

Adaptive neuro fuzzy system for modelling and prediction of distance pantograph catenary in railway transportation

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Abstract. This research presents an adaptive neuro-fuzzy system which is used in the prediction of the distance between the pantograph and contact line of the electrical locomotives used in railway transportation. In railway transportation any incident that occurs in the electrical system can have major negative effects: traffic interrupts, equipment destroying. Therefore, a prediction as good as possible of such situations is very useful. In the paper was analyzing the possibility of modeling and prediction the variation of the distance between the pantograph and the contact line using intelligent techniques

1. Introduction

The problem of modeling is an important step in any activity that requires the identification of an engineering solution to a real problem. Solving a new problem involves: identifying and developing a model; using techniques to find an optimal solution based on the developed model (this can be done by simulation); using the optimal solution to the needs of the real problem

Modeling and simulation are the use of statistical or dynamic (timely) models to obtain data and decision making information. Modeling and simulation help reduce costs and increase product and system quality. The modeling and simulation technique is cheaper and more secure than real-world experiments in many practical situations. It is also sometimes closer to reality than traditional experiments and allowing the configuration of environmental parameters to the values encountered in the application domain. Simulation is (often) much faster than a real process, allowing for an efficient analysis of different situations (the most unfavorable case.) Once is identified and developed a model, this can be used many times.

The present paper uses modeling and simulation techniques based on fuzzy logic and neural calculus having the prediction of a time series, namely the variation in time of the catenary pantograph distance to electric locomotives. For the validation of the identified model, results of measurements of electrical quantities performed on a laboratory model were used. The catenary pantograph system has a dynamic oscillatory behavior and can be disturbed by certain turbulences during operation. It has been observed that at speeds of over 180 km / h the contact between the pantograph and the catenary can be interrupted and electric arcs can occur. There is no adequate mathematical model describing this behavior. Figure 1 shows the pantograph and figure 2 shows the aliasing of this movement.





Figure 1. The pantograph

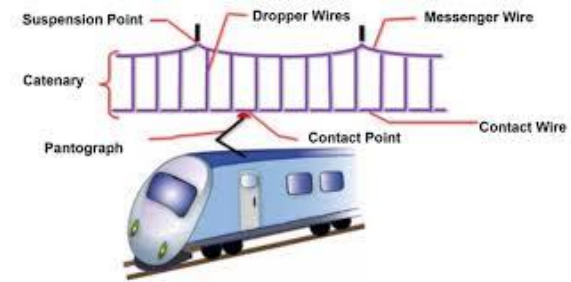


Figure 2. The aliasing of the pantograph catenary movement

The researches were made on a laboratory model for the pantograph realized at the scale 1:2 and controlled by a pneumatic system. The pantograph-contact wire assembly describes a trajectory in horizontal plan (zigzag) and another trajectory in vertical plan [1-3]. Measurements of the distance were made using a NI device by using optical tracking the pantograph motion and for acquiring the trajectory coordinates for statistics. Figure 3 shows the laboratory model of the pantograph used for tests.



Figure 3. The laboratory model of the pantograph made at 1:2 scale

Folowing the measurements presented in [1-3] a variation of the pantograph – catenary distance in time was obtained and figure 4 shows this variation.

2. Adaptive Neuro-Fuzzy Inference Systems

ANFIS hybrid neuro-fuzzy systems are equivalent adaptive neural networks from the functional point of view with Tagaki Sugeno fuzzy systems [4]. Compared to the classical fuzzy systems, ANFIS neuro-fuzzy systems have the capability to adapt during a learning process. In this way, by using an

optimization method, the fuzzy membership functions can be adapted [5]. In order to explain the structure of a hybrid neuro-fuzzy system of ANFIS type it is considered a fuzzy system of Tagaki and Sugeno type of first order, which has two input values, x and y , and an output value, f . Fuzzy system rules base is considered made of two rules [5]:

- Rule 1: if x is A_1 and y is B_1 then $f_1 = p_1 \cdot x + q_1 \cdot y + r_1$
- Rule 2: if x is A_2 and y is B_2 then $f_2 = p_2 \cdot x + q_2 \cdot y + r_2$

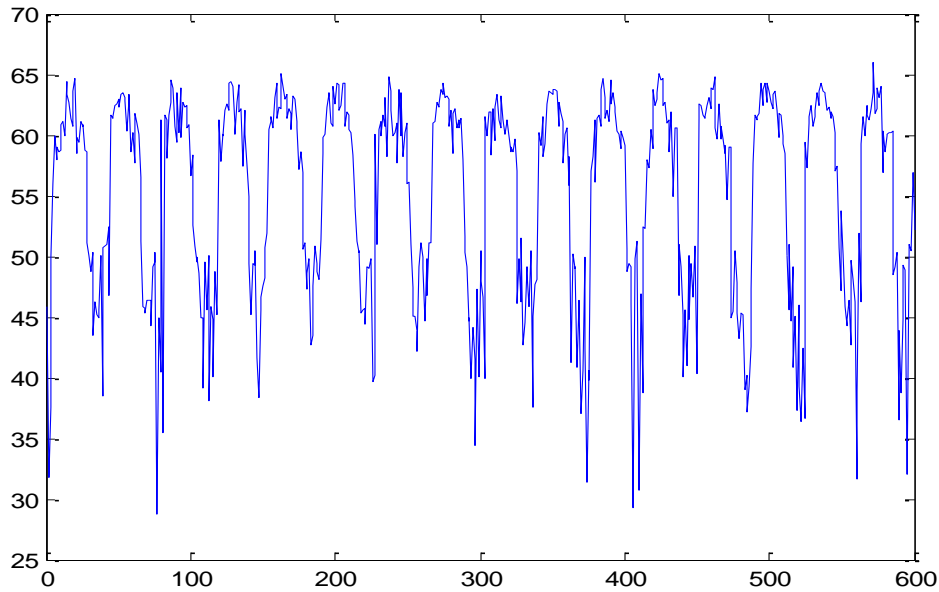


Figure 4. The variation in time of the pantograph – catenary distance

In Figure 5a is intuitively shown the way in which is made the reasoning in a fuzzy system of Tagaki and Sugeno type of first order, its output being computed as follow:

$$f = \frac{w_1 \cdot f_1 + w_2 \cdot f_2}{w_1 + w_2} = \overline{w_1} \cdot f_1 + \overline{w_2} \cdot f_2 \quad (1)$$

Figure 4b illustrates the structure of a considered neuro-fuzzy adaptive system. Equivalent ANFIS structure of the fuzzy system of first order is conditioned by 5 layers [4-8].

- Layer 1 has the output:

$$O_{1,i} = \mu_{A_i}(x), i = 1, 2, \text{ or } O_{1,i} = \mu_{B_{i-2}}(y), i = 3, 4 \quad (2)$$

Parameters of this layer are called premise parameters.

If the Bell activation function is used, given by three parameters a_i, b_i, c_i then:

$$\mu_{A_i}(x) = \frac{1}{1 + \left[\left(\frac{x - c_i}{a_i} \right)^2 \right]^{b_i}}, \quad (3)$$

or

$$\mu_{A_i}(x) = e^{-\left[\left(\frac{x - c_i}{a_i} \right)^2 \right]^{b_i}} \quad (4)$$

where, $\{a_i, b_i, c_i\}$ is the parameter set of the membership functions referred to as premise parameters.

- Layer 2 has the output:

$$O_{2,k} = w_k = \mu_{A_i}(x) \times \mu_{B_j}(y), i = 1, 2, j = 1, 2, k = 1, \dots, 4 \quad (5)$$

Each node represents the activation value for a rule.

- Layer 3 has fixed nodes with the outputs:

$$O_{3,i} = \bar{w}_i = \frac{w_i}{w_1 + w_2}, i=1,2 \quad (7)$$

- Layer 4 has adaptive nodes with the activation function

$$O_{4,i} = \bar{w}_i \cdot f_i = w_i (f_i = p_1 \cdot x + q_1 \cdot y + r_1) \quad (8)$$

- Layer 5 is made of a fix node that computes the ANFIS overall output

$$f = O_{5i} = \sum_{i=1}^2 \bar{w}_i \cdot f_i = \frac{\sum_{i=1}^2 w_i \cdot f_i}{\sum_{i=1}^2 w_i} \quad (9)$$

Learning within an ANFIS system is hybrid [3], [4].

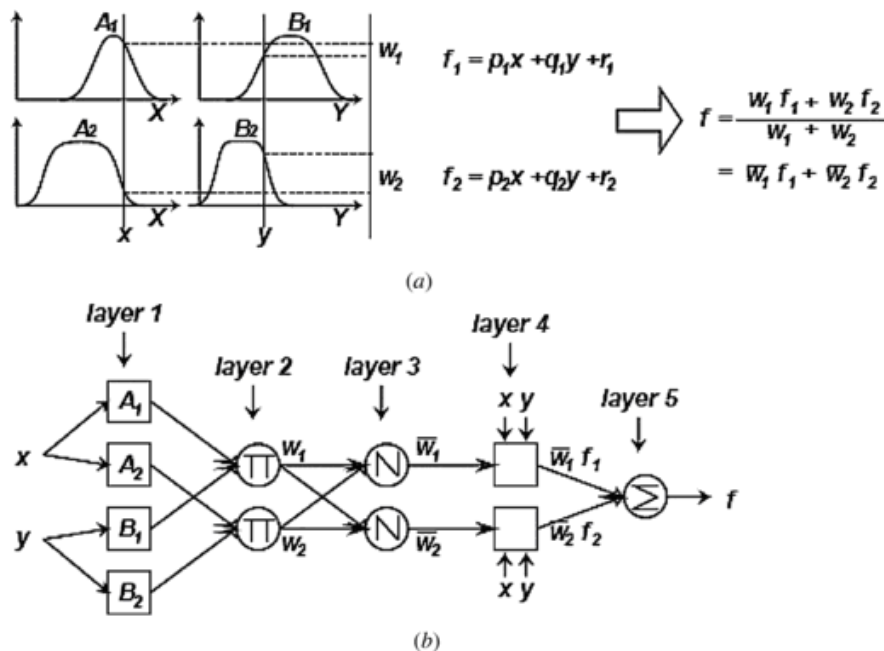


Figure 5. A two input first order Sugeno fuzzy model with two rules; (b) Equivalent ANFIS structure [3-7]

3. The ANFIS prediction of the pantograph catenary distance

In order to make a time series prediction, series values will be used up to the time T to predict the value at a time $t + P$ [4-8]. The standard method for this type of prediction is to create a mapping from D samples, time-sampled, $x(t - (D - 1)), \dots, x(t - 1), x(t)$ To predict a future value $x(t + P)$.

For example, it can be choose $D = 4$ and $\Delta = P = 6$. For each t , the input data for the anfis training will be represented by a vector with 4 dimensions:

$$W(t) = [x(t - 18) \ x(t - 12) \ x(t - 6) \ x(t)] \quad (10)$$

The Output data for training corresponds to the prediction of the trajectory:

$$S(t) = x(t + 6) \quad (11)$$

For each t within the selected range, the input / output training data will be represented by a structure whose first component is the four-dimensional input, and the second component is the output s [4].

The structure of ANFIS system and the datasets used to train the system play a vital role in evaluating the performance of the system.

In order to generate the FIS (Fuzzy Inference System), three methods were used: grid partition, subtractive clustering, and FCM.

This paper is based on the design of Sugeno type ANFIS designed with all three methods and the usage of different datasets to train the system using MATLAB.

For training the ANFIS the measured data where used. The data were measured in the laboratory prototype [1].

3.1. ANFIS based on grid partition

If it is desired a prediction for the moment $t=4$, samples $d=3$, sample time $s=4$:

$$\text{trn} = [x(t-8) \quad x(t-4) \quad x(t)]$$

and corresponds to the prediction for the output value $y=x(t+4)$.

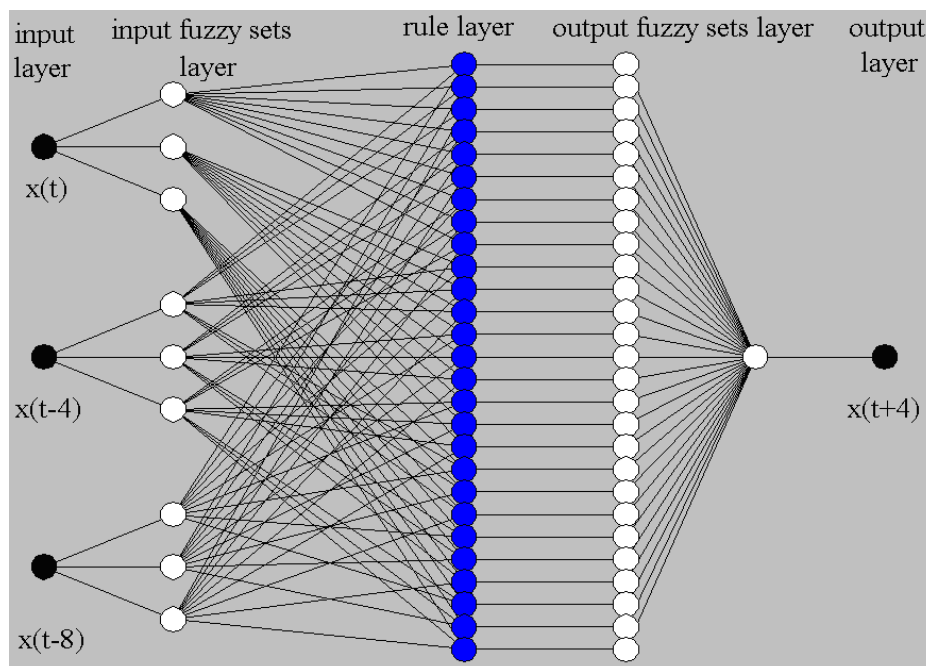


Figure 5. The ANFIS structure based on grid partition

3.1.1. ANFIS based on grid partition. Results. The grid partition method, is the default method used in Matlab for FIS (Fuzzy Inference System) generation. The method generates a Sugeno-type FIS structure used as initial conditions (initialization of the membership function parameters) [14].

The results obtained after the ANFIS is trained can be seen in the figure 6. Thus, in figure 6 a can be seen the output of the ANFIS when the input data are the training data. As mentioned from the 600 samples, 450 were used to train ANFIS and the other 150 samples were used for testing. Thus, Figure 6b shows the output of the ANFIS for the test data and Figure 6c shows the system output for the entire dataset, that is, the 600 samples. Figure 6d shows the regression coefficients of the ANFIS: for the training dataset, for the testing dataset and also for the entire dataset.

3.2. ANFIS with subtractive clustering

3.2.1. Principles of Subtractive Clustering For Rules Selection. In a fuzzy inference system, the number of rules from a fuzzy inference system is decided by an expert familiar with the system to be modeled [9], [11]. The number of membership functions for the input variables is chosen empirically [10], [11].

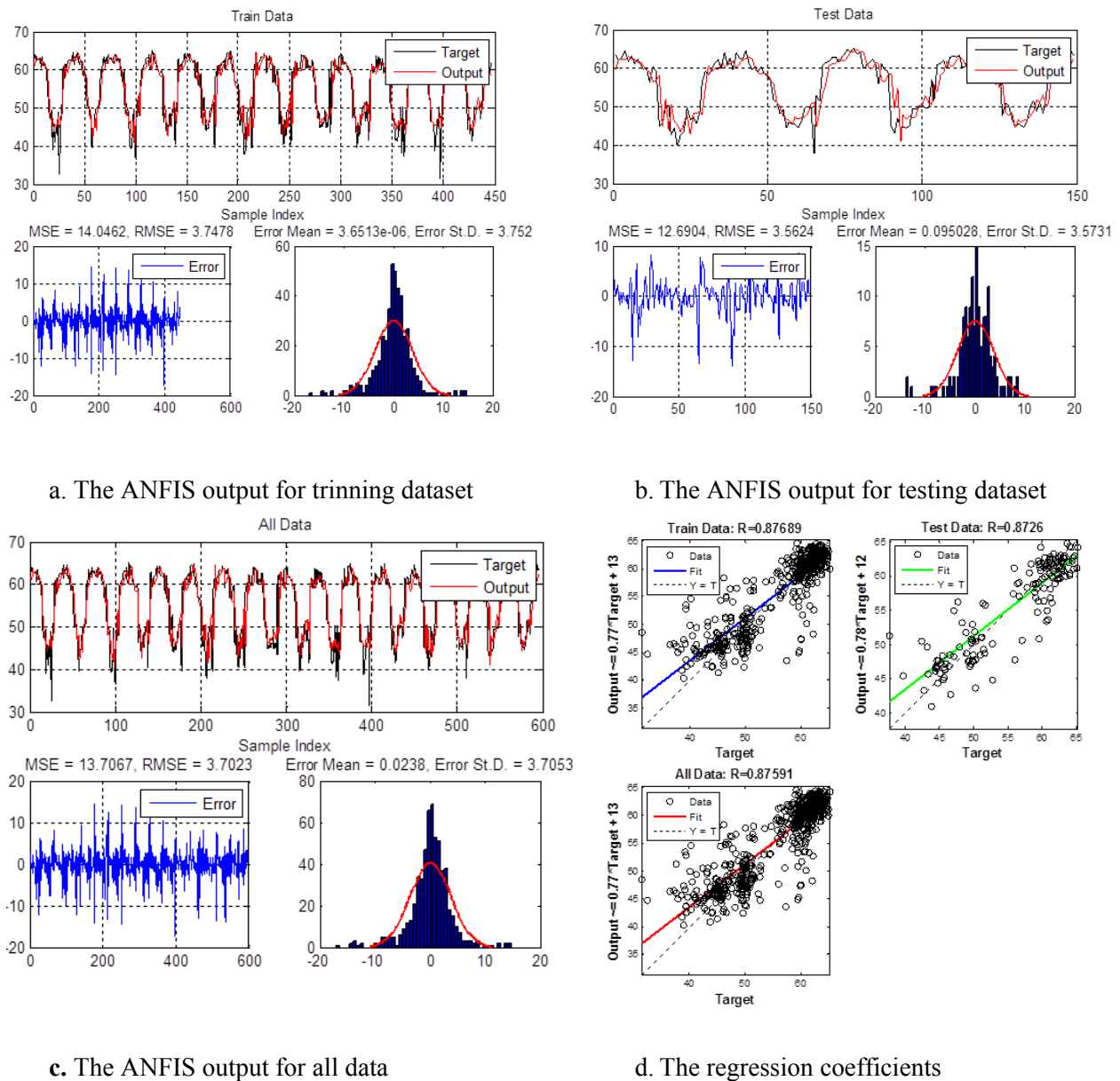


Figure 6. The results of ANFIS modelling and prediction with grid partition method

It is very difficult to establish the rules manually in order to obtain the precision with the minimized number of Membership Functions(MF), when the number of rules are larger than 3 [11]. The subtractive clustering algorithm is an approach to the synthesis of ANFIS, which estimates the cluster number and the cluster location automatically. In subtractive clustering algorithm, each sample point is seen as a potential cluster center [11].

3.2.2. ANFIS with subtractive clustering. Results. The results obtained after the ANFIS is trained can be seen in the figure 7. In figure 7a can be seen the output of the ANFIS for the training data. As in the above section, from the 600 samples, 450 were used to train ANFIS and the other 150 samples were used for testing. Figure 7b shows the output of the ANFIS for the test data and Figure 7c shows the system output for the entire dataset, the 600 samples. Figure 7d shows the regression coefficients of the ANFIS: for the training dataset, for the testing dataset and also for the entire dataset.

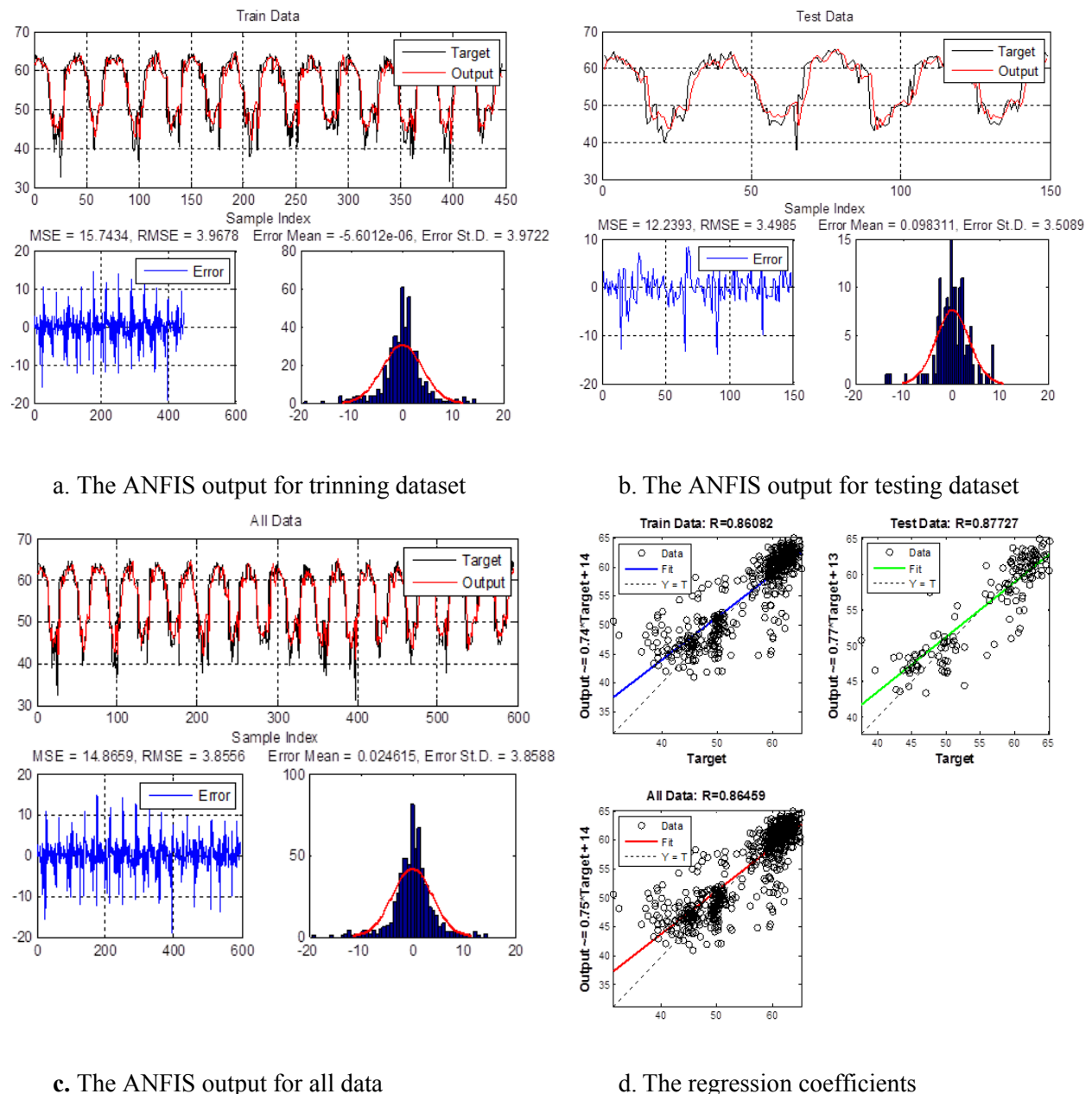


Figure 7. The results of ANFIS modelling and with subtractive clustering method

3.3. ANFIS with Fuzzy *c*-means clustering method

The FCM is a data clustering algorithm [12] in which each data point belongs to a cluster to a degree specified by a membership grade. FCM partitions a collection of n vector X_i , $i=1,2,\dots,n$, into C fuzzy groups, and finds a cluster center in each group such that a cost function of dissimilarity measure is minimized [13] as can be seen in Figure 8.

3.3.1. ANFIS with Fuzzy *c*-means clustering. Results. The results obtained after the ANFIS is trained can be seen in the figure 9. As in the other two methods of generating FIS, Figure 9a shows the output of the ANFIS for the training data. The 600 Data Samples were split in the same way like in the previous two methods, 450 for training and 150 for testing. Figure 9b shows the output of the ANFIS

for the test data and Figure 9c shows the system output for the entire dataset, the 600 samples. Figure 9d shows the regression coefficients of the ANFIS: for the training dataset, for the testing dataset and also for the entire dataset.

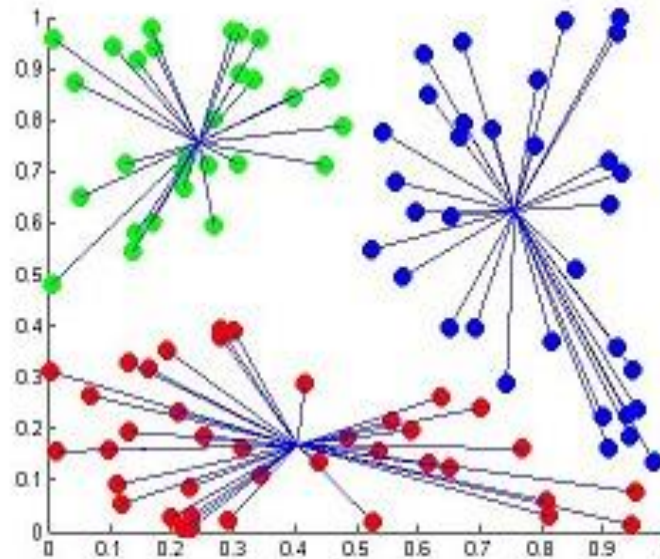


Figure 8. Assigning data points to clusters

4. Conclusions

From the analysis of the results obtained from the simulations we can find that the modeling and the prediction of the distance between the catenary and the pantograph was made with good results. It can be observed from Table 1 the Error Mean, the RMSE and the regression coefficients.

Analyzing the data in Table 1, it can be seen that all three methods offer good results.

Table 1. The results of simulation using the three methods of ANFIS design

ANFIS design method	Data set	RMSE	Error mean	Regression coefficients
Grid partition (3 Fuzzy sets)	Training set	3.7478	3.6513×10^{-6}	0.87689
	Testing set	3.5624	0.095028	0.8726
	All data	3.7023	0.0238	0.87591
Subtractive clustering	Training set	3.9678	-5.6×10^{-6}	0.86082
	Testing set	3.4985	0.098311	0.87727
	All data	3.8556	0.024615	0.86459
Fuzzy C-means (4 clusters)	Training set	3.4911	8.03×10^{-5}	0.89415
	Testing set	3.5501	0.30474	0.87716
	All data	3.506	0.076374	0.88972

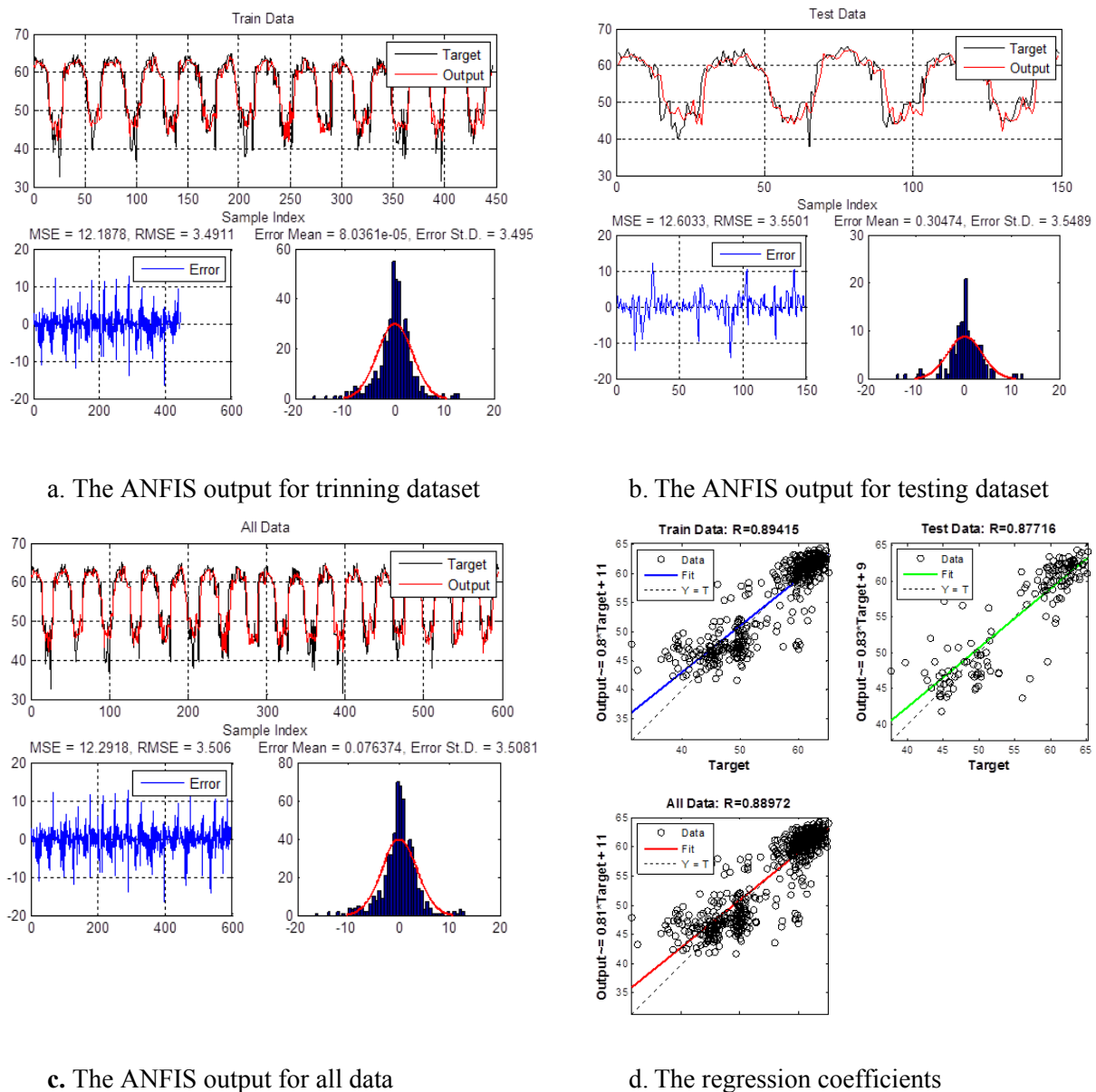


Figure 9. The results of ANFIS modelling and prediction with fuzzy C-means clustering method

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