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Prediction of Excitation Current of Synchronous Machines Based on Neural Network Model

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Abstract

There are several difficulties found to estimate the excitation current and optimum input parameters of synchronous motors. Heuristic methods are frequently used to weight the problem's parameters or optimum coefficients. As a result, a neural network model is modified in this study to explore the best parameters and estimate the excitation current of a synchronous motor with minimal prediction errors for both the testing dataset and cross validation. Excitation current variations are affected by four input factors, including load current, power factor, error, and changes in excitation current, when training this model. The experimental results reflect that the proposed neural network predicts the new data set effectively as well as enables to predict best weighted value for optimum excitation current of synchronous motors.

Keywords: Synchronous machine, exciting current, neural network, prediction

INTRODUCTION

In this study, synchronous machine saturation is modelled using an innovative feedforward artificial neural network technique. The modelling procedure considers the motor locations, excitation levels, and machine loading circumstances [1]. By adjusting the synchronous motor's available excitation current, the power system can provide the best answer for the need for reactive power. The excitation current estimate issue for synchronous motors is addressed in this study using a successful implementation of Neural Network [2]. In order to achieve quick reaction and high accuracy performances as well as to ensure the system's tolerance to external disturbance and parameter uncertainty, this article suggests a unique decoupling strategy for a bearing less permanent-magnet synchronous motor. The suggested control strategy uses internal model controllers with two degrees of freedom and the neural network inverse methodology [3]. To maintain the smooth and high-quality functioning of the synchronous machine itself, it is crucial to continually monitor any potential value changes in the excitation current, a crucial parameter of the synchronous machine [4]. The excitation current of synchronous motors may be modeled simply using this paper adaptive artificial neural network-based technique. The network layout is straightforward, and there are fewer processing units (nodes) than in a traditional ANN. This methodology is designed to increase the effectiveness of the traditional ANN-based approach while estimating the excitation current, helping architects easily model excitation current, and helping them create complicated driver software with little programming work [5]. A unique index is presented in this paper for the identification of static as well as dynamic eccentricity faults in permanent magnet

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synchronous motors. The classification of the findings shows that the proposed index may be used to properly identify the kind, classify, and predict the degree of eccentricity [6].

LITERATURE REVIEW

In order to solve problems with parameter weighting and excitation current estimate of synchronous motors, the author in [4] presented an innovative and effective technique in this study. Intuitive/heuristic methods are frequently used to weight the parameters or look for the best coefficients in issues. Because of this, an adaptive algorithm-based k-nearest neighbor estimator (also known as an intuitive k-NN estimator or IKE) is modified in this paper to explore the best parameters and produce accurate estimations of the excitation current of synchronous motors. Excitation current variations, load current, power factor, error, and other motor characteristics are weighted based on their impacts on the excitation current. The suggested technique's estimation results are contrasted with the experimental findings using standard deviations from the well-known Neural Network-based method and k-NN-based estimator. The outcomes demonstrate that the suggested estimator outperforms the other two well-known approaches described in the literature in terms of task accomplishment in terms of high accuracies, stabilities, robustness, and low error rates [7]. The paper introduced [8] a novel feedforward artificial neural network (ANN) model-based method for simulating synchronous generator saturation. The modelling technique considers the rotor locations, excitation levels, and machine loading circumstances. The ANN model is used to examine the nonlinear saturation properties of a three-phase in nature salient-pole synchronous machine. The machines are rated at 5 kVA and 240 V. The on-line small-disturbance responses and the well-known maximum-likelihood estimation algorithm are used. And the algorithm is used to generate input and output pattern for NN model on an error back-propagation scheme [8]. The authors in [9] investigated the feasibility of calculating rotor angles for use in real-time electric power system transient (angle) stability. The suggested method for estimating dynamic state is based on a multilayer perceptron that was trained off-line using simulations and current as well as voltage phasors. And it is collected from a phasor measurement unit that is intended to be set up on the extra-high voltage side of a power plant substation. They showed that the direct mapping of phasor measurement values to generate rotor angle in a neural network is not a good way to achieve satisfactory results [9]. Through the presented paper in [10] the authors proposed that a permanent magnetic synchronous motor's (PMSM) heat loss and cooling modes have a direct impact on how quickly the temperature rises. For PMSMs to operate safely and reliably, stator winding temperature must be accurately assessed and predicted. The authors [10] provides a computer model for PMSM temperature prediction in order to investigate the elements that affect prevent motor insulation ageing and stator winding temperature, permanent magnet demagnetization, insulation burning, and other defects brought on by high stator winding temperature. The authors [10] constructed a deep neural network model for synchronous machine temperature predictions. This model can efficiently forecast the stator winding's temperature change, offers technical assistance to temperature monitoring systems, and guarantee the secure functioning of synchronous machines [10]. Through the paper presented in [11] the author proposed that, to train the complex feed forward neural network, a set of training data is produced from a simulation of the synchronous machine's dynamics. The two structures are contrasted. The first structure consists of a three-layer feedforward mechanism network with 10 nodes in the hidden layer. The second structure also uses a three-layer feedforward mechanism network, with 20 nodes in the hidden layer. A step response is simulated on field voltage to the step input. The simulation findings demonstrate that artificial neural networks can effectively represent the dynamics of synchronous machines, and an increase in the number of undetectable nodes per layer can improve the model's accuracy [11]. The methods presented in the article in [12] can be used to estimate and track a synchronous generator characteristic from time-domain continuous disturbance data using Neural Network (NN) observers. The offline computations of synchronous machines running in a one-machine, infinite-bus scenario provide the data needed to train the neural network observers. The machine model uses nominal values for parameter values. Following training, the ANN observer is put to the test using simulated online measurements to track simulated adjustments to machine parameters and offers estimations of undetectable rotor body currents [12].

MATERIALS AND METHODS

The SM used for data collection is given in the section of Materials and Techniques. The input and output variables are described along with the dataset. Before using ML algorithms, the input data and statistical analysis are presented. The potential difficulties are also mentioned, and the significance of implementing AI is stressed [13]. There are numerous losses in SM (iron losses, winding losses, and ventilation losses) that add complexity and non-determinism to the machine and demand additional power, in addition to the aspects that are overlooked when modeling synchronous machines [14]. Naturally, these losses depend on the environment in which the devices are operated, which makes it challenging to quantify parameters using conventional monitoring techniques [15]. Synchronous machines consist of both synchronous generators and motors. There are various benefits of an AC system. As a result, The AC system can generate, transmit and distribute the electric power. The synchronous can transform mechanical energy to alternative current. That is why it is also called as alternator [16]. In order to identify the excitation current of synchronous machines, neural network architecture is utilized. The significant aspects, such as the voltage, power factor of the machine is captured by the input layer. The neural network learns to identify patterns in the input data in the hidden layers. Depending on how complicated the problem is, both the actual number of layers that are concealed and the quantity of neurons in each layer might change. The expected excitation current is represented by a single number output layer [17].

DATASET ANALYSIS

In this research work, four input parameters are used i.e., I_y (Load current, The quantity of electrical current flowing from a power source to the object or circuit gaining the power), P_f (power factor), p_{fe} (power factor error) and d_{if} (Change of excitation current of synchronous machine), as presented in Figure 1 and output is I_f (Excitation current of synchronous machine) as shown in Figure 2. In this research work, total 171 samples are analyzed. Total 154 samples are train data and total 17 samples are tasting data.

Hence, 17 sample train data are calculated and characteristics graph between experimental data and calculated output for testing datasets are plotted.

In the Figure 3, characteristics graph between experimental value and calculated values are plotted for the testing dataset. And after that, the deviation of experimental data and calculated data is calculated (Table 1). And then sum of deviation is required, so, sum of deviation is calculated, and RSME values and % error are calculated.

In the Figure 4, characteristics graph for Deviation vs. number of trials in testing datasets are plotted. And the minimum value for the deviation is 0.000205191 and the maximum value is 0.004001. Hence, the cross validation of the train dataset is calculated (Table 2). The derivation of cross validation data is calculated. And then sum of deviation is required so, it is calculated.

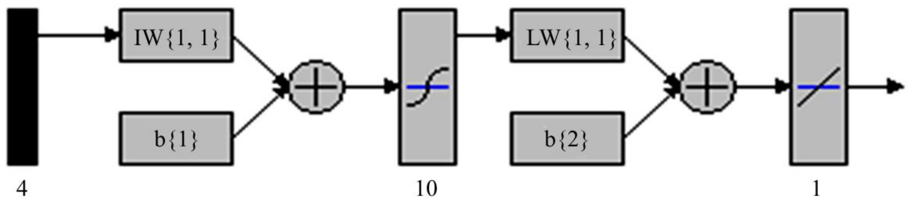

Figure 1. Basic model of NN for present research.

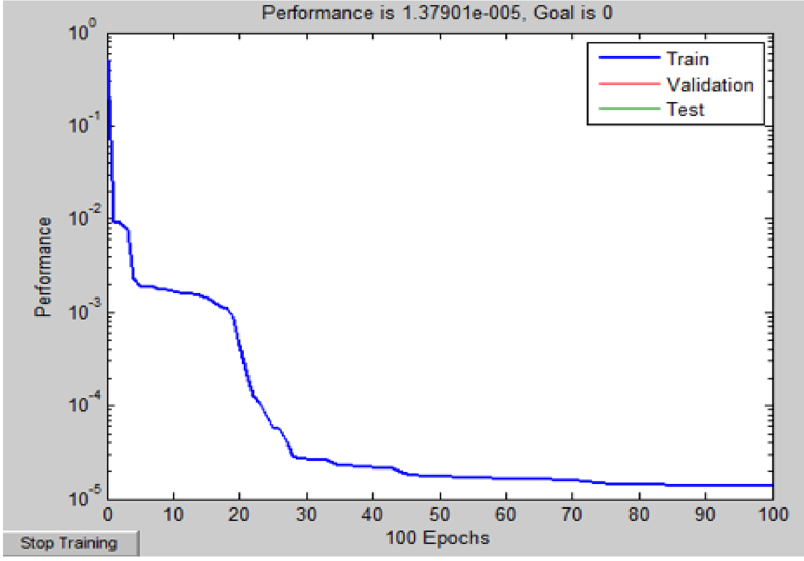

Figure 2. Characteristics graph of train, test and validation dataset corresponding to the number of epochs.

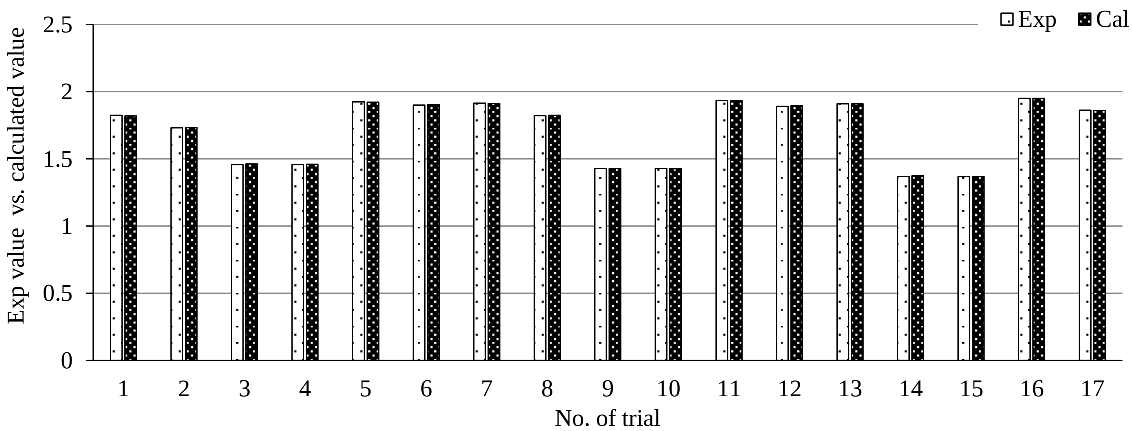

Figure 3. Characteristics graph between experimental and calculated output for testing datasets.

Table 1. Result obtained after testing validation.

Result	Value
Sum of deviation	5.51E-05
RSME value	0.0018
% error	0.179

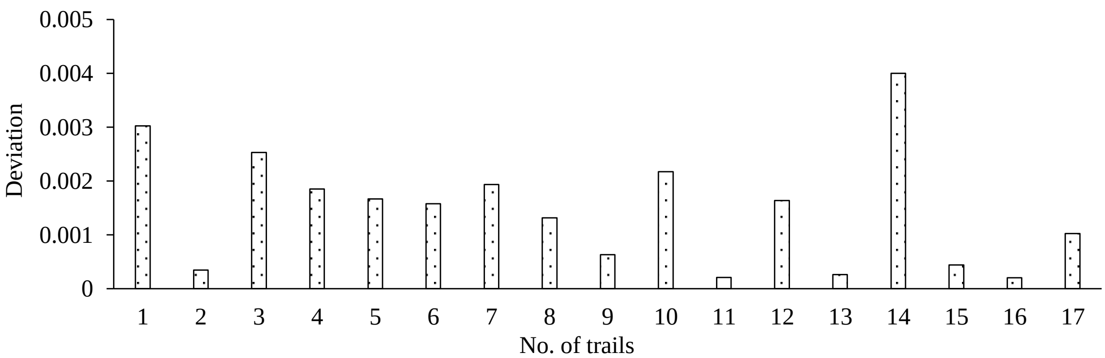

Figure 4. Characteristics graph for deviation vs. number of trials in testing datasets.

Table 2. Result obtained after cross validation.

Result	Value
Sum of deviation	0.001017
RSME value	0.00257
% error	0.257025

Table 3. Result obtained after testing and cross validation.

Model	% Error	% Accuracy
Cross validation	0.257025	99.742975
Testing model	0.179	99.821

In the Table 3, % error and % accuracy are shown for cross validation and the testing model. For the cross validation, the % error and % accuracy are 0.257025 and 99.742975 respectively. For testing model, the % error and % accuracy are 0.179 and 99.821 respectively.

The optimum input parameters of the proposed model which have been obtained from simulation are: Load is maximum (6 A), Power factor minimum (0.65), error in power factor moderate (0.035) and changing of excitation current maximum (0.769 A).

CONCLUSION

In this study, Neural Network Simulator is used to find out the error between the experimental data and the calculated data for a Synchronous Machine. The Sum of deviation, RSME values %error, %accuracy are calculated for both Cross Validation as well as Testing models. When looking at the results, it is seen that there is an output difference for Experimental output and the calculated output in both cases of Testing model and Cross Validation.

To recap and with regards to possible future study objectives, one thing should be kept in mind that initially, the supplied dataset must be updated with newer data points, such as load current, power factor and power factor error, by modifying the values of these variables. Second, a variety of methods should be implemented to identify the error; this is the most effective approach. The dataset will be constructed with the best possible solution to forecast the excitation current and parameter weightings of synchronous machines using a neural network model if the following points are implemented.

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