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Research Article

Calculation of Minimum Train Voltage With a Simulation Model Depending on Train Performance Data in A 1500 V DC Subway Line Using Artificial Intelligence Methods

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Abstract In this study, calculation of the minimum train voltage for a 1500 V DC-fed rail system by means of the adaptive n euro-fuzzy inference system (ANFIS), support vector machines (SVM) and artificial neural networks (ANN). The catanery voltage occurring on the train was calculated with regard to the operating parameters by means of the ANN and ANFIS. The train voltage on the line important for the operation performance The ANN and ANFIS simulations were made. The minimum train voltage needs to be provided in the limits of the EN 50122. This value must be kept within certain limits for the continuity of the railway operation.

Keywords artificial intelligence, anfis, ann, railway, voltage

Introduction

Electrical power used for the train transmitted by catenary and rail. In DC electrified railways catenary system is used for the positive conductor whereas rail is used for the negative conductor. In electrified railways the supply voltage of the train must be in some limits. These limits are determined by EN 50122. In 1500 V DC electrified railways these value must be higher than 1000 V in permanent state [1-4]. Power transmission of train given with Figure 1.

Operation power demand depends on some operation conditions as headway, electrical characteristics of train, speed profile of the train. These all parameter affects the minimum train voltage of the line [5-8].

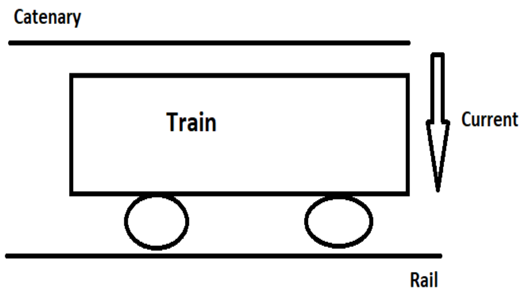

Figure 1: Power transmission of train

Material and Method

For this study, The artificial neural network and adaptive fuzzy inference system among the artificial intelligence applications were used for the simulation. The ANFIS uses the parallel computing and learning capability of artificial neural networks and the inferential characteristic of fuzzy logic which is a hybrid artificial intelligence method. The ANN is a method which functions by imitating the way of work of a simple biological nervous system.

2000 data arrays different from each other were used for the mat lab simulation. 2000 different operation conditions simulated for this study Mat lab is used for these simulations.

Adaptive Neuro Fuzzy Inference System (ANFIS)

The ANFIS is a class of adaptive networks functionally equivalent to the fuzzy inference system. The ANFIS can be given more integrated with some characteristics of controllers, learning ability, parallel processing, structured knowledge representation, other supervision and design methods [9].

The ANFIS consists of 6 layers. This system is displayed in Figure 2. The node functions of every layer in the ANFIS structure and the operation of the layers are respectively as follows [10]. Input layer is the first layer. Every node in this layer has input signals are transmitted to other layers. The fuzzification layer is the second layer. In separating the input values into fuzzy sets, Jang's ANFIS model uses the Bell activation function generalized as a membership function.

$\mu_{A_j}(x)$ ×and $\mu_{B_j}(y)$ are presented as the membership values obtained from the 2nd layer . Rules are in the third layer. Each node in this layer expresses the rules established in accordance with the Sugeno fuzzy logic inference system and their number. The output of each rule node μ_i turns out to be the multiplication of membership degrees which arrive from the 2nd layer. The acquisition of μ_i values, on the condition that (j=1, 2) and (i=1,….,n), is as follows:

$$y_i^3 = \Pi_i = \mu_{A_j}(x) \times \mu_{B_j}(y) = \mu_i \qquad (1)$$

y_i^3 is the output values of the 3rd layer; n represents the number of nodes in this layer. The normalization layer is the fourth layer. The normalized ignition level of each rule is computed. The computing of the normalized ignition level $\bar{\mu}_i$ is performed in accordance with the following formula:

$$y_i^4 = N_i = \frac{\mu_i}{\sum_{i=1}^{n} \mu_i} = \overline{\mu_i}\text{(i=1,n)} \qquad (2)$$

Fifth layer is the purification layer. The weighted resulting values of a given rule in each node in the purification layer are calculated. The output value of the ith node in the 5th layer is as follows.

$$y_i^5 = \overline{\mu_i}[p_i x_1 + q_i x_2 + r_i],\ \text{(i=1,n)} \qquad (3)$$

The (pi , qi , ri) variables here are the outcome parameters. Sum layer is the sixth layer.

The computing of y, which is the output value of the system, is performed in accordance with the equation below [14].

$$y = \sum_{i=1}^{n} \overline{\mu_i}\,[p_i x_1 + q_i x_2 + r_i]$$

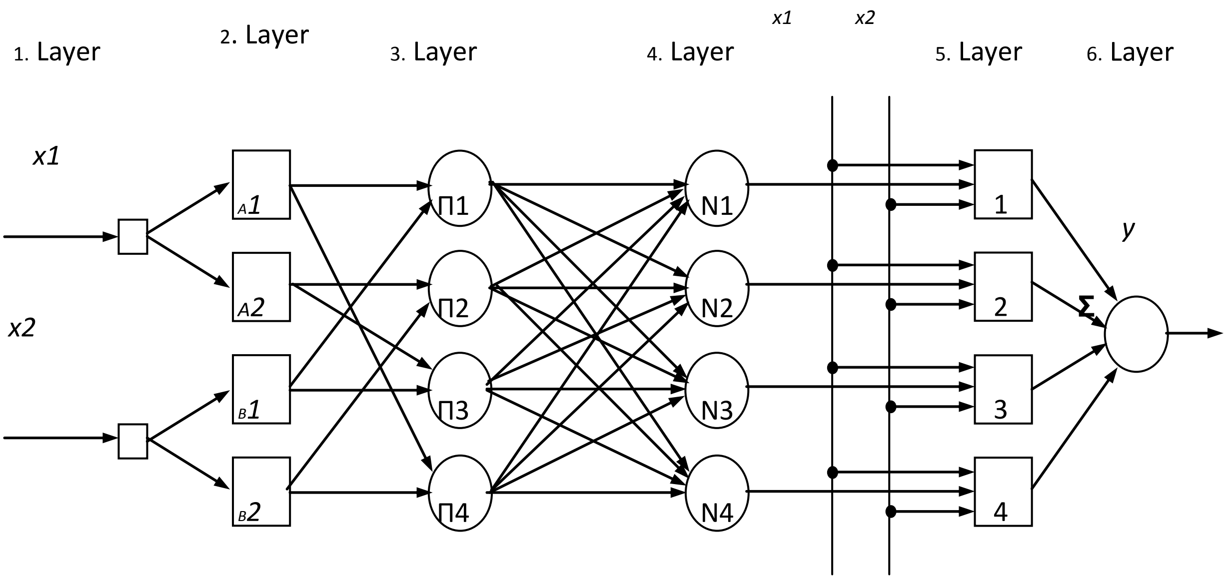

Figure 2: ANFIS structure

Artificial Neural Networks (ANN)

Artificial neural networks is a mathematical method to study and imitate human nature. Artificial neural networks take computing and data processing power from their parallel distributed structure, their capability to learn and generalize. Generalisation is defined as artificial neural networks' producing proper reactions to the inputs which have not been experienced in the course of education or learning. These all properties obtain the problem-solving capability of artificial neural networks [11-15].

Nucleus, body and two extensions compose the biological neuron. The structure of the artificial neural network is given in Figure 3.

Input layer is the first layer. In this layer received data are entered into the other layers. The hidden layer is the 2nd layer which depends on the simulation. The output layer is the 3rd layer. Inputs are processed and received from here. Each sphere (nerve) has a function and a threshold value. Filled small circles indicate bonding weights [16].

The output of a neuron is given with (5) as a function formed by adding a bias value to the sum of the input data in specific weights. "I" is input, "W" is the coefficients for the inputs.

$$Output = f(i_1 W_1 + i_2 W_2 + i_3 W_3 + bias) \quad (5)$$

Simulation Results

2000 data obtained for the simulation with different operation conditions. The structure of the system created for the ANFIS and the simulation results are given below. A structure with 4 inputs 2 membership functions created for the ANFIS. In the simulation a triangular-shaped membership function was used.

For the ANFIS design, 16 rules were established The ANFIS architecture is shown in Figure 4.

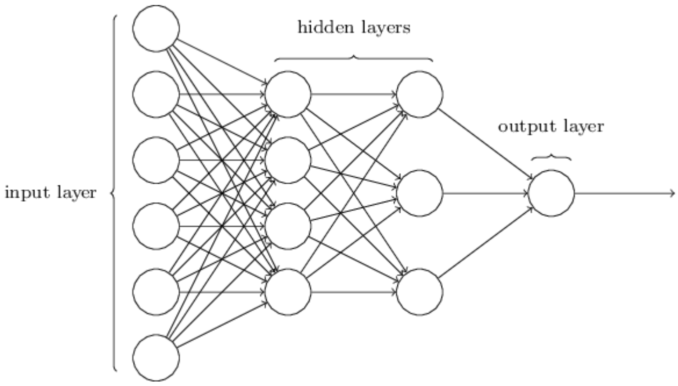

Figure 3: The structure of the artificial neural network

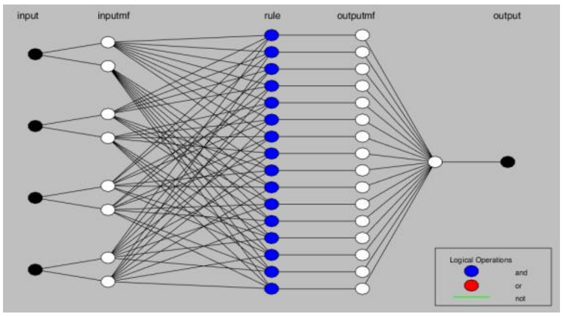

Figure 4: ANFIS architecture

The input, input MF, Rule, output MF and output modules composes the ANFIS structure. 70% of the data used for simulation were used for training, 15% for validation, 15% for the test.

The realized and calculated values of the training, validation and test data are seen in Figure 5. The regression value for all data is 0.99976 is given with Figure 5.

In ANN simulation, 4 input data, 10 hidden neurons, 1 output neuron and 1 output data were used for the architecture used in the design. The ANN architecture used is given in Figure 6.

70% of the data used for simulation were used for training, 15% for validation, 15% for the test.

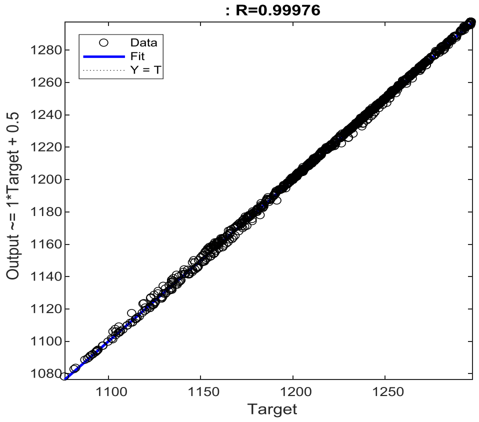

Figure 5: ANFIS regression graph

The Levenberg Marquardt algorithm is used for the simulation. The realized and calculated values of the training, validation and test data are seen in Figure 7. The regression value is shown with R, and as seen in the Figure 7, these values are 0.99982 for training, 0.99984 for validation, 0.9998 for the test data. The regression value is 0.99982 for all data.

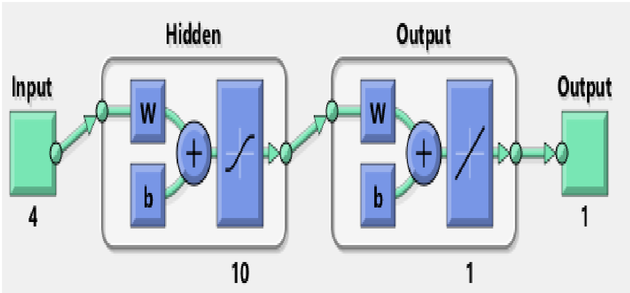

Figure 6: ANN architecture designed [MATLAB R2015b]

As this value approaches 1, the accuracy of the data calculated by the system increases. As the ANN and ANFIS results are compared, the ANN results are observed to be better.

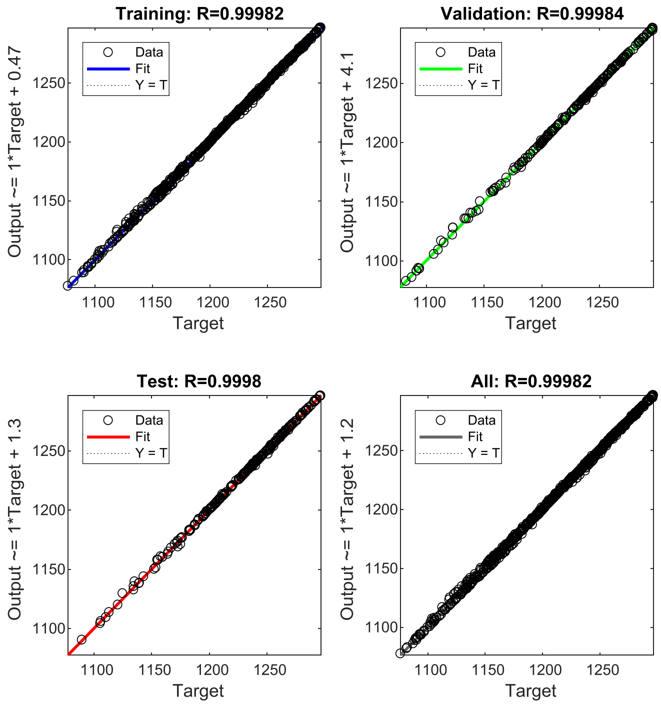

Figure 7: ANN regression graph

The simulation results of both methods are given in Table 1.

Table 1: The Simulation Results of Both Methods

Performance Measures	**Method**	
	ANFIS	***ANN***
Mean absolute error (MAE)	0.59	0.42
Root mean squared error (RMSE)	0.95	0.82
Relative absolute error (RAE)	0.020	0.017
Root relative squared error (RRSE)	0.024	0.022
Total Number of Instances	2000	2000

Conclusion

In this study, the prediction of the minimum train voltage on and 1500 V DC supplied railway with regard to the operating data was performed. 2000 random input data arrays and the calculated output data were used for the simulation. In the analyses carried out, the ANN and ANFIS techniques were used. The train voltage calculated and predicted. The RRSE value in the data obtained for the ANFIS in the calculations carried out is 2.4% this value is 2.2% in the ANN. The RMSE values are 0.95 V for the ANFIS simulation and 0.82 V for the ANN. The MAE value acquired in the ANFIS is 0.59 V this value is 0.42 V in the ANN. The RAE value in the ANFIS is 2% this value is 1.7% in the ANN. When the data obtained from the simulations are compared, the prediction values produced with the ANN are observed to be better. As the prediction data produced for ANN and ANFIS techniques are compared with the real data, it is observed that errors are at an acceptable rate. Calculated prediction dates are well enough and usable.

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