Hall Effect Sensor and Artificial Neural Networks Application in Current Transformer

G.Gokmen, Y.Ozel, N.Ekren

***Abstract*—** Nowadays, The open loop and closed loop Hall Effect Current transformers are being widely used for industrial applications because of AC, DC and complex waveform current measurement capability. Current, power, magnetic field and distance sensing and measurement are the most important application fields. Especially, it facilities the flux density sensing of the magnetic material inside for which the flux density measurement is very difficult. In this study, linear Hall Effect sensor based closed loop current measurement was carried out. The relationship between input and output parameters (Primary MMF and measurement voltage) of The Hall Effect current transformer was examined and estimation of measurement voltage was carried out by means of the artificial neural network.. When estimation results are compared to measurement values, it is shown that the artificial neural network model produces reliable estimates of measurement voltage of a Hall Effect current transformer.

***Keywords*—** Artificial Neural Network, Closed Loop Current Transformer, Current Measurement, Current Sensing, Hall Effect, Hall Effect Current Transformer

I. Introduction

ONE of the most widespread application fields of the Hall Effect sensors is the current sensing. The Hall Effect current transformer is a kind of electronically compensated current transformer based on the principle of zero flux. These types of device are referred to as active current transformer because of the use of electronic amplifier and feedback circuits. If current sensing will be analog, linear Hall Effect sensors are preferred. Core of the transformer is made by using ferit or steel. The core is coated with plastic layer to ensure isolation.

The Hall Effect current transformer uses a Hall sensor placed in the split core to detect transformer ampere-turn unbalance between primary and secondary circuits. The unbalance represents an error in ratio and phase angle of the transformer. The largest of the errors is due to the core magnetization current and magnetic reluctance caused by the cutting of the core material. When current is passed through the conductor placed inside of the core, magnetic field established around it is caught by the core and a flux is circled in the Hall sensor. The linear response of sensed current is rather convenient for motor control feedback circuits and they can be preferred for external measuring devices, telemetry systems, monitoring applications [1],[2],[3].

The output voltage of sensor is same with the AC and DC wave shape of measured current. Placement of the sensor in air gap of the core isolates the sensor electrically and so, damage of over current or high voltage transients on sensor is prevented. It also eliminates DC insertion loss [1]. The number of all measurements results obtained from experiments is 60. 20 of this data were used for training, 20 of this data were used for validation, and 20 of this data were used for testing the neural network. Based on experimental results, the artificial neural network model produces reliable estimates of measurement voltage of a Hall Effect current transformer.

II. Hall Effect Current Measurements

The Hall sensor based current measurement can be realized as open loop or closed loop. While in open loop, there is only primary winding and it can be coiled as 1 turn for practical applications such as clamp meter but to increase measurement accuracy it should be coiled as multi turns. The Hall sensor produces an output voltage proportional to primary current. Generally intensity of output voltage is not adequate for measurement and it is necessary to be amplified by an op-amp.

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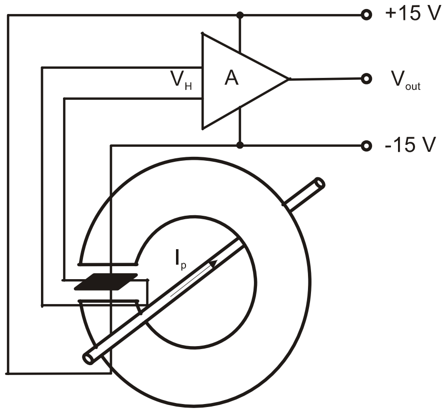

Fig. 1. Basic connection scheme of an open loop current transformer

In closed loop, operating principle is very similar to open loop. Output voltage of the Hall sensor is transformed to current by means of a transistor circuit and passed from a secondary winding. The purpose is compensating of the magnetic flux created by primary winding. The basic connection schemes of open loop and closed loop Hall Effect current transformer are given in Fig. 1. and Fig2. [1].

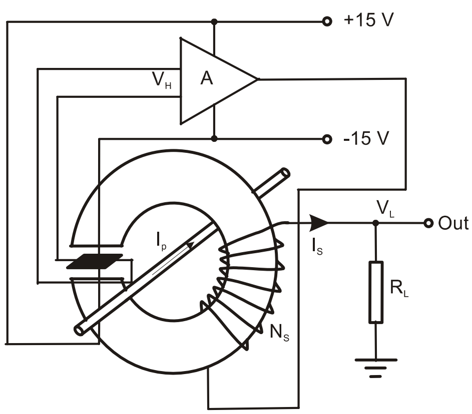

Fig. 2. Basic connection scheme of a closed loop current transformer

The primary current to be measured creates magnetic flux in the core. The Hall sensor produces voltage in proportion to the magnetic flux in the core. In other words, the primary current and output voltage of sensor is proportional. The output voltage is amplified by means of the amplifier circuit. Generally, an operational amplifier is preferred. The amplified voltage is applied to a push-pull transistor circuit and transformed to secondary current passed from the secondary winding. In this way, a second magnetic flux is created in the core. The secondary current is symmetric of the primary current and its secondary winding is generally coiled as 1000 turns. In this manner, secondary current create secondary magnetic flux to balance primary magnetic flux. [1],[4],[5].

The basic equation is;

$$N_p \times I_p = N_s \times I_s \tag{1}$$

The measurement resistor is serial coupled to secondary winding so Voltage of the measurement resistor will be proportional to the primary current [1].

In selection of core in which the Hall sensor will be placed, there are two important criteria. These are permeability of material and length of core respectively. Besides, inner area of the selected core must be in size capable of taking both the primary winding and secondary winding. The air gap length is an important factor both in determination of effective permeability and providing homogenous magnetic flux in air gap. The magnetic flux density in air gap must not be bigger than the maximum flux density that can be sensed by the sensor [6],[7].

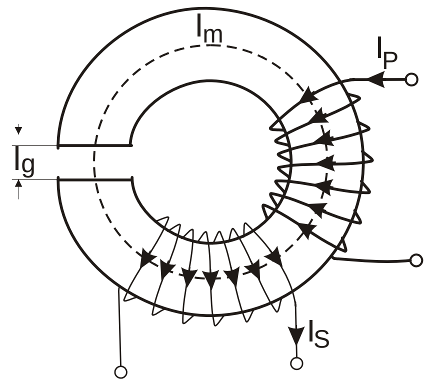

Fig. 3 Air gap and mean length of toroid core

In Fig. 3. The maximum flux is created when the secondary current is 0 and calculated with the expression of

$$B = \frac{4 \times \pi \times 10^{-7} \times \mu_i \times N_P \times I_P}{l_m + l_g \times \mu_i} \tag{2}$$

In this equation, B is the magnetic flux density (T), μ_i is the initial permeability of core determined by the core manufacturer company, $N_P \times I_P$ is the primary mmf, l_m is the mean length of core and l_g is the length of air gap. The effective permeability of core is

$$\mu_e = \frac{B \times l_m}{N_P \times I_P} \tag{3}$$

[6],[7],[8].

The main advantages of the Hall Effect current transformer;

- It can measure current wide bandwidth frequency, from 0 to 100 Hz.
- It's ability of taking burden is remarkably improved and it has good accuracy at the condition that the burden is either resistance or inductance
- It has good surge and transient response, because the

Hall element needs very short time to build Hall voltage, so it can measure pulse current.

- Transformer core magnetization has little effect on the performance of the Hall Effect current transformer because the principle of this current transformer is sero flux in normal working condition, there are very small flux in the core. It can not be saturation.
- It has higher ratio between performance and price than ordinary current transformer [2].

A. Design Example and Application Results

In this study, Allegro A 3515 linear Hall sensor is preferred. The sensitivity of this sensor is 5×10^4 mV/T (5 mV/G), the operating voltage range is 4, 5 V and 5, 5 V and nominal operating voltage is 5V. The operating magnetic flux range is ± 40 mT and ± 80 mT (± 400 G and ± 800 G) and operating temperature range is - 40 ^{0}C and + 150 ^{0}C [9].

If the mmf value is 30 At and primary winding turn is 1, the primary current shall be 30 A. If the winding turn is 10, primary current shall be 3 A. For l_m =54,2 mm, l_g =1,8 mm and $\mu_i = 3000$ values, the magnetic flux density is calculated as 0,0207 T. In this magnetic flux density, the output voltage of Hall sensor with sensitivity of 5×10^4 mV/T (5 m V/G) is 1,035 V. the effective permeability of core is calculated as $\mu_e = 3,738\times10^{-5}$ H/m. The connection scheme of the designed Hall Effect current transformer is given in Fig. 4 [10].

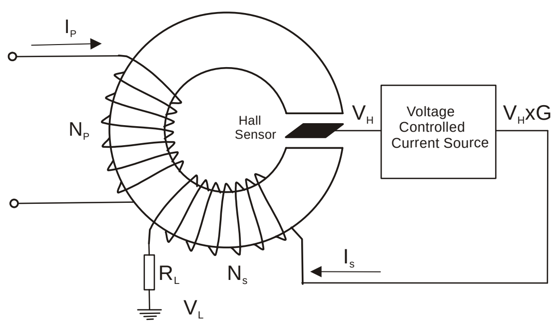

Fig. 4. The connection scheme of the designed Hall Effect current transformer

The voltage controlled current source is a circuit that purifies the Hall sensor output voltage from quiescent voltage output, amplifies it and passes it through the secondary winding as current. (Fig. 5) [10].

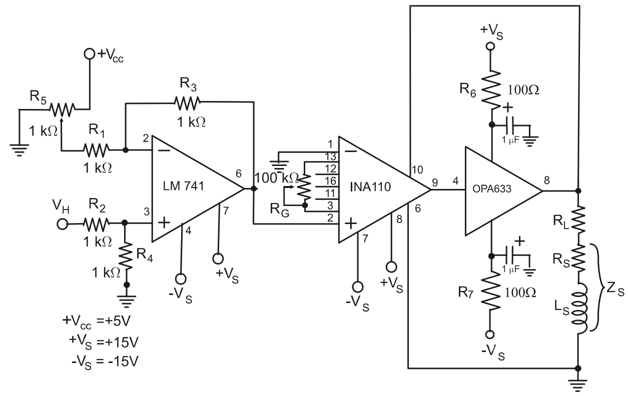

Fig. 5. Voltage controlled current source

The quiescent voltage output is the voltage of the sensor when there is no applied magnetic field and it is generally half of the supply voltage ($V_{cc}/2$) and specially important for DC current measurement [7],[9]. Cristaldi [11] proposes third compensation winding except for primary and secondary winding to compensate for the quiescent voltage. In this method, third winding requires constant current to eliminate the quiescent voltage of the Hall sensor but op-amps can easily compensate for the quiescent voltage. In this study, for compensation of quiescent voltage output LM 741 op-amp and for voltage amplification INA 110 KP instrumentation amplifier are preferred. With selecting gain resistor value as 81,58 kΩ, voltage gain ratio is set to 1,49 [12],[13],[14]. The expression of the external gain resistor (R_G) is

$$R_G = \frac{40\times10^3}{G-1} - 50 \tag{4}$$

In this equation G indicates voltage gain ratio of amplifier [14]. The value of external gain resistor connected to input of the INA 110 KP is 81, 58 kΩ and is obtained by 100 kΩ potentiometer so voltage gain ratio is 1,49 (Fig. 5).

To provide secondary current in required magnitude in closed loop operating condition, OPA 633 KP buffer is connected to output of the voltage amplification circuit. A voltage controlled current source is obtained by driving the output of INA 110 KP with OPA 633 KP. [15], [16].

The secondary current is found with the expression of

$$I_S = \frac{V_H \times G}{R_L + Z_S} \tag{5}$$

In this equation, V_H indicates Hall sensor voltage, R_L indicates measurement resistor, Z_S indicates secondary winding impedance. As the Hall sensor voltage is proportional to primary current, the secondary current will be proportional to the primary current. So the measurement voltage (V_L) will be proportional to the primary current.

$$V_L = I_S \times R_L \tag{6}$$

If $I_P \times N_P / N_S$ expression is used instead of I_S, expression of the primary current depending on measurement voltage can be found.

$$V_L = \frac{I_P \times N_P}{N_S} \times R_L$$

$$I_P = \frac{V_L \times N_S}{N_P \times R_L} \tag{7}$$

For the application, necessary air gap is established on the Magnetics OF-42206-TC ferrite core and primary and secondary windings are coiled. The parameters of designed Hall Effect current transformer are given in Table 1.

TABLE 1.THE PARAMETERS OF DESIGNED HALL EFFECT CURRENT TRANSFORMER

Parameter	Symbol	Value
Hall Sensor Sensitivity	S_H	*5x104 mV/T*
Mean Core Length	l_m	*54,2 mm*
Hall Sensor Sensitivity	S_H	*5x104 mV/T*
Mean Core Length	l_m	*54,2 mm*
Air Gap Length	l_g	*1,8 mm*
Initial Permeability	μ_i	*3000*
Effective Permeability	μ_e	*3,738x10-5 mV/T*
Primary Winding Turns	N_P	*10*
Measurement Resistor	R_L	*1000 ohm*

The core with Hall sensor and upper side view of the electronic circuit is given in Fig. 6 [10].

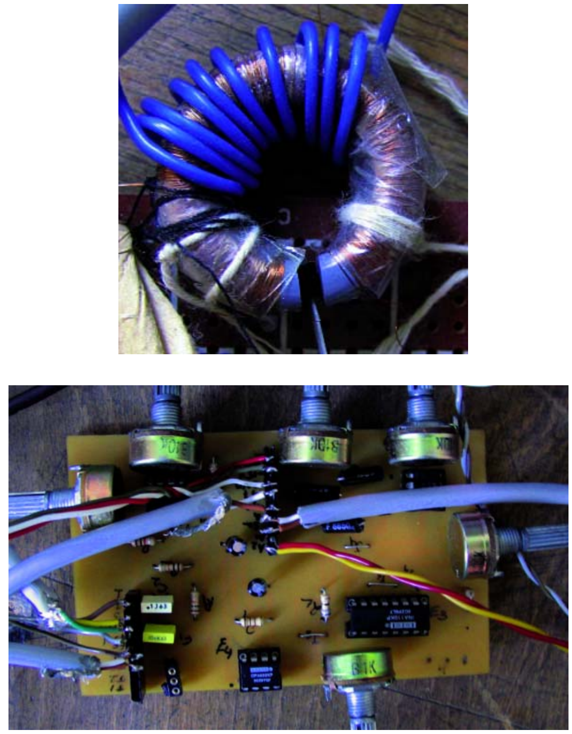

Fig. 6. The Core with Hall Sensor and Upper Side View of the Electronic Circuit

Primary current of current transformer is increased by 0.05 A intervals and corresponding secondary currents and measurement voltages are measured. The direct current and sinusoidal alternative current RMS values are measured respectively. The environment temperature is 27,3 ^{0}C. The change of measurement voltage with primary current is given in Fig. 7 [10].

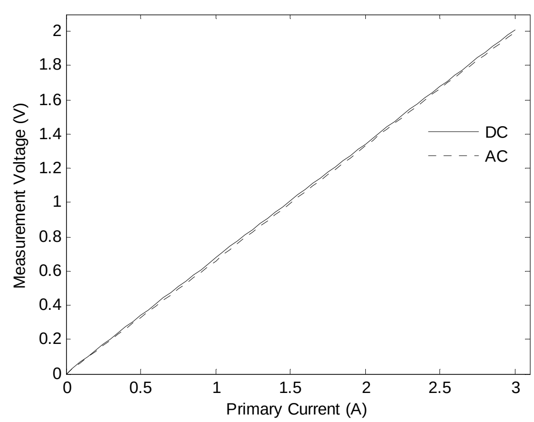

Fig. 7. Primary current -measurement voltage change for Closed Loop Current Transformer

III. NEURAL NETWORK

Neurally inspired models, also known as parallel distributed processing (PDP) or connectionist systems, de-emphasize the explicit use of symbols in problem solving. Processing in these systems is distributed across collections or layers of neurons. Problem solving is parallel in the sense that all the neurons within the collection or layer process their inputs simultaneously and independently. In connectionist systems, processing is parallel and distributed with no manipulation of symbols as symbols. Pattern in a domain are encoded as numerical vectors. The connections between components, or neurons, are also represented by numerical values. Finally, the transformation of patterns is the result of a numerical operations, usually, matrix multiplications. These "designer's choices" for a connectionist archicture constitute the inductive bias of the system [17]. The basis of neural networks is the artificial neuron, as in Fig 8-(a). An artificial neuron consists of: input signals (xi), a set of real value weights (wi), an activation level (∑wixi), a threshold function (f).

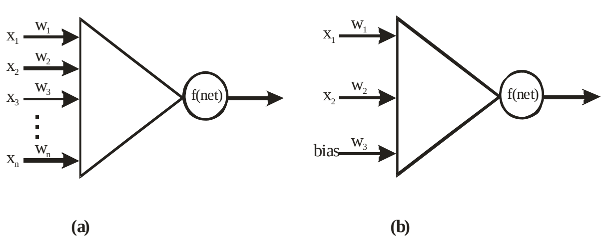

Fig 8 (a) An artificial neuron, (b) the perceptron net

The earliest example of neural computing is the McCulloch-Pitts neuron [18]. The inputs to a McCulloch-Pitts neuron are either excitatory (+1) or inhibitory (-1). The activation function multiplies each input by its corresponding weight and sum the results; if the sum is greater than or equal to zero, the neuron returns 1, otherwise, -1. McCulloch and Pitts showed how these neurons could be constructed to compute any logical function, demonstrating that systems of these neurons provide a complete computational model.

Although McCulloch and Pitts demonstrated the power of neural computation, interest in the approach only began to flourish with the development of practical learning algorithms. Early learning models drew heavily on the work of the psychologist D. O. Hebb[19], who speculated that learning occurred in brains through the modification of synapses. Hepp theorized that repeated firings across a synapse increased its sensitivity and the future likelihood of its firing. If a particular stimulus repeatedly caused activity in a groups of cells, those cells come to be strongly associated. In the future, similar stimuli would tend to excite the same neural pathways, resulting in the recognition of the stimuli. Hebb's model of learning worked purely on reinforcement of used paths and ignored inhibition punishment for error, or attrition. Modern psychologists attempted to recreate Hebb's model but failed to produce general results without addition of an inhibitory mechanism [20, 21].

In the late 1950s, Frank Rosenblatt devised a learning algorithm for a type of single-layer network called a perceptron [22]. In its signal propagation the perceptron was similar to the McCulloch-Pitts neuron; see, for example, Fig. 8-(b). The input values and activation levels of the perceptron are either -1 or 1; weights are real valued. The activation level of the perceptron is given by summing the weighted input values, ∑xiwi. Perceptrons use a simple hard-limiting threshold function, where activation above a threshold results in an output value of 1, and -1 otherwise. The perceptron uses a simple form of supervised learning. After attempting to solve a problem instance, a teacher gives it the correct result. The perceptron then changes its weights in order to reduce the error.

Perceptrons were initially greeted with enthusiasm. However, Nils Nilsson[23] and others analyzed the limitations of the perceptron model. They demonstrated that perceptrons could not solve a certain difficult class of problems, namely problems in which the data points are not linearly separable. Although various enhancements of the perceptron model, including multi-layered perceptrons, were envisioned at the time, Marvin Minsky and Seymour Papert, argued that the linear separability problem could not be overcome by any form of the perceptron network.

A. *Selecting the ANN Architecture*

Experimental data used in the study are totally 60 data used in modeling were used during the training of the network while 20 of them were used to test the system.

Data were organized so that more reliable results could be obtained and changed into numerical values in order for the network to understand them. Before the separation of the data to be used during the training and testing, data selections were carried out randomly. Thus, the system is trained with data reflecting the parameters of the whole system and random data were selected to be able to achieve the best result.

As training algorithm that determines the application process and one of the significant factors, back propagation algorithm Levenberg-Marquardt was used. Marquardt parameter accelerates the zero error approach of the neural network. In return for the given input, the output calculated by the network is compared with the real (desired) output. The gap between the output of the network and the real output is calculated as error. The average of the total of the fault is attempted to minimize. This value to be minimized MSE (Mean Squared Error) enable the network to have smaller weight and performance values that is one of the factors affecting the training performance. In this study, the best result was obtained by the use of mean squared error function.

Activation function that is to affect the results to reflect the modeling best was determined after the normalization process of input and output data in order to prevent the adverse effects following the excessive swinging results that were fed by the network. In the neural network models, the minimum error value was achieved with the use of tangent hyperbolic activation function. Different training algorithms and activation functions were selected in order to evaluate the result correctly and to be able to compare them.

The training process has been stopped when the error has become stable.

In the test, an unknown input pattern has been presented to the ANN, and the output has been calculated. Linear regression between the ANN output and target is performed.

Choosing the number of layer parameters to a feed forward back propagation topology is the art of the ANN designer. There is no quantifiable, best answer to the layout of the network for any particular application. There are only general rules picked up over time and followed by most researchers and engineers applying this architecture to their problems. The first rule states that if the complexity in the relationship between the input data and the desired output increases, then the number of the processing elements in the hidden layer should also increase. The second rule says that if the process being modeled is separable into multiple stages, then additional hidden layer(s) may be required. The result of the tests has showed that the optimal number of neurons in the first layer can be chosen as 16 also, the activation function has been chosen as a hyperbolic tangent sigmoid function for all of the layers [15], [16],[20],[21].

B. ANN Model Results

As a result of comparing the test results or the formed single and multi-layer artificial neural networks, multi-layer artificial neural network learned better values that those of single layer ones.

ANN simulators have been trained different epochs. The training process has been stopped when the error has become stable. Variation of the total absolute error through the epochs was shown in Fig 9 and Fig 10.

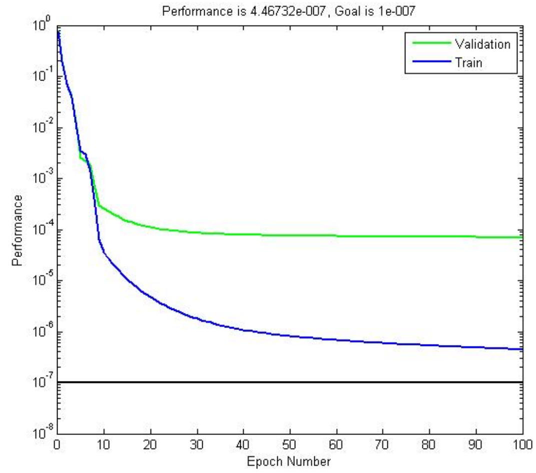

Fig 9. Train steps of closed-loop Hall Effect current transformer for DC current measurement

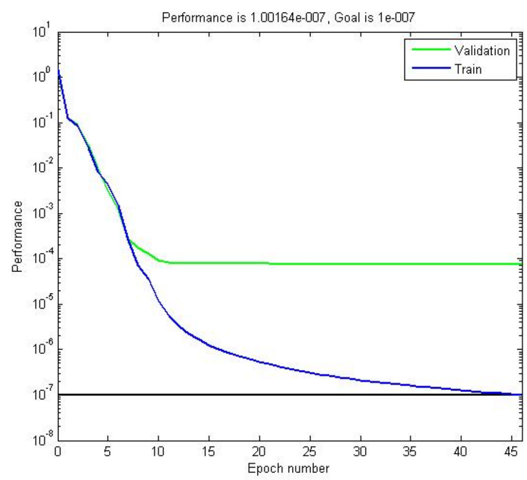

Fig 10. Train steps of closed-loop Hall Effect current transformer for AC current measurement

ANN output datas with the target data for under DC voltage were shown Fig 11 and ANN output datas with the target data for under AC voltage are shown Fig 13.

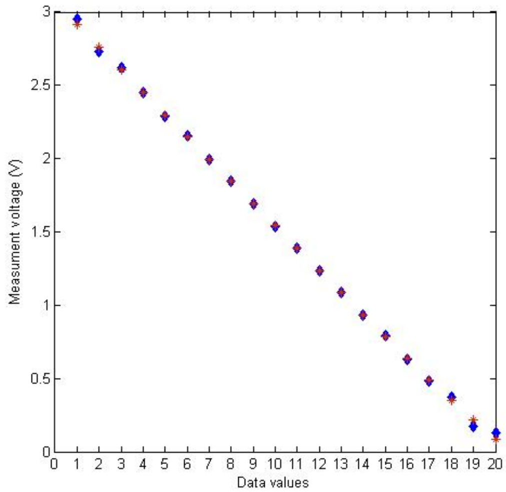

Fig 11. Variation of the ANN output data with the target data for under DC voltage.

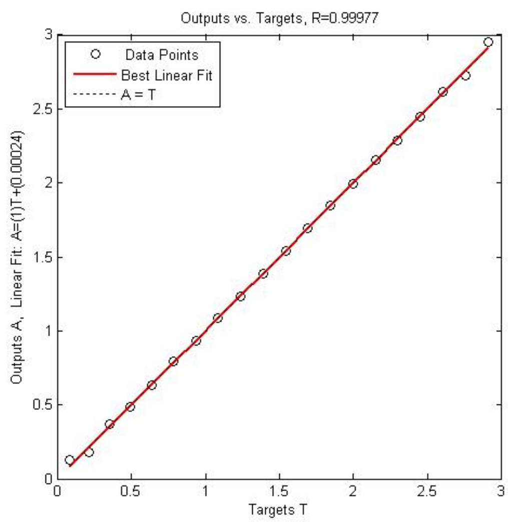

Fig 12. Linear regression results between the ANN output and target voltage regression for under DC voltage

Linear regression between the ANN output and target was performed. Linear regression results were shown Fig 12 for DC voltage and linear regression between the ANN output and target measurement voltage was given Fig 14.

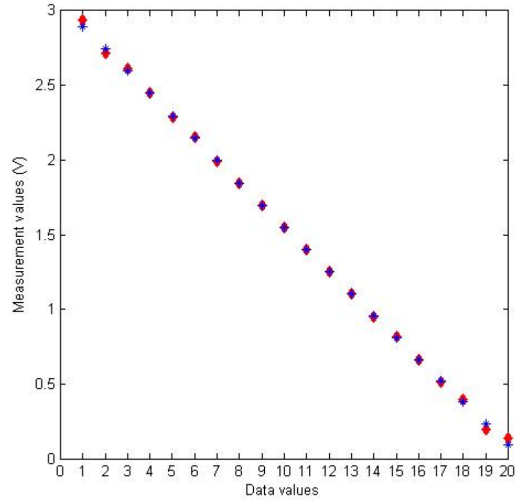

Fig 13. Variation of the ANN output data with the target data for under AC voltage

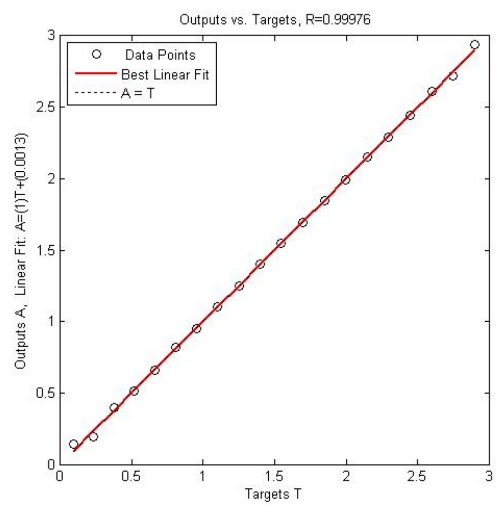

Fig 14. Linear regression results between the ANN output and target voltage regression for under AC voltage

IV. CONCLUSION

In this study, ANN is used for examination of compatibility of input and output parameters of closed loop Hall Effect current transformer

After ANN learning and test steps founded regression coefficients (R= 0. 99977 for DC current measurement, R=0.99976 for AC current measurement) shows that target and ANN output values were very related each other. The regression analysis was shown for learning step in Figure 5, 6, 7 and 8. These coefficient shows that target and ANN output values were very related each other. So the ANN model produces reliable estimates of measurement voltage values of A Hall Effect Current Transformer. ANN facilitates determination of physical parameters of the established model and making of calibration. The results have also pointed out that ANN can implement many other data prediction efforts easily and successfully.

For further studies, AAN can be used for determination of linearity of the Hall Effect Current Transformers without using classical approaches such as the least squares method also can help to make projection of bigger current measurement

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