Hot Resistance Estimation for Dry Type Transformer Using Multiple Variable Regression, Multiple Polynomial Regression and Soft Computing Techniques

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Abstract: Problem statement: This study presents a novel method for the determination of average winding temperature rise of transformers under its predetermined field operating conditions. Rise in the winding temperature was determined from the estimated values of winding resistance during the heat run test conducted as per IEC standard. **Approach:** The estimation of hot resistance was modeled using Multiple Variable Regression (MVR), Multiple Polynomial Regression (MPR) and soft computing techniques such as Artificial Neural Network (ANN) and Adaptive Neuro Fuzzy Inference System (ANFIS). The modeled hot resistance will help to find the load losses at any load situation without using complicated measurement set up in transformers. **Results:** These techniques were applied for the hot resistance estimation for dry type transformer by using the input variables cold resistance, ambient temperature and temperature rise. The results are compared and they show a good agreement between measured and computed values. **Conclusion:** According to our experiments, the proposed methods are verified using experimental results, which have been obtained from temperature rise test performed on a 55 kVA dry-type transformer.

Key words: Multiple Variable Regression (MVR), Adaptive Neuro Fuzzy Inference System (ANFIS), Artificial Neural Network (ANN), Fuzzy Inference System (FIS)

INTRODUCTION

The reliability of a dry type electrical transformer depends on its ability to dissipate the internally generated heat from the windings to the surroundings. The transformer manufacturers use some standard design curves or thermal network method to estimate temperature rise in the windings (Meshkatoddini, 2008). Using the standard curves, the average temperature rise in windings can be estimated. There are a few theoretical and experimental studies on hot spot temperature prediction and average temperature calculation of windings for dry type transformer. Based on a number of thermal tests on ventilated dry type transformers, (Amoda *et al*., 2011) developed a mathematical model to predict hot spot temperature rise in ventilated dry type transformer. The model has been used to study the effects of various parameters on the ratio of hottest spot to average windings temperature rise.

The temperature rise of transformers is measured by determining the change in winding resistance in accordance with the IEC standards for dry type power transformers. Various techniques are suggested for the measurement of temperature rise in regard to dry type transformers and oil immersed transformers (Popescu *et al*., 2009a). On the other hand direct temperature measurement at hot spots and temperature rise in windings are done using optic fiber sensors (Lesieutre *et al*., 1997). But this method is rarely used due to the difficulties that are faced during mounting as well as it needs to be maintained. The present study suggests a method for the determination of hot winding resistance in transformers using statistical methods such as Multiple Variable Regression (MVR), Multiple Polynomial Regression (MPR) and soft computing techniques namely Artificial Neural Networks (ANN) and Adaptive Neuro Fuzzy Inference System (ANFIS). The estimation of hot-resistance in the course of a heat-run test is conducted as per the IEC standard followed by the computation of winding temperature rise. Also the estimation is compared with experimental results. In the present study, work has been carried out in a dry type welding transformer rated at 55kVA, 415/55V, 50

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Hz, three phase, 1000 amps, star/star connected, H class and core type.

The study is organized as follows: the temperature rise measurements, the hot resistance Modeling using MVR, MPR, Artificial Neural Networks (ANN) and Adaptive Neuro Fuzzy Inference System (ANFIS), an experimental set up for hot resistance measurement, simulations and experimental results. Finally the discussions and conclusions regarding the proposed technique are reported.

Review on temperature rise in transformers and ambient temperature measurement: There are three methods widely used to determine the temperature rise in transformers.

Surface temperature sensor: Surface temperature sensor method uses the temperature sensor at the surface of winding where in typically thermocouples and resistance thermometers are widely used. Bulb thermometers shall not be used for measuring temperatures of windings and surfaces. Normally Temperature sensors are placed at accessible spots of the transformer where the maximum temperature is likely to be reached. It is advisable to locate the predictable hot spots by means of a preliminary check. Also the size and spread of hot spots in windings depend on the design of the transformer. Efficient heat transmission between the point of measurement and the temperature sensor shall be ensured and protection shall be provided for the temperature sensor against the effect of air currents and radiation.

Embedded temperature sensor: In this method the small size temperature sensors are embedded in the winding to measure the hot test temperature of the winding. In this method, mounting is very important to ensure that there is no damage on the conductors or windings' insulation. But this method is rarely used due to the difficulties that are faced during mounting as well as its maintenance.

Resistance measurement: The temperature rise in the windings is easily found by measuring the cold and hot resistance of the transformer:

$$t_f - t_a = \frac{(235 + t_i)(R_f - R_i)}{R_i} \qquad (1)$$

Where:
t_i = The temperature of the winding at the moment when R_i is measured (°C)

t_f = The calculated temperature of the winding at the end of the test (°C)

t_a = The ambient air temperature at the end of the test(°C)

R_i = The initial resistance of the winding in ohms

R_f = The final resistance of the winding in ohms

For aluminum conductors the above value 235 is replaced by 225 in Eq. 1.

The temperature t_i shall be within ±3 K of the ambient air temperature.

Determination of the ambient air temperature (t_a): The ambient air temperature is determined by at least three thermocouples. These thermo couples are uniformly spaced around the transformer, at approximately one-half of its height and 1 m to 2 m from its surface. These thermocouples should be protected from draughts and abnormal heating. Measurement of three thermocouples reading is to be noted and the mean value of the temperature readings are considered as the temperature of the ambient air.

Hot resistance modeling using MVR and MPR:
Hot resistance modeling using MVR: Regression models involve the following variables:

- The unknown parameters denoted as β; this maybe a scalar or a vector
- The independent variables, X
- The dependent variable, Y

In various fields of application, different terminologies are used in place of dependent and independent variables. A regression model relates Y to a function of X and β. The approximation is usually formalized as $E(Y | X) = f(X, β)$. To carry out regression analysis, the form of the function f must be specified. Sometimes the form of this function is based on the knowledge about the relationship between Y and X that does not rely on the data. If no such knowledge is available, a flexible or convenient form for f is chosen. Assume now that the vector of unknown parameters β is of length k. In order to perform a regression analysis the user must provide information about the dependent variable Y.

If N data points of the form (Y, X) are observed, where N < k, most classical approaches to regression analysis cannot be performed: since the system of equations defining the regression model is underdetermined, there is not enough data to recover β.

If exactly N = k data points are observed and the function f is linear, the equations Y = f(X, β) can be

solved exactly rather than approximately. This reduces to solving a set of N equations with N unknowns (the elements of β), which has a unique solution as long as the X are linearly independent. If f is nonlinear, a solution may not exist, or many solutions may exist.

The most common situation is where N > k data points are observed. In this case, there is enough information in the data to estimate a unique value for β that best fits the data in some sense and the regression model when applied to the data can be viewed as an over determined system in β.

In the last case, the regression analysis provides the tools for:

- Finding a solution for unknown parameters β that will, for example, minimize the distance between the measured and predicted values of the dependent variable Y (also known as method of least squares)
- Under certain statistical assumptions, the regression analysis uses the surplus of information to provide statistical information about the unknown parameters β and predicted values of the dependent variable Y

The complete equation for hot resistance modeling is given Eq. 2:

$$1.928E-11*x_1 + 5.496E-13*x_2 + \\ 1.499*x_3 - 2.516E-10 \tag{2}$$

Hot resistance modeling using MPR: Polynomial models are generalized to any number of predictor variables x_i (i = 1, ..., N) as follows Eq. 3:

$$y(x) = a_0 + \sum_{i=0}^{N} a_i x_i + \sum_{i<j}^{N} a_{ij} x_i x_j + \sum_{i=0}^{N} a_{ij} x_i^2 + \tag{3}$$

The model includes, from left to right, an intercept, linear terms, quadratic interaction terms and squared terms. Higher order terms would follow, as necessary. The complete equation for hot resistance modeling is given in Eq. 4.

Soft computing techniques:
Neural network:
Introduction to back-propagation networks: In 1985, Rumelhart McClelland added a buried layer to the back-propagation network and changed the operation function into smooth and differentiable transfer function. Back-propagation network is a multiple layer feed-forward network that has learning capability; the concept of the gradient steepest descent

method is used to adjust the parameters, then after iterative operations, the error is minimized and the most accurate solution is obtained. Since back-propagation network has higher learning accuracy and faster recall speed, the output value can is continuous and complicated sample identification as well as highly nonlinear function issue can be handled. Therefore, back-propagation network is the most representative one among the current neural network learning models and is the most used neural network:

$$Y = -1.51090898*10^{-3}x_1^2 + 2.238413188*10^{-8} \\ X_1X_2 + 2.2987711X_1X_3 + 6.503151906*10^{-10}X_2^2 \\ -4.64857941*10^{-5}X_2X_3 - 873.934204X_3^2 \\ -2.769135404*10^{-3}X_1 + 1.108699048*10^{-5}X_2 \\ +3.605305672X_3 - 1.262240345*10^{-3} \tag{4}$$

Network Architecture of back-propagation network: Figure 1 is the architecture of back-propagation network, where there are N neural units in the input layer, L neural units in the buried layer and K neural units in the output layer; here the number of neural unit in the buried layer will be dependent on the problem and there is no specific method to decide it; usually, the optimum number is found by trial and error Method (Pylvanainen *et al.*, 2007). Back-propagation network is a way of setting up mapping input value and output value; it assembles simple and nonlinear function and after many times of assemblies, a complicated function form is set up to solve the complicated mapping issue (Sozen and Arcaklioglu, 2007). Figure 2 shows the learning process flow of back-propagation network.

Neural network based prediction of hot resistance in a dry type transformer: An artificial neural network is composed of neurons with a deterministic activation function. The neural network is trained by adjusting the numerical value of the weights and will contain the non-linearity of the desired mapping, so that difficulties in the mathematical modeling can be avoided. The BP training algorithm is used to adjust the numerical values of the weights and the internal threshold of each neuron. The network is trained by, initially selecting small random weights and internal threshold and then presenting all training data. Weights and thresholds are adjusted after every training example is presented to the network; until the weight converges or the error is reduced to acceptable value. Figure 3 shows the structure of BP Network for prediction of hot winding resistance.
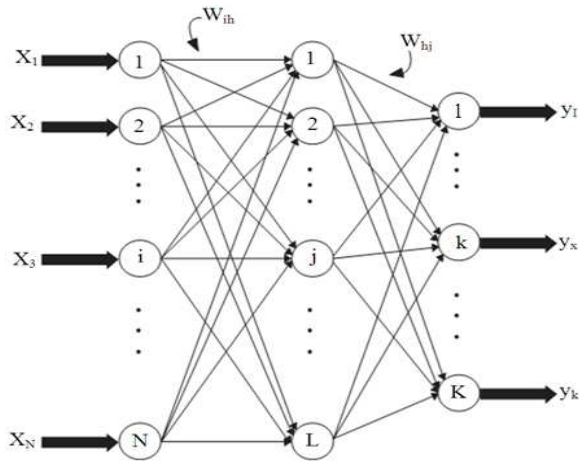
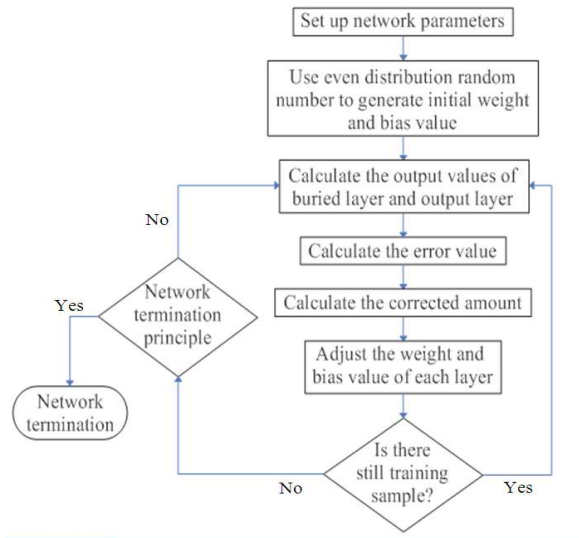Fig. 1: Architecture of back-propagation network

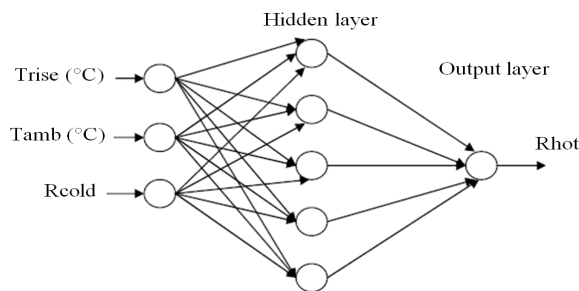Fig. 2: The learning process flow chart of back-propagation network

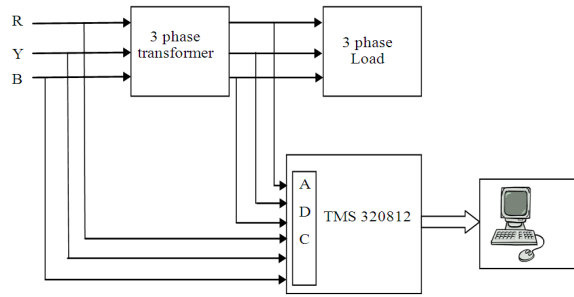Fig. 3: Structure of BP Network for prediction of hot winding resistance

Fig. 4: Block diagram of the hot resistance measurement system

Adaptive Neuro Fuzzy Inference System (ANFIS):
Adaptive Neuro Fuzzy Inference System (ANFIS) is a combination of fuzzy logic and neuron computing. Using a given input/output data set, the ANFIS constructs a Fuzzy Inference System (FIS) whose membership function parameters are adjusted using a back propagation algorithm method (Pylvanainen *et al*., 2007; Hell *et al*., 2008). This allows fuzzy systems to learn from the data they are modeling. In the present work, soft computing techniques are used to predict the winding hot resistance of a transformer. The three independent variables namely ambient temperature, cold resistance and temperature rise are used as the inputs to predict the hot winding resistance.

MATERIALS AND METHODS

The low cost digital temperature rise measurement system is made up of several distinct subsystems and is illustrated in Fig. 4. The subsystem consists of a, PC, sensing and signal conditioning circuit and the eZdsp F2812 board from Texas Instruments as a development tool board.

The three phase transformer constructed with three primary and secondary windings. The sensing and single conditioning are designed with simple resistors. The controller is implemented by software and executed by an eZdsp F2812 board (Srinivasan *et al*., 2011). This experimental setup enables to measure the hot resistance as per IEC standard and the results are stored in the register.

RESULTS AND DISCUSSION

Experimental result: The hot resistance test measurement was built and tested to plot the hot resistance of a transformer. The algorithm hot resistance and temperature rise of transformer is implemented through TMS320F2812 digital signal processor. Table 1 shows the experimental results of hot resistance measurement of transformer.

Table 1: Measured hot resistance

Out -put Index	Trise (°C)	Rcold (Ω)	Rhot (Ω)	Tamb (°C)
1	0.000000	0.027507	0.041261	
2	1.023460	0.027617	0.041425	
3	4.093838	0.027726	0.041589	
4	9.211136	0.027836	0.041754	
5	16.37535	0.027945	0.041918	
6	25.58649	0.028055	0.042083	
7	36.84454	0.028165	0.042247	20
8	50.14952	0.028274	0.042411	
9	65.50141	0.028384	0.042576	
10	82.90022	0.028493	0.042740	
11	102.3460	0.028603	0.042904	
12	123.8386	0.028713	0.043069	
:				:
:				:
169	0.000000	0.045918	0.068877	
170	1.080545	0.046028	0.069042	
171	4.322180	0.046137	0.069206	
172	9.724904	0.046247	0.069370	
173	17.28872	0.046357	0.069535	
174	27.01362	0.046466	0.069699	34
175	38.89962	0.046576	0.069864	
176	52.94670	0.046685	0.070028	
177	69.15487	0.046795	0.070192	
178	87.52414	0.046904	0.070357	
179	108.0545	0.047014	0.070521	
180	130.7459	0.047124	0.070685	

Table 2: Hot resistance estimation using MVR with errors

Tamb	Rhot measured (Ω)	Estimated rhot_MVR	Error due to MVR
	0.041261	0.0412606	4.2300E-07
	0.041425	0.0414250	3.8000E-08
	0.041589	0.0415893	-3.4600E-07
	0.041754	0.0417537	2.6900E-07
	0.041918	0.0419181	-1.1600E-07
20	0.042083	0.0420825	4.9900E-07
	0.042247	0.0422469	1.1400E-07
	0.042411	0.0424113	-2.7000E-07
	0.042576	0.0425757	3.4500E-07
	0.042740	0.0427400	-4.0000E-08
	0.042904	0.0429044	-4.2500E-07
	0.043069	0.0430688	1.9100E-07
:	:	:	:
:	:	:	:
	0.068877	0.0688772	-2.1800E-07
	0.069042	0.0690416	3.9700E-07
	0.069206	0.0692060	1.2000E-08
	0.069370	0.0693704	-3.7300E-07
34	0.069535	0.0695348	2.4300E-07
	0.069699	0.0696991	-1.4200E-07
	0.069864	0.0698635	4.7300E-07
	0.070028	0.0700279	8.8000E-08
	0.070192	0.0701923	-2.9600E-07
	0.070357	0.0703567	3.1900E-07
	0.070521	0.0705211	-6.6000E-08
	0.070685	0.0706855	-4.5100E-07

The variation in hot resistance and cold resistance with the increase in temperature is shown in Fig. 5 and 6 respectively.

Table 3: Hot resistance estimation using MPR with errors

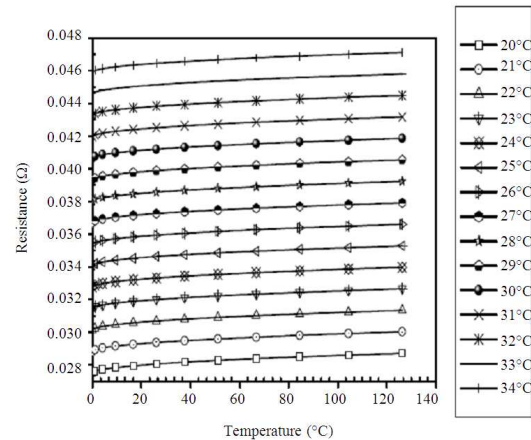| Tamb	Rhot measured (Ω)	Estimated Rhot_MPR	Error due to MPR
	0.041261	0.041036248	0.000224752
	0.041425	0.041209402	0.000215598
	0.041589	0.041381921	0.000207079
	0.041754	0.041554098	0.000199902
	0.041918	0.041726207	0.000191793
	0.042083	0.041898504	0.000184496
20	0.042247	0.042071228	0.000175772
	0.042411	0.042244596	0.000166404
	0.042576	0.042418811	0.000157189
	0.042740	0.042594054	0.000145946
	0.042904	0.042770490	0.000133510
	0.043069	0.042948264	0.000120736
:	:	:	:
:	:	:	:
	0.068877	0.068771452	0.0001055480
	0.069042	0.068951056	0.0000909440
	0.069206	0.069128502	0.0000774980
	0.069370	0.069304098	0.0000659020
	0.069535	0.069478132	0.0000568680
34	0.069699	0.069650869	0.0000481310
	0.069864	0.069822556	0.0000414440
	0.070028	0.069993418	0.0000345820
	0.070192	0.070163660	0.0000283400
	0.070357	0.070333467	0.0000235330
	0.070521	0.070503003	0.0000179970
	0.070685	0.070672410	0.0000125900

Fig. 5: Cold resistance against winding temperature rise for various ambient temperatures

Simulation results: It has been observed from the results obtained are compared with the estimated hot resistance using MVR MPR are tabulated in Table 2 and 3. It's observed from the table that cold and hot resistance errors are less than 0.1% of its actual value in MVR and MPR. Hence it is proved that this MVR and MPR are capable of accurately predicting hot resistance for transformers which will help us to find the load and MPR. The hot resistance values through MVR and MPR assess indirectly for different loads.
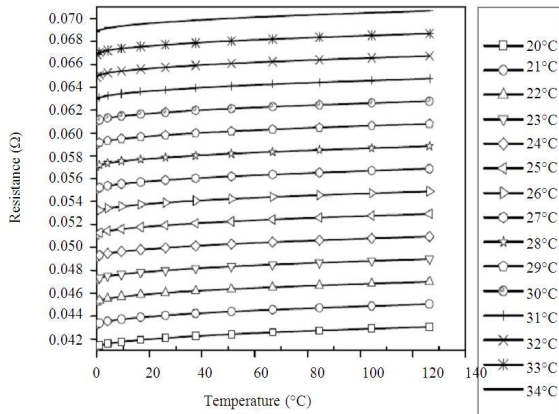
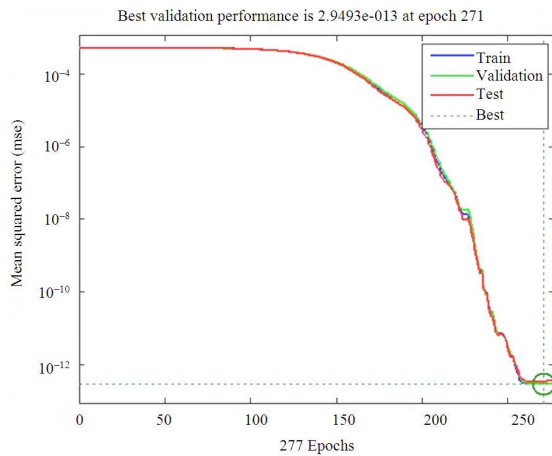Fig. 6: Hot resistance against winding temperature rise for various ambient temperatures

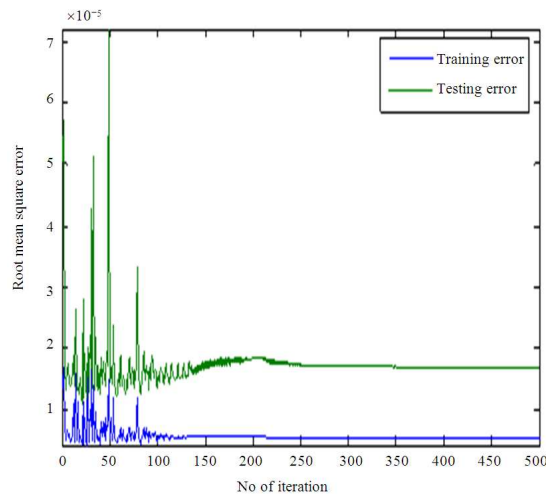Fig. 7: Epoch Vs error characteristics

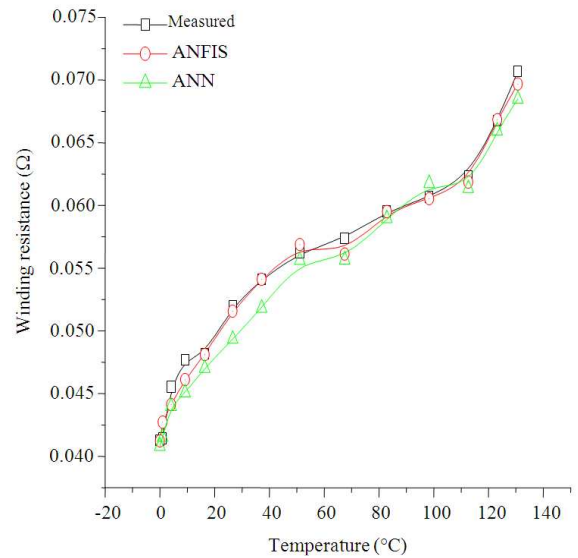Fig. 8: Iteration Vs error characteristics

Fig. 9: Variation of winding resistance with temperature rise

ANN result: Feed forward neural networks with two layers are used. The network consists of three input neurons, five hidden neurons and one output neuron. Back Propagation algorithm is used for training. The first layer and the output layer transfer function are purely linear. The training function used is training.dx. Learning rate is 0.012762815625 and the momentum factor is 0.85. The error obtained in BPNN is 0.127%. Fig. 7 shows the performance characteristics of the BP network.

ANFIS result: Steepest descent algorithm is used to update parameters namely ambient temperature, cold resistance, temperature rise (back-propagation). Using the three input variables, hot resistances are found by this approach and the root mean square errors are represented in Fig. 8. The error obtained ANFIS back propagation algorithm method is 0.1%. Figure 8 shows the performance characteristics of the ANFIS BP network. Figure 9 shows the variation of winding resistance with temperature rise of experimental values compared with ANN and ANFIS simulated values.

CONCLUSION

Hot resistance estimation using regression analysis and soft computing technique have been modeled in the present work and some have been verified for 3 phase transformer using a TMS320F2812 programmed DSP kit with software that has been developed and it is used to measure the hot resistance. The results are compared

with the simulation and the same is presented. It is observed from the mathematical modeling that MVR predicts accurately hot resistance than the MPR. Also, from the mathematical modeling that ANFIS predicts the hot resistance more accurately than the ANN. Experimental results in the work show that measurement system for a hot resistance using a TMS320F2812 is accurately matching the MVR, MPR, ANN and ANFIS estimated results.

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