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TOPICAL COLLECTION: ELECTRONIC MATERIALS FOR RENEWABLE ENERGY APPLICATIONS

A Neural Network Design for the Estimation of Nonlinear Behavior of a Magnetically-Excited Piezoelectric Harvester

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An application of an artificial neural network (ANN) has been implemented in this article to model the nonlinear relationship of the harvested electrical power of a recently developed piezoelectric pendulum with respect to its resistive load R_L and magnetic excitation frequency *f*. Prediction of harvested power for a wide range is a difficult task, because it increases dramatically when *f* gets closer to the natural frequency f_0 of the system. The neural model of the concerned system is designed upon the basis of a standard multi-layer network with a back propagation learning algorithm. Input data, termed input patterns, to present to the network and the respective output data, termed output patterns, describing desired network output that are carefully collected from the experiment under several conditions in order to train the developed network accurately. Results have indicated that the designed ANN is an effective means for predicting the harvested power of the piezoelectric harvester as functions of R_L and *f* with a root mean square error of 6.65×10^{-3} for training and 1.40 for different test conditions. Using the proposed approach, the harvested power can be estimated reasonably without tackling the difficulty of experimental studies and complexity of analytical formulas representing the concerned system.

Key words: Artificial neural network, power, estimation, piezoelectric harvester, excitation frequency

INTRODUCTION

Owing to the increased energy demand depending upon the growing technology all over the world, the idea of energy harvesting has attracted great attention over the past few decades. The term "energy harvesting" comes from the generation of energy from sources such as air flow, ambient temperature or vibration. Converting the available energy from such sources available in various forms in nature can be benefitted by a self-sufficient supply using proper electronics for electrical devices such as sensors, actuators or radio transmitters. Among the available energy, kinetic energy obtained from background ambient vibrations or impact external forces can be transformed into electrical energy via a piezoelectric material. This harvesting mechanism is the most common one as compared with other harvesting mechanisms and piezoelectric power generation is one of the alternative energy sources. This is why there have been a great number of studies in the related literature devoted to this esteemed field of piezoelectric effect-based energy harvesting due to piezoelectric materials' high power density.

The works that use vibrations of the piezoelectric plates as a wind energy harvester have been realized for energy generation at a low scale.[1–3]

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Thanks to these small-sized systems, it is possible to achieve power over 3 mW. Systems obtaining energy from wind can also be designed to be contactless using permanent magnets.[2,3] Thus, the life of the system is made longer because of the reduced deformation on the plates. Electrical energy can also be generated in human movements by using piezoelectric energy harvesting systems. Wang et al. have been able to obtain 30 μW of power from a person running at a speed of 7 km/h with attaching a piezoelectric energy harvesting system to a human leg.[4] It was also possible to operate a pedometer without a battery using a piezoelectric energy harvester placed in the shoes.[5] One of the most important problems in piezoelectric energy harvesting systems is that these systems can only work effectively in a narrow frequency range. This situation makes it impossible to effectively utilize vibrations which have highly variable frequency in the environment. Many successful studies have been carried out to extend the effective operating frequency range of these systems.[6–8] Stein et al.[6] have worked effectively in a frequency range of about 15 Hz. In our previous work,[8] we used the plates with different stiffness coefficients to make effective work at a wider wind speed range. Experimental studies with piezoelectric energy harvesting systems may not be possible to perform in every condition for a variety of reasons. In these cases, experimental results can be approximated by deploying artificial neural networks (ANNs). To this end, in this article, an ANN design is performed and its prediction capability is checked on a real piezoelectric energy harvester excited by an electromagnet which was theoretically and experimentally studied previously.[9,10]

ANNs or simply neural networks (NNs), which are computing systems dedicated to mimic the essential behavior of a biological neural system, have been the focus of much attention due to their capabilities in solving nonlinear problems by learning ability. Through many nonlinear computational elements operating in parallel and connected to each other in between layers with intensive interconnections, ANNs are able to accomplish the task of approximating the nonlinear behavior between input and output data of a nonlinear model without prior knowledge about those data. They are very efficient and useful when the equations representing the respective model are nonlinear, complex, distributed in nature, as well as being particularly vague or totally unknown with uncertain parameters.[11] As an alternative to ANN-based modelling, there are also studies that make use of fuzzy logic (FL) for prediction of output parameters of a process according to its input parameters by stimulating the qualitative thinking process of human beings.[12–16] However, many characteristic parameters such as scaling factors, fuzzy-expert rules, and shape of membership functions are required to be tuned during the design of a FL system, which is an ill-defined problem, and based upon the experiences and knowledge of a skilled operator. These difficulties regarding the FL design guide us to choose the neural network approach in this article.

As we focus on the estimation property of NN, it would be appropriate to give some introductory literature survey about that topic. In Ref. 11, ANN-based estimation of the output power and efficiency of a new designed axial flux permanent magnet synchronous generator is introduced. In the network structure, generator resistive load and rotational speed are the input variables and outputs are the generator output power and its efficiency, respectively. Results show that the developed network is able to predict the experimental results with good accuracy. Online estimation for the rotor and stator resistances of an induction motor is performed in Ref. 17 using NNs. For rotor resistance estimation, the error between the rotor flux linkages based on the designed NN and induction motor voltage model is back propagated to train the network. For stator resistance estimation, the error between the measured stator current and the estimated one based on the NN is back propagated to train the network. At the end of the study, it is shown that rotor and stator resistance variations can be effectively estimated by benefitting from the adaptation capabilities of the designed NNs. Using these estimated crucial parameters in the state equations, the authors achieve a good correlation between the measured speed and the estimated speed of the induction motor speed, enabling efficient and high-performance operation of the drive. In Ref. 18, a trained NN is devoted to predicting burr height produced in a sheet metal blanking process according to tool wear state and punch-die clearance. Results obtained under a variety of blanking conditions show that the ANN computations are in good agreement with the experimental values with a deviation of 10%. With an aim to determine optimal clearance prediction of the sheared part, an estimation approach based on an ANN is presented in Ref. 19, where the ANN proves its reliability and effectiveness in predicting the optimum clearance against the material elongation. Thus, the proposed NN can be taken as a useful means in the optimization of sheet metal blanking processes. An essential NN application to the estimation of distorted waveforms in power electronics is made in Ref. 20. In the study, line-side total rms current, fundamental rms current, displacement factor and a power factor associated with the distorted line current waves in a single-phase thyristor ac controller and three-phase diode rectifier are estimated from the known waveform of line current which is characterized by its width (W) and height (H). Results obtained by training a 2-8-4 network confirm the excellent estimator performance of the used NN after a great number of training processes. In Ref. 21, an estimation study of wind power generation is conducted as a diagnostic tool, which is a necessity for the power generation stations due to the fact that wind power lower than the expectation might indicate a need for maintenance for a variety of reasons in the station. In another study given by Ref. 22, a new approach is presented for the position estimation task of a speed sensorless switched reluctance motor drive system. The study intends to eliminate complex flux estimation algorithms by introducing NN. After the flux and current information are acquired from the line currents and line voltages in the ac link, and presented to the network, the corresponding angular position is estimated by the designed NN. It is stated that using the sufficiently trained NN, rotor position can be accurately estimated by obliterating the need for a conventional position sensor and that the resulting computational burden and hardware complexity are relatively low as compared with the classical flux estimation techniques. On the other hand, since the absorbed power from a photovoltaic (PV) panel depends on various environmental factors such as geographical location, ground reflectivity and the atmosphere clearness index, the study in Ref. 23 is encouraging in order to find the optimal tilt angle at which PV panels should be placed in order to maximize the solar power from the sun. Results dictate that the proposed network can learn the nonlinear relationship among the irradiation, ground reflectivity and tilt angle, and its estimation of the optimum tilt angles is found to have a small error within 3° of the analytical actual values.

Although the theoretical derivation of the piezoelectric harvester is given in Ref. 10, it has sophisticated equations depending upon electrical and mechanical parameters such as magnetic force coefficient, elastic stiffness coefficient, inductance and resistance of electromagnetic coil, etc. In practice, knowledge of these constants is rarely available or may not be known accurately. Besides, they might be influenced by environmental changes when the piezoelectric energy harvester is in operation. In such a case, the calculated power will be different from the actual power generated. By taking into account this phenomena, the present study is devoted to estimate the nonlinear relationship using an ANN among the load resistance, excitation frequency and the electrical power harvested from a recently developed piezoelectric energy harvesting system, which constitutes our main contribution. In the established system, load resistance and magnetic excitation frequency are considered to be inputs, while the output is the corresponding power harvested. With the data collected from various experiments, the designed feedforward network is trained using standard back propagation (BP) training algorithm until the estimated power matches the exact one with an acceptable degree of accuracy. Investigations launched in this paper demonstrate that ANN-based estimator of power output in a piezoelectric energy harvesting system is promising and able to predict the experimental results with good accuracy. Therefore, with this contribution, at a given load resistance and excitation frequency, harvested power can be estimated without tackling the complex mathematical model and difficulty of experimental studies.

ARTIFICIAL NEURAL NETWORKS

Principles

Conventional estimation algorithms use mathematical models of a system to make estimations. By iterating the program in steps, the required results are achieved. However, there are various practical reasons for which the mathematical model and system parameters might either be totally unknown or they are indeed hard to discover. In such conditions, conventional estimation approaches fail, and, accordingly, they cannot be used in modelling of the above-mentioned problems.[19] At this point, ANNs become an attractive choice and can offer desired objectives in terms of accuracy. At the end of a successful training process, a trained network is expected to reflect the actual system in certain accuracy, and it should be able not only to remember the training data, but also to make a good matching of the output data for unseen input data, which is over the universe covered by the example patterns.

An ANN is a structure tending to simulate the nervous system of the human brain in which a large number of processing elements called neurons are organized in layers and interconnected to each other. Neurons create the power of ANNs which is useful in the modelling of nonlinear cases.[24] According to the nature of the concerned problem, a network can receive multiple inputs x_1, x_2,..., x_r, and generate a single output for each processing element after weighting the respective inputs with the weights of interconnections and then passing the sum of them through a transfer function. Selection of transfer functions are somewhat problem-dependent and can be threshold type, signum type, sigmoid, or it can be defined even as any nonlinear continuously varying type by the user. Note that the transfer function has a remarkable impact upon the estimation performance and its nonlinearity gives the network ability to attain nonlinear mapping property. The generated output signal of an individual processing element is then sent to other processing elements as input signals in the next layer by flowing through the interconnections. This forward pass is continued until reaching the output layer. After an error value is obtained for each output neuron by comparing the desired output value and the actual one, connection weights are adjusted iteratively by a training algorithm until the pattern matching occurs, i.e., the error falls below an acceptable value for all the example patterns. BP is an effective weight adjustment mechanism widely applied for training feedforward neural network models.[25]

ANN Design for Estimation of Harvested Power

To find the relation among resistive load, excitation frequency and corresponding harvested power in a piezoelectric energy harvesting system, a feedforward multilayer network with an input layer, two hidden layers and an output layer is considered as in Fig. 1. Since input layer neurons do not have transfer functions, such a network structure is often called a three-layer network. In this design, measured resistive load R_L and magnetic excitation frequency f are the inputs while the corresponding output is the measured harvested power P_{out}. The input and output layers have a number of neurons equal to the respective number of variables. There are 15 neurons in the 1st hidden layer with hyperbolic tangent activation function, ten neurons in the 2nd hidden layer with linear activation function, which is also used for the output neuron. This particular network, 2-15-10-1 plus bias nodes with the relative activation functions, is selected based on a combination of trial-and-error and our prior experience in Ref. 11.

The aforementioned design is trained by employing the BP algorithm. Prior to the training process, we transform all input and output training data into the interval of [0, 1] using Eq. 1. This data normalization is highly important for increased estimator performance and accelerating the neural computations significantly. Although there are different techniques proposed to accomplish such data normalization devoted to make the training process easier and effective, no certain approach has been around yet.

$$x_n = \frac{x_r - x_{\min}}{x_{\max} - x_{\min}}, \tag{1}$$

where x_r and x_n are the actual and normalized value of a variable while $x_{\max}$ and $x_{\min}$ symbolize the maximum and minimum values of the respective variable.

To prepare the network for training, we begin with the training data gathered together which comes from the various experiments conducted on the concerned system. The power measurements are realized for variable resistive loads R_L such as 10 MΩ, 5.6 MΩ, 3.2 MΩ, and 1.0 MΩ and meanwhile magnetic excitation frequency is varied from 4.25 Hz to 6.53 Hz for each resistive load in certain steps so that 28 frequency samples are obtained. Thus, there are a total of $4 \times 28 = 112$ training data. The training is initially started by assigning the connection weights random numbers within the range [− 1, 1]. As stated before, the weights are adjusted according to the BP learning rule with an off-line computer simulation conducted in ANSI C. Following the completion of a satisfactory training, the prediction or generalization capability of NN is checked for the cases difference and unseen

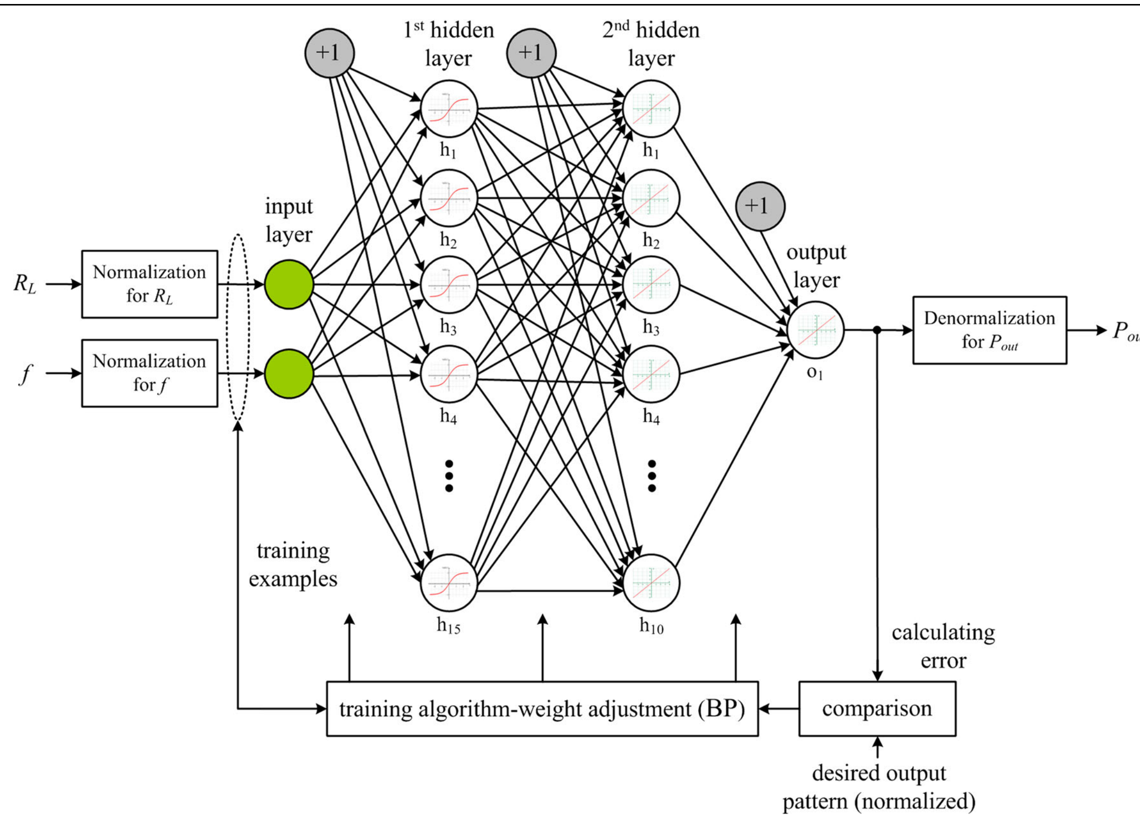

Fig. 1. Three-layer network for harvested power estimation.

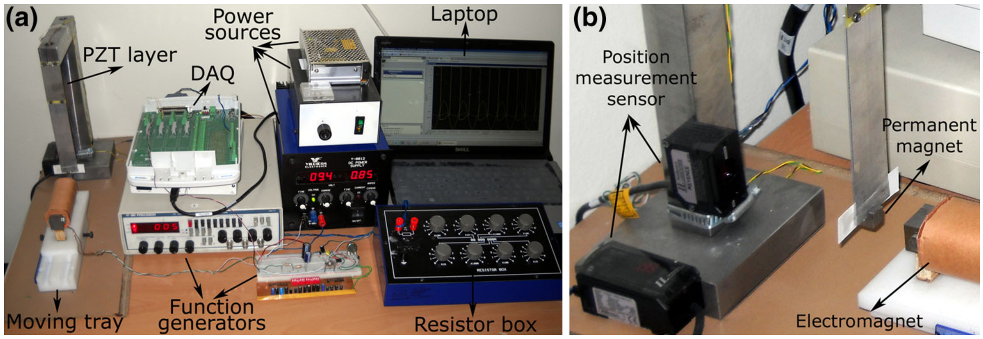

Fig. 2. (a) The overall experimental setup (b) the magnified piezoelectric energy harvester.

resistive loads are applied to the trained network to predict the required outputs.

EXPERIMENTAL RESULTS

In the experimental work, piezoelectric (PZT) layer, electromagnet, position measurement sensor, data acquisition (DAQ) card, signal generator, resistor box, laptop and software are used. The piezoelectric layer has the sizes of 70 mm × 32 mm × 1.5 mm, the weight of 10 g, the capacitance of 232 nF and stiffness of 188 N/m. A small permanent magnet is attached to the end of the piezoelectric layer to interact with the electromagnet to create vibration. The electromagnet consists of 1050 turns of inductor placed on a core obtained by packing thin steel sheets coated by silicon. The electromagnet is placed on a table moving back and forth. Thus, the distance between the electromagnet and the piezoelectric layer can be adjusted to the desired level. The signal generator applies a square wave with desired frequencies to the electromagnet so that the piezoelectric layer can be vibrated at the desired frequency. It is observed how much power can be obtained from the piezoelectric layer at a different load value by using a resistor box. The maximum power transmission is realized from which load value is determined. The laser position measuring sensor measures the vibration of the piezoelectric layer with a laser system. The data acquisition card instantly transfers the position and voltage data of the piezoelectric layer to the computer. Observation and recording of the data on the computer is performed with LabView software.

Figure 2 shows the experimental setup of the proposed system. In the setup, there exists a PZT layer attached a heavy housing, an electromagnet, DAQ, power sources, function generators, resistances and a laptop. When the electromagnet is excited by a square waveform in Fig. 2b, the electromagnet attracts the ferromagnet knob. The displacement, velocity and voltage can be recorded and calculated in the experiments with 1000 data points per second.

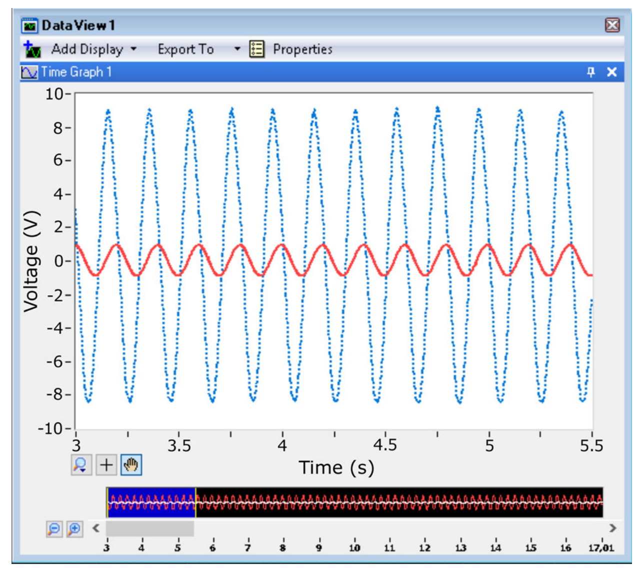

Fig. 3. The screenshot of piezoelectric layer tip displacement and obtained voltage (f = 5 Hz, R_L = 1 MΩ).

Figure 3 shows a screenshot of the tip displacement and obtained voltage for a frequency of 5 Hz over a load resistance of 1 MΩ. It is clear that there is a phase shifting between displacement and voltage signals due to PZT layer capacitance.

Obtained power from the system versus the load resistance at 4.76 Hz is provided in Fig. 4. This frequency value is the resonance frequency of the proposed system at which maximum power can be obtained from the system depending upon the load resistance. Here, the graph is plotted logarithmically to better observe the effect of load resistance on the obtained power. As seen from Fig. 4, obtained power from the system decreases at low and high load resistance values. The maximum power from the system is obtained when the load resistance is around 1 MΩ. The internal impedance of the PZT layer approximately equals this value. Therefore, the load resistance must be kept close to this value in order to get maximum efficiency from the system. Since this is not always possible in practice, it is necessary to use an impedance matching circuit for maximum efficiency.

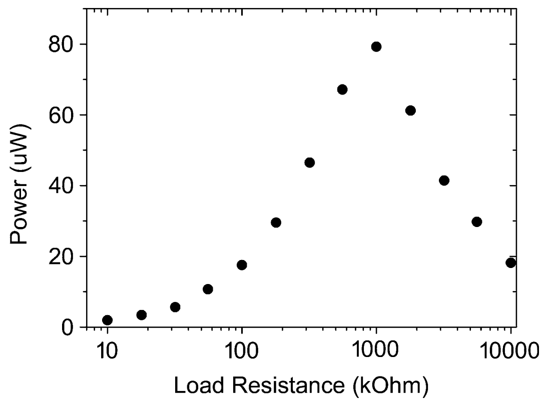

Fig. 4. The obtained power depending on the load resistance at the resonance frequency.

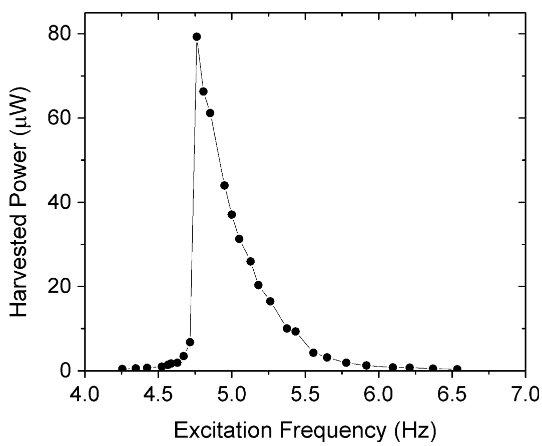

Fig. 5. The obtained power depending on the excitation frequency at the load resistance 1 MΩ.

Excitation frequency is one of the most important parameters determining the bending level of the PZT layer, and the amount of bending level directly determines the obtained power from the system. If the piezoelectric layer is excited at a value close to its resonance frequency, which was calculated as 4.76 Hz in the study, the maximum bending will occur. The relation of obtained power with regard to the excitation frequency is sketched in Fig. 5. Note that the output power decreases rapidly at below and above this frequency value. Therefore, when the PZT harvester system is to be applied to a real system, the frequency of the vibration in the environment should be known and the system design must be done according to this frequency value.

Figure 6 shows the obtained power from the PZT harvester depending on the excitation frequency and the load resistance. In the experiments, the excitation frequency was kept close to the resonance frequency of 4.76 Hz owing to the fact that the power reduces to almost zero, when the excitation frequency changes from this value as seen in Figs. 4 and 5. In addition, the load resistance was increased

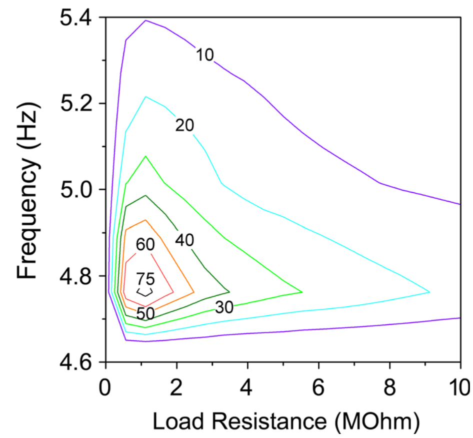

Fig. 6. The surface plot of power on the load resistance and the excitation frequency plane.

from 10 Ω to 10 MΩ at certain ranges during the experiments. It is inferred that the condition of maximal power transfer occurs at a load value of around 1 MΩ and excitation frequency of 4.76 Hz. Output power values are relatively high between 500 kΩ and 1200 kΩ. However, the power value has been drastically decreased for other load resistance values.

As the result of the experimental data, we conclude that the most important parameters determining the obtained power from the system are both load resistance and excitation frequency. In order to get the maximum power, these parameters that are directly related to the physical and electrical characteristics of the piezoelectric layer should be selected appropriately. A proper ANN can be deployed as an assistant tool to estimate the output power of the buckled piezoelectric layer.

ESTIMATION RESULTS OF HARVESTED POWER BASED ON ANN MODEL

This section is devoted to the resulting training and testing performance of the network. The relation of harvested power to both resistive load and excitation frequency is highly nonlinear, and quite difficult to be modelled with an ANN. As such, there is a certain load value around the internal impedance of the harvesting system that leads to harvest maximum power possible from the PZT material in accordance with the maximum power transfer theorem.[9,26] Above and below this load value, harvested power begins to reduce significantly. In addition, magnetic excitation frequency has also a crucial impact over the output power generation. In the case of driving the harvester with an excitation frequency equal to the natural one, then maximal power can be gained from the system in the same way. When the system oscillates at higher frequencies, output power amplitude decreases in a similar trend to that in a varying load condition. When it starts to oscillate at lower frequencies, that time amplitude falls off quite abruptly. These are the nonlinearities of the system that make the ANN training a challenging problem. During our many attempts of the training process, we have faced inefficient ANN performance from time to time at the training start, even after thousands of training epochs due to randomly generated initial weights and to improper tuning of learning and momentum parameters. This issue prompts us to choose learning and momentum rates in very small values, and a very large number of training epochs to obtain a training error curve that gradually converges to a minimal value in a stable trend. Figure 7 displays a representative convergence curve of the root mean square (RMS) error between the desired output and the output from the network for all the training data at the end of each epoch. Compatible with what we desire during training, the RMS error gives a sharp fall at first, then it continues to decrease gradually and becomes stabile with time.

At the end of a very large number (8×10^5) of training epochs finished in about 10 min on an Intel 3.30 GHz computer with 8 GB RAM, the error is found to be 6.65×10^{-3}, which is an indicator that our network is trained successfully and ready for testing. Note that this does not always guarantee satisfactory testing results owing to an overtraining problem as is previously stated in Ref. 11.

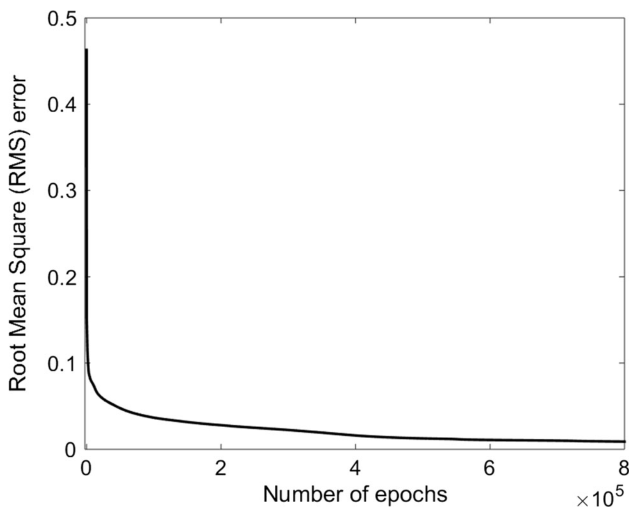

Fig. 7. RMS error evolution versus epoch during training.

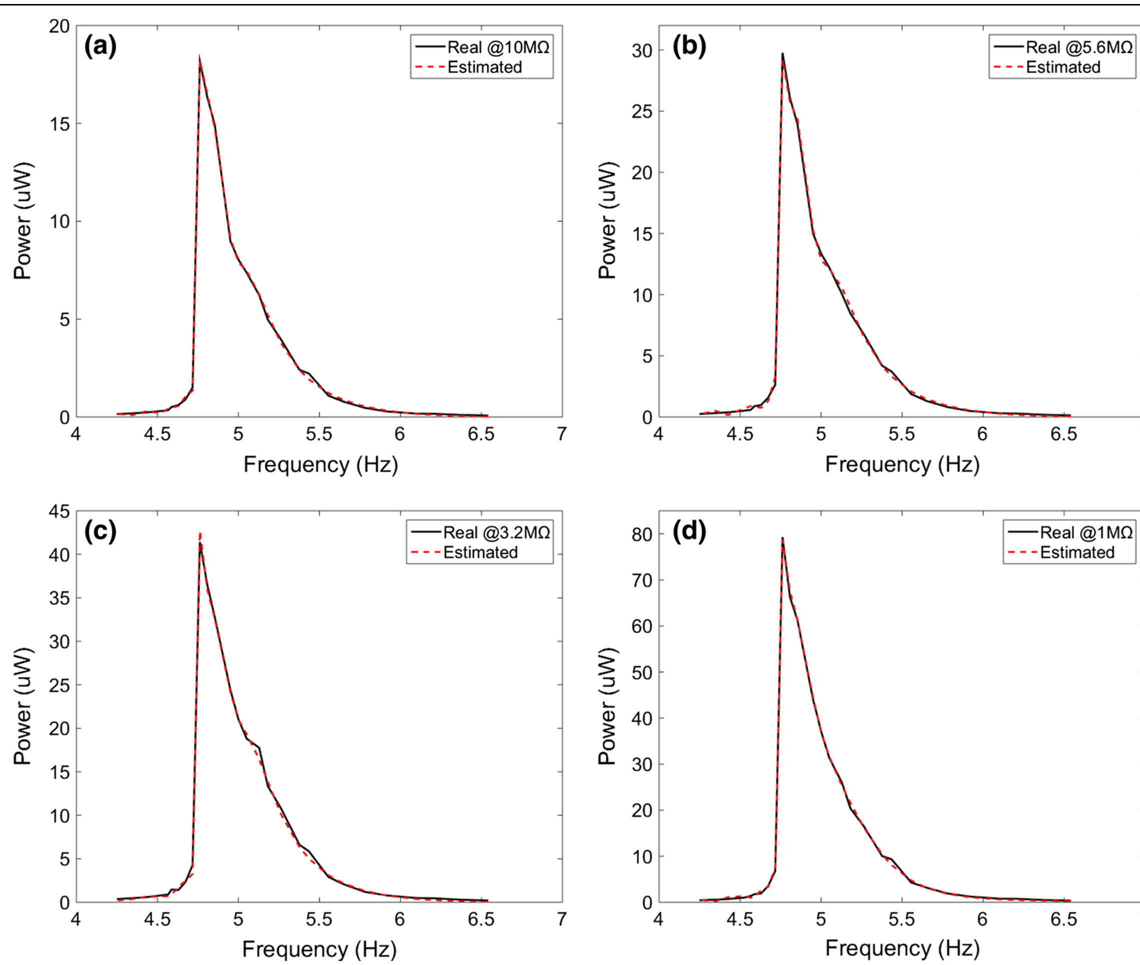

Fig. 8. Network estimation capability of the example patterns for the load resistance (a) 10 MΩ (b) 5.6 MΩ (c) 3.2 MΩ (d) 1 MΩ.

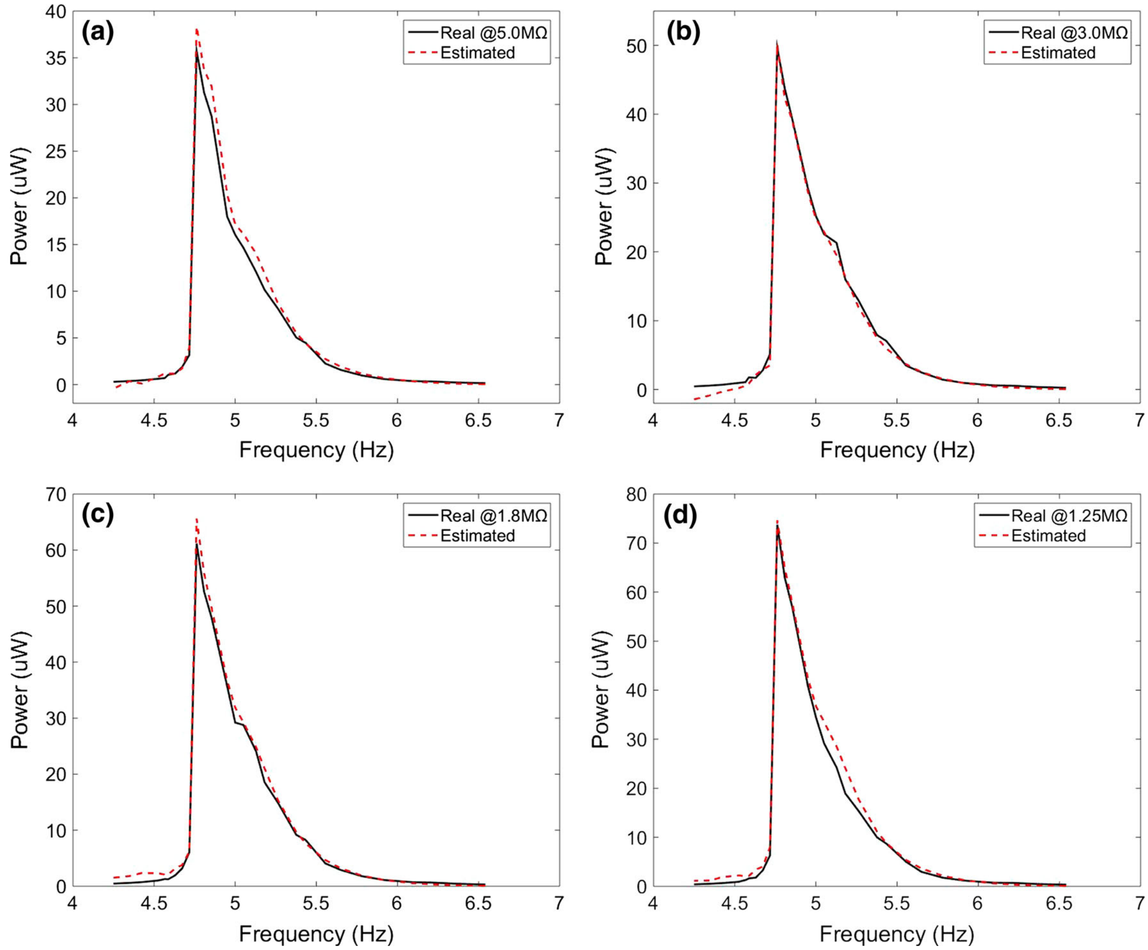

Fig. 9. Validation course of the network in the case of unseen inputs (a) 5 MΩ (b) 3.0 MΩ (c) 1.8 MΩ (d) 1.25 MΩ.

Figure 8 shows the network estimation capability of the example patterns used during training. Obviously, there is indeed a perfect match between the real power and the estimated power in each case.

These figures given above are somewhat related to the training performance of the network. As is stated before, it is expected from a well-trained network to have the ability to remember the training data, and also to gain generalization capability for an unseen input data. To check this performance measure as the validation course, we present the trained network four different load values of 5.0 MΩ, 3.0 MΩ, 1.8 MΩ, and 1.25 MΩ, which are not used during the training.

Obtained results based on the measured power output and the ANN estimation are superimposed in Fig. 9. It can be inferred that the network performance is promising. The total RMS error value between the real power and the ANN output is calculated as 1.40 for all test conditions. This makes the resulting estimation curves have a quite tendency to vary in a way similar to those based on the experiments.

CONCLUSIONS

With the help of a trained feedforward ANN, an important parameter, electric power, harvested from a recently developed piezoelectric energy harvesting system is estimated in this study in terms of load resistance and magnetic excitation frequency. In this system, load resistance and magnetic excitation frequency are considered to be complicated inputs, while the output is the corresponding power to be estimated. In all cases of estimation, training data collection is generated properly from various experiments performed upon the concerned system, and then the designed network is trained using the standard BP algorithm. Both training and testing results demonstrate the effectiveness of the presented model in estimating the power output versus the load resistance and excitation frequency, which have a highly nonlinear relation. If the estimation performance is to be improved further, training data collection should be intensified within the specified range, which requires the sampling rate of measurement equipment to be increased.

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