness should increase relating to sound pressure level.

The same phenomenon could be obtained by representing the relation between sound pressure level and sharpness of two cars in Figure 6. As can be seen Figure 6, the proposed neural network predictor has followed the variation of results between sound pressure and sharpness of two cars. From Figure 6, on the linearity, at the case of B car the relation between sound pressure level and sharpness does not have the same linearity compared with A car. Also, the magnitude of sharpness of B car is lower than that of A car.

The frequency analysis is carried out two cars, increasing their travelling speed. It could be obtained that the 1 KHz frequency component is dominant in A car, comparing to B car. The sound pressure level of high frequency component of A car is higher that of B car, while increasing the travelling speed is increasing.

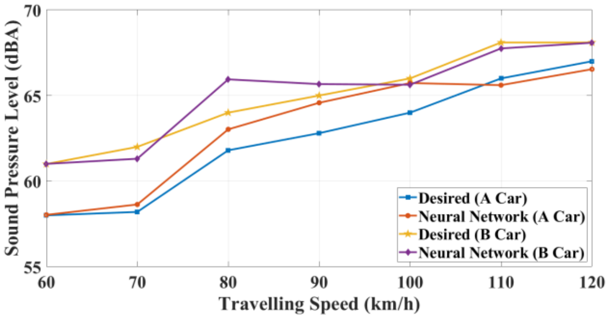

Figure 4: Variation of Sound pressure level relating to travelling speed using neural network

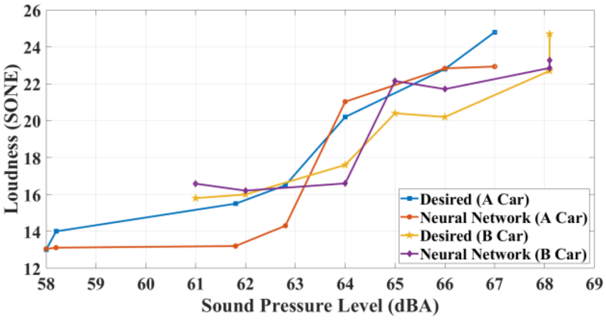

Figure 5: Relation between sound pressure and loudness for two cars using neural network

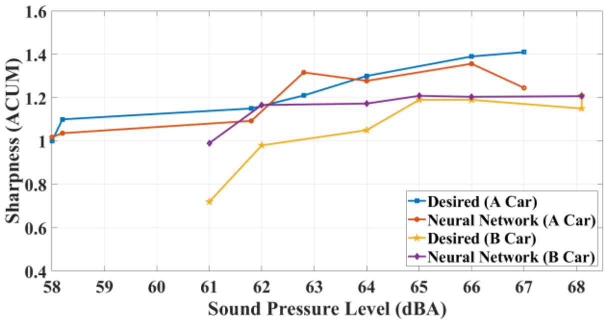

Figure 6: Relation between Sound pressure level and sharpness for two cars using neural network

6. Conclusion

In this investigation, sound quality evaluation of two types of car has been analysed using a proposed neural network predictor. As could be seen results of the two cars for six cases, the neural network is followed successfully desired results of the analysing system.

It could be obtained through sound quality test and analysis, while the passenger vehicle runs on the proving ground, between sound pressure level and sound quality parameter. The relation between sound pressure level and sound quality parameter could be cleared. The proposed neural network would be utilised as a hardware predictor to evaluate the vehicle interior sound comparing to sound pressure level by a computerised system.

Simulation results proved that the proposed neural network predictor enables car systems to have precise prediction performance. On the other hand, the sound quality parameter might be mostly affected by sound pressure level near the 1 KHz frequency component

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References

[1] Takao, H., Hatano, S. and Hashimoto, T. Relation between unpleasantness of artificial amplitude-modulated and real car interior and roughness level modulation frequency range causing maximum unpleasantness. Proc. of JSAE, 991, 455-458 (1991).
[2] Murata, H., Tanaka, H., Takada, H. and Ohsasa, Y. Sound quality evaluation of passenger vehicle interior noise. Journal of SAE, 931347, (1993).
[3] Mian, T., Choudhary, A., and Fatima, S. An efficient diagnosis approach for bearing faults using sound quality metrics. Applied Acoustics, 195, 108839, (2022).
[4] Zhou, M., Wu, S., Ji, S., Li, Z., and Li, W. A holistic evaluation of piano sound quality. arXiv preprint arXiv:2310.04722, (2023).
[5] Mishra, R. K., Mian, T., Fatima, S., Mohanty, A. R., and Panigrahi, B. K. Motor and bearing multi-fault diagnosis with sound quality metrics. In Inter-Noise and Noise-Con Congress and Conference Proceedings (Vol. 268, No. 8, pp. 57-67). Institute of Noise Control Engineering, November, (2023).
[6] Nasim, F., Masood, S., Jaffar, A., Ahmad, U., and Rashid, M. Intelligent sound-based early fault detection system for vehicles. Computer Systems Science & Engineering, 46(3), (2023).
[7] Singh, S., Potala, S., and Mohanty, A. R. An improved method of detecting engine misfire by sound quality metrics of radiated sound. Proceedings of the Institution of Mechanical

Engineers, Part D: Journal of Automobile Engineering, 233(12), 3112-3124, (2019).
[8] Shirdel, S., Teimoortashloo, M., Mohammadiun, M., and Gharahbagh, A. A. A hybrid method based on deep learning and ensemble learning for induction motor fault detection using sound signals. Multimedia Tools and Applications, 1-19, (2023).
[9] Ding, S., Zhang, S., and Yang, C. Machine tool fault classification diagnosis based on audio parameters. Results in Engineering, 19, 101308, (2023).
[10] Wang, Y., Guo, H., and Yang, C. Introduction to vehicle interior sound quality. in vehicle interior sound quality: analysis, evaluation and control. Singapore: Springer Nature Singapore, 1-3, (2022).
[11] Liu, H., Zhang, H., Huang, X., Kong, Z., Yang, J., and Yang, Y. Research on noise source separation and sound quality prediction for electric powertrain. Applied Acoustics, 199, 109034, (2022).
[12] Kim, S. Y., Ryu, S. C., Jun, Y. D., Kim, Y. C., and Oh, J. S. Methodology for sound quality analysis of motors for automotive interior parts through subjective evaluation. Sensors, 22(18), 6898, (2022).
[13] Greco, G. F., Merino-Martínez, R., Osses, A., and Langer, S. C. SQAT: a MATLAB-based toolbox for quantitative sound quality analysis. In Inter-Noise and Noise-Con Congress and Conference Proceedings (Vol. 268, No. 1, pp. 7172-7183). Institute of Noise Control Engineering, November, (2023).
[14] Boucher, M. A., Krishnamurthy, S., Christian, A. W., and Rizzi, S. A. Sound quality metric indicators of rotorcraft noise annoyance using multilevel analysis. The Journal of the Acoustical Society of America, 153(2), 867-876, (2023).
[15] Huang, H., Lim, T. C., Wu, J., Ding, W., and Pang, J. Multitarget prediction and optimization of pure electric vehicle tire/road airborne noise sound quality based on a knowledge-and data-driven method. Mechanical Systems and Signal Processing, 197, 110361, (2023).
[16] Lee, S. K., An, K., Cho, H. Y., and Hwang, S. U. Prediction and sound quality analysis of tire pattern noise based on system identification by utilizing an optimal adaptive filter. Applied Sciences, 9(19), 3995, (2019).
[17] Zhang, E., Hou, L., Shen, C., Shi, Y., and Zhang, Y. Sound quality prediction of vehicle interior noise and mathematical modeling using a back propagation neural network (BPNN) based on particle swarm optimization (PSO). Measurement Science and Technology, 27(1), 015801, (2015).
[18] Pandey, C., Baghel, N., Gupta, R., and Dutta, M. K. Nocturnal sleep sounds classification with artificial neural network for sleep monitoring. Multimedia Tools and Applications, 83(6), 15693-15709, (2024).
[19] Ricardo Souza, M., Haris, A., Rodrigues, L., Offner, G., Sopouch, M., Diwoky, F., Mohammadpour, M., and Theodossiades, S. (2024). The use of an artificial neural network for assessing tone perception in electric powertrain noise, vibration and harshness. Meccanica, 1-27.
[20] Yildirim, S., and Eski, I. Sound quality analysis of cars using hybrid neural networks. Simulation Modelling Practice and Theory, 16(4), 410-418, (2008).
[21] Mollah, A., Mahanta, T. K., and Balide, V. Intelligent classification of automotive horn sound quality. SAE Technical Paper, No. 2024-26-0204 (2024).
[22] Yildirim, S. and Uzmay, I. Kinematic analysis of cranes using neural networks. Proceedings of 16 th IAARC/IFAC/IEEE Int. Symposium on Automation and Robotics in Construction, 429-432, (1999).
[23] Yildirim, S. and Uzmay, I. Statistical analysis of vehicles' vibration due to road roughness using radial basis artificial neural network. Applied Artificial Intelligence, 419-427, (2001).
[24] Yildirim, S. Neural network for control of bipeds. Electronics Letters 35(23), 2064-2065, (1999).
[25] Eski, I., Erkaya, S., Savas, S., and Yildirim, S. Fault detection on robot manipulators using artificial neural networks. Robotics and Computer-Integrated Manufacturing, 27, 115–123, (2011).
[26] Esim, E, and Yildirim, S. Drilling performance analysis of drill column machine using proposed neural networks. Neural Computing and Applications, 28, 79–90, (2017).