www.ijecs.in
International Journal Of Engineering And Computer Science ISSN:2319-7242
Volume 2 Issue 8 August, 2013 Page No. 2434-2439

Traffic Flow Prediction Based on Optimized Type-2 Neuro-Fuzzy Systems

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Abstract

A correct predict of traffic flow is an important issue in intelligent transportation systems (ITS). Because traffic flow influenced by nonlinear various factors such as driver behavior ... Constitutes a non-linear robust system that changes with time. In this paper, traffic system of azadi- Hojat intersection in Mashhad city intended and actual data from years 2009 and 2010 have been collected from SCATS system. Since ANFIS is a fuzzy - Adaptive Neural system so with their training, there may be an optimal controller, the number of additional parameters that give for adjust the system with training, A set of conditions gets. In this paper, a method for long-term prediction of upper and lower bounds of traffic volume using type-2 fuzzy systems based on type-1 Neuro-fuzzy systems are presented. For this purpose, at first , effective inputs selected and type-1 fuzzy systems training with them. Then equivalent fuzzy type 2 system with that replaced and in final, type-2 fuzzy system parameters are optimized by genetic algorithm. The results show that the prediction based on type-2 fuzzy logic is admirable.

Key Words: Bounded prediction, Intelligent Transportation Systems, IT2FLS, Type-2 Neuro-Fuzzy, ANFIS, Sequential search

1- Introduction

Performance of many components in the intelligent transportation systems depends heavily on the quality of the traffic forecast. Therefore, in intelligent transportation systems, traffic flow prediction is a basic component of many control systems. Accordingly, the prediction of traffic flow plays an important role in traffic control and management. So far, for traffic flow forecasting and modeling ,many techniques have been applied, Flow distribution methods, Sequential training and based previous methods fall into this category. Sequential search algorithm is used to select the set with better features. that mean stead to system training with all datas, datas with high verification effect and neural network training based that. In this paper , we are going to offerd a adaptive method for traffic long-term forecasting based type-2 neuro-fuzzy. Distinct advantage of usage type-2 fuzzy logic for forecasting is that can generate interval forecasting as product of fuzzy type reduction process.

2- Type-2 Fuzzy Neural Network

Herein, we consider a type-2 FLS system with a rule base of R rules in type-2 FNN system, e.g., n-input m-output with R rules. The jth control rule is described as the following form:

$$R^j : IF x_1 is \tilde{A}_1^j \ \& \cdots x_n is \tilde{A}_n^j THEN y_1 is \tilde{\beta}_1^j \ \& \cdots y_m is \tilde{\beta}_m^j .$$

where j is a rule number, the $\tilde{A}_1^j$'s are type-2 MFs of the antecedent part, and $\tilde{\beta}_1^j$'s are type-1 fuzzy sets of the consequent part. Herein, the antecedent part MFs are represented as an upper MF and a lower MF, denote $\overline{A}(x)$ and $\underline{A}(x)$ (see Fig. 1). The consequent part is a interval set $\tilde{\beta} = [\underline{\beta}, \overline{\beta}]$. The rules let us simultaneously account for uncertainty about antecedent membership functions and consequent parameters values.

Note that, if rule number R is even $M=\frac{R}{2}$. On the other hand, R is odd, $M=\frac{R-1}{2}$ and

$$y=\frac{y_l+y_r}{2}+\frac{\left(\underline{\mu}^i_{M+1}+\overline{\mu}^i_{M+1}\right)\cdot\left(\underline{\beta}^i_{M+1}+\overline{\beta}^i_{M+1}\right)}{4} \tag{5}$$

Herein, we simplify the computation procedure for computing y_r and y_l which is difference from literature. Details of comparison can be found in literature.

Figure 5 summarizes above discussion and shows a fuzzy inference system (jth rule) of type-2 FNN system.

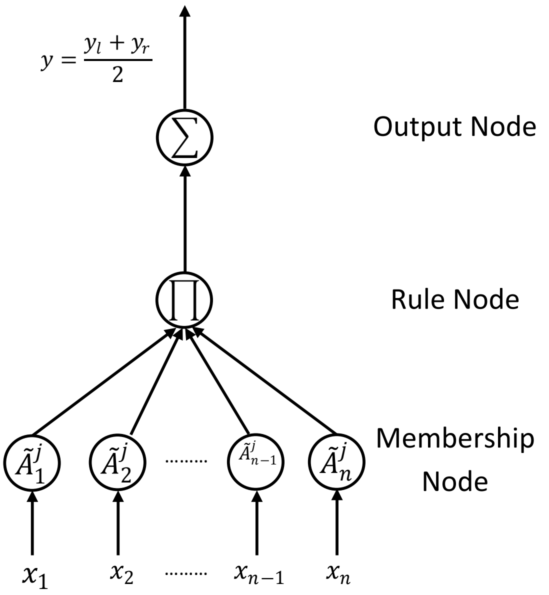


Figure 2. Fuzzy inference of Type-2 FNN.

Example: Computation of type-2 FNN system with two rules. If a type-2 FNN system has two rules as follows:

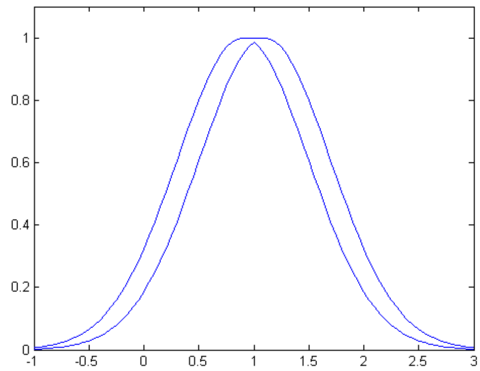
$$R^1 : IF x_1 is \tilde{A}_1 \;\&\; x_2 is \tilde{B}_1 THEN y_1 = \overline{w}_1.$$

$$R^2 : IF x_1 is \tilde{A}_2 \;\&\; x_2 is \tilde{B}_2 THEN y_2 = \underline{w}_2.$$

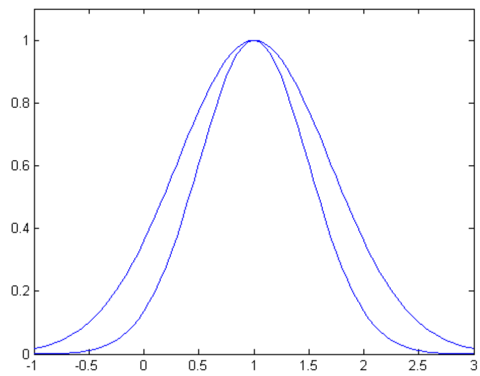
Figure 6 summaries the computation of type-2 FNN system. In the first layer, the output values are the input x1 and x2, respectively. In layer 2, one determines the MF grads by type-2 MFs, i.e., MF grads of upper MF and lower MF. Thus, one obtains $\left[\underline{A}_i(x),\overline{A}_i(x)\right]$ and $\left[\underline{B}_i(x),\overline{B}_i(x)\right]$, i=1,2.

Thus, using the operation in layer-product, one can have $\left[\underline{\mu}_i(x_1,x_2),\overline{\mu}_i(x_1,x_2)\right]=\left[\underline{A}_i(x_1)\cdot\underline{B}_i(x_2),\overline{A}_i(x_1)\cdot\overline{B}_i(x_2)\right]$ Finally, y_r and y_l should be determined.

Note that $\tilde{w}_i=\left[\underline{w}_i,\overline{w}_i\right]$, one has $y_l=\overline{\mu}_1\underline{w}_1+\underline{\mu}_2\underline{w}_2$, $y_r=\underline{\mu}_1\overline{w}_1+\overline{\mu}_2\overline{\mu}_2$ and the defuzzified value $y=\frac{y_r+y_l}{2}$.



(a)



(b)

Fig 1. Type-2 fuzzy set- (a) Gaussian MFs with uncertain mean (b) Gaussian MFs with uncertain STD.

When the input are given, the firing strength of the jth rule is:

$$\tilde{\mu}_m=\tilde{A}^m_1(x_1)\cap\tilde{A}^m_2(x_2)\cap\cdots\cap\tilde{A}^m_n(x_n) \tag{1}$$

where $\cap$ is the meet operation . Herein, the antecedent operation is product t-norm. That is, equation (1) can be calculated by

$$\underline{\mu}_m=\underline{\mu}_{\tilde{A}^m_1}(x_1)\cdot\underline{\mu}_{\tilde{A}^m_2}(x_2)\cdot\ldots\cdot\underline{\mu}_{\tilde{A}^m_n}(x_n)$$

$$\overline{\mu}_m=\overline{\mu}_{\tilde{A}^m_1}(x_1)\cdot\overline{\mu}_{\tilde{A}^m_2}(x_2)\cdot\ldots\cdot\overline{\mu}_{\tilde{A}^m_n}(x_n) \tag{2}$$

Finally, the type reduction and defuzzification should be considered. Similar to the FNN, herein the center of sets (COS) type reduction method is used to find

$$y^i_l=\sum_{i=1}^{M}\mu^i_l\beta^i_l \quad y^i_r=\sum_{i=1}^{M}\mu^i_r\beta^i_r \tag{3}$$

where μ^i_l, μ^i_r denotes the firing strength membership grad (either $\overline{\mu}^i$ or $\underline{\mu}^i$). Hence, the defuzzified output of an interval type-2 FLS is:

$$y^i=\frac{y^i_r+y^i_l}{2} \tag{4}$$

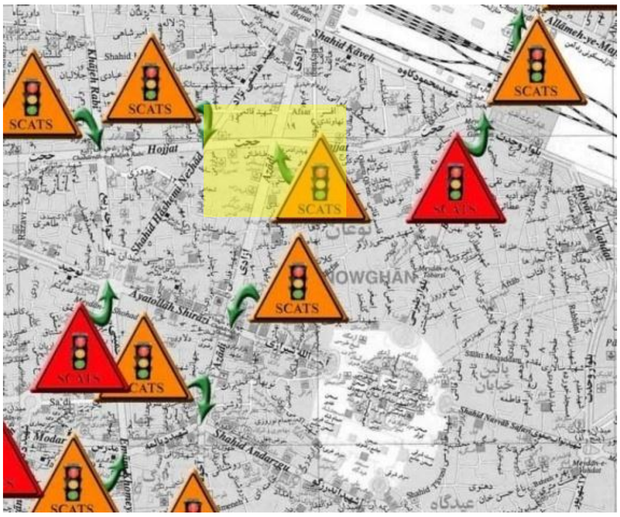


Figure 4. The intersection studied

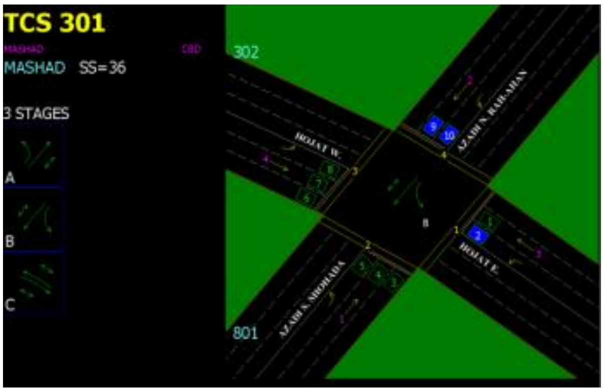


Figure 5. The intersection studied, Extracted from the SCATS

4- Data preparation

In here, input data composed from 24 samples of before, hence we want to forecast after amount data from 24 sample of before. In use of data should be attention to that's normalization. Because too small data not less it's effectivity against too big data. Amount of normalized of data achived from equation 5.

$$q_i = \frac{Q_i - \min(Q)}{\max(Q) - \min(Q)} \quad i = 1,2,\cdots,n \tag{5}$$

That $Q = [Q_1, Q_2, \cdots, Q_n]$ are the actual values and $q = [q_1, q_2, \cdots, q_n]$ are normalized data.

Table.1 Normalized data

		1	2	...	17500
Selectable inputs	$y(t-1)$	0.384	0.249	...	0.435
	$y(t-2)$	0.663	0.384	...	0.274
	$y(t-3)$	0.690	0.663	...	0.435
	$y(t-4)$	0.736	0.690	...	0.550
	...	...	...	...	...
	...	...	...	...	...
	$u(t-23)$	0.066	0.064	...	0.082

Remark: It is trivial that the type-2 FNN system is a generalization of the FNN system. That is, the type-2 FNN system can be reduce to a type-1 one if the fuzzy sets is type-1. We can find that details computation of these systems are the same.

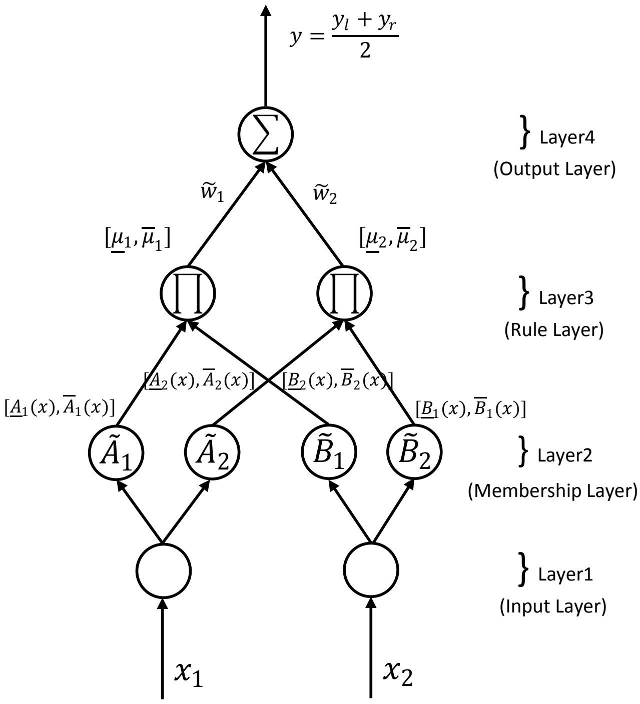


Figure 3. Computation example of a Type-2 FNN.

The Study interval type-2 fuzzy toolbox provided by reference [7] have been used.

3- System Introduction and Objective

System that studid is Azadi street and Shahid Mohsen Kashani (Hojat) intersection in Mashhad. As seen in figure 4, this intersection is one of a busy intersections of Mashhad.i here further forecast traffic flow, we forecast maximum and minimum bound of traffic volume. Actual data cumulate from SCATS system for years 2009 and 2010 with one hour sampling . at total we collect 17500 sample that used as training from 2009 samples and as offered model evaluation from 2010 samples.

the amount of uncertainty will be adjusted by genetic algorithm.

$$f(x;a,b,c)=\frac{1}{1+\left|\frac{x-c}{a}\right|^{2b}} \qquad (6)$$

$$c_1=c-\sigma \quad , \quad c_2=c+\sigma \qquad (7)$$

$$f(x;a,b,c_1,c_2)=\frac{1}{1+\left|\frac{x-c_1}{a}\right|^{2b}} \cup \frac{1}{1+\left|\frac{x-c_2}{a}\right|^{2b}} \qquad (8)$$

In part of type reduction and defuzzification of the type-2 fuzzy system, between the left and right values of output according to equation 4 is averaged. here this equation as shown in equation 9 will change and after optimization of the membership function uncertainty of type 2 fuzzy controller, also variable α optimized by genetic algorithm.

$$y=(0.5+\alpha)y_l+(0.5-\alpha)y_r \qquad (9)$$

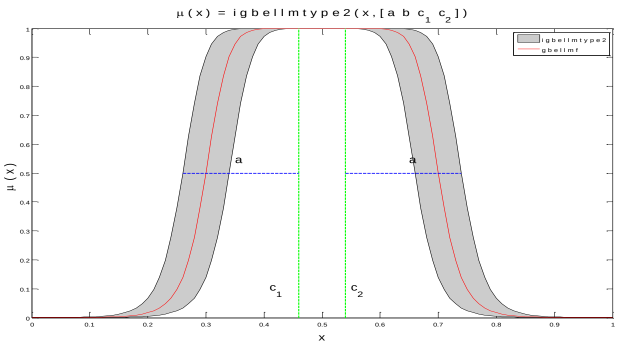


Figure.7 Displays the membership function gbellmf, igbellmtype2 and their parameters

7- Education of type 2 neuro-fuzzy network using genetic algorithm[6]

Genetic algorithm is one of evolutionary algorithm that is based on biology techniques. Briefly, we can say that use from the evolution genetics as a method of problem solving or optimizing. These parameters can be structured by a string of values and are regarded as the genes of a chromosome. Herein, we briefly introduce it. A population consists of a finite number of chromosomes (or parameters). The GA evaluates a population and generates a new one iteratively, with each successive population referred to as a generation. Fitness value, a positive value is used to reflect the degree of “goodness” of the chromosome for solving the problem, and this value is closely related to its objective value. In operation process, an initial population P(0) is given, and then the GA generates a new generation P(t) based on the previous generation P(t-1). The GA uses three basic operators to manipulate the genetic composition of a population: reproduction, crossover, and mutation. The most common representation in GA is binary. The chromosomes consist of a set of genes, which are generally characters belonging to an alphabeta {0,1}. In this paper, the real-coded GA is used to tune the parameters. It is more natural to

	$y(t-24)$	0.695	0.066	...	0.274
Output	$y(t)$	0.249	0.103	...	0.274

5- Inputs selection

Select the input stage of educational systems is difficult. Especially when in system modeling and identification, datas have many changes. Thus, redundant inputs in addition to disturb of model, increase The complexity of computing and decrease the efficiency of offered model. For this reason, the goal is select the appropriate input among existing datas. Therefore, from the 24 data, more efficient should be selected as input. The method used to select entries, called Sequential Forward Search (SFS). In this manner, the inputs are regularly chosen to be optimal Root Mean Square Error (RMSE). You can do it in the *Matlab* software environment using the *Seqsrch* command. The result of this search is brought in figure 6.

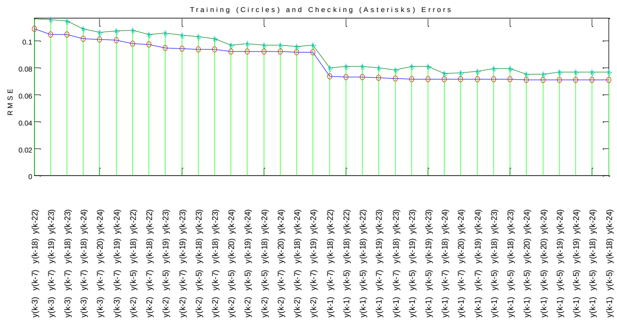


Figure 5. Result of Sequential Forward Search for Inputs selection

The result of progressive sequential search method illustrate the best inputs for traffic flow forecasting is traffic status in 1,5,18 and 24 before sample.

6- Proposed model

Here, we provide a type-2 neuro-fuzzy model based on type-1 neuro-fuzzy systems. therefore, understandable fuzzy rules are combined with the ability to train the neural network. At first, we do predict by *ANFIS* toolbox in *Matlab* software and then placed the characteristics of trained fuzzy system with some uncertainty in a type-2 fuzzy system bases. In final, amount of the uncertainty use of genetic algorithm with aim of reduction the prediction error and also reduce prediction range optimized so that the actual data for training not going out of this range.

The provided model have follow characteristices:

Fuzzy inference engine(TSK), average weights of defuzzifier (wtaver), function of the belongs gbellmf and hybrid optimization method considered. As equation 6 turns out the type 1 belong function (gbellmf) involved 3 parameters. Whereas type2 belong function (igbellmtype2) according to equation 8 have 4 parameters, that three of them are extracted from the trained fuzzy system type-1. Finally, according to equation7 where σ is the fourth parameter that specifies

Figure.10 Results of the model in training data with range of predictions

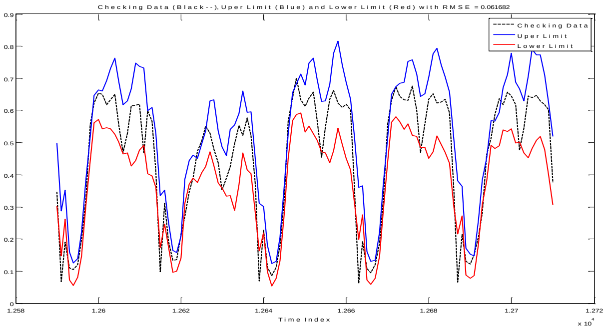
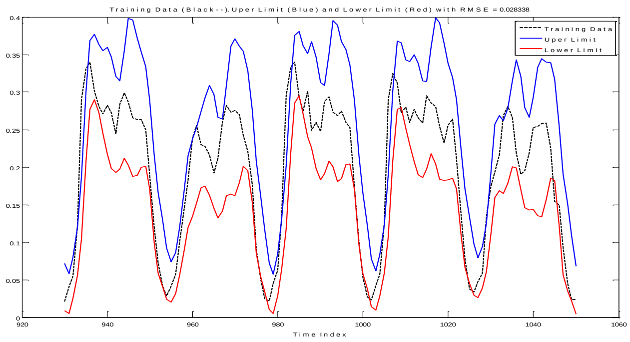
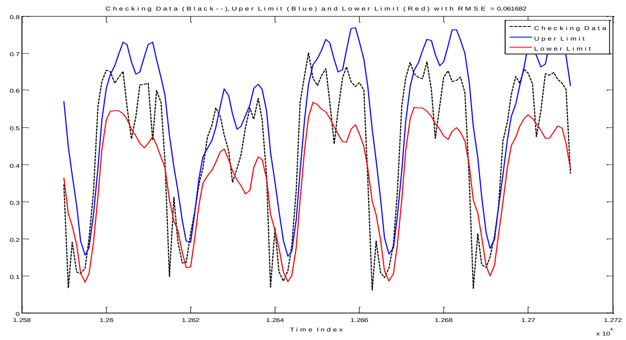


Figure.11 Results of the model in validation data with range of predictions

Having anticipated maximum and minimum values of traffic volume is very important and very applicable on long-term planning of center traffic managers. But in many cases have a very precise value not necessary. For this purpose and for softer the upper and lower limit of curves, data related to them cross from a low pass filter with gain=1 and a pole in point z=-1. The results of the filter is shown in figure 12.



(a)



(b)

Figure.12 Results of filtering down to the training data (a) and evaluation data (b)

8- Results

Process is done on a computer system with the following characteristics:

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Q740 @ 1.73GHz Processor

represent the genes directly as real numbers since the representations of the solutions are very close to the natural formulation. Therefore, a chromo-some here is a vector of floating point numbers. Herein, the training process using real-code genetic algorithm is described as follows.

Learning Process:

Step 1: Constructing and initializing the type-1 FNN system

Step 2: Using the back-propagation algorithm to train the type-1 FNN and obtain a set of Gaussian functions (mean, variance) and weighting vector.

Step 3: Using the results of Step 2 and add a uncertainty in antecedent and consequent part, i.e., $m1, m2 = m \pm \Delta m$ $w1, w2 = w \pm \Delta w$ $\sigma 1, \sigma 2 = \sigma \pm \Delta \sigma$

Step 4: Constructing the chromosome ($2 \times$ R mean + R STD + $2 \times$ R weight).

Step 5: Using the GA to train the type-2 FNN to find the optimal values.

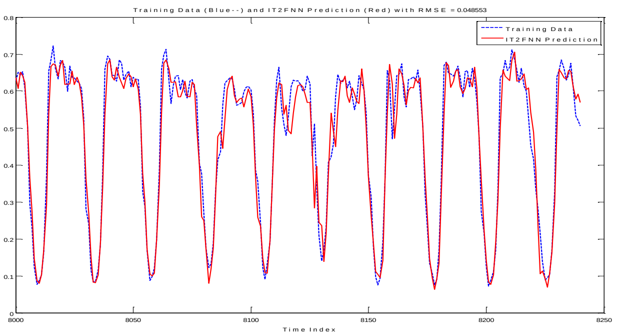


Figure.8 Results of the proposed model on training data

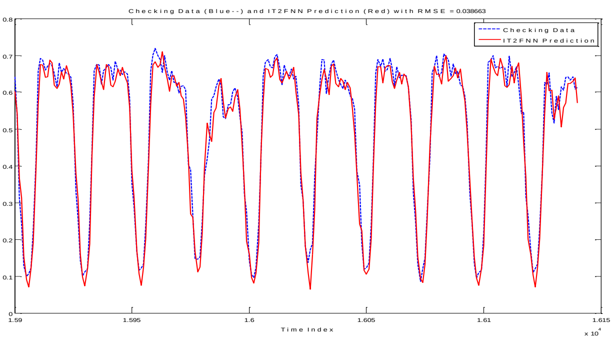
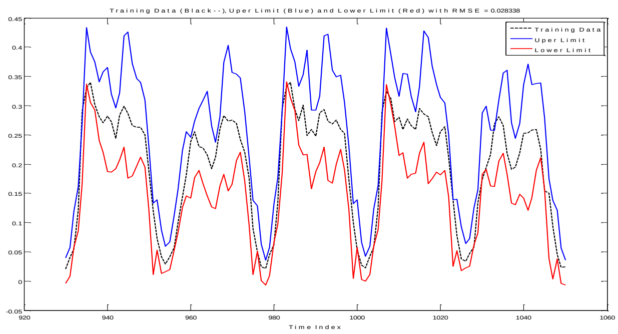


Figure.9 Results of the model in validation data



2.92 GB RAM

The results in same condition shown in table 2.

Table.2 Compares the results

model		RMSE	
		Training error	Validation error
ARX[10]		0.618	0.728
ANN-ARX[10]		0.129	0.138
Our Results	ANFIS	0.0699	0.0761
	IT2FNN+GA	0.04208	0.05977

The results show ability of type-2 fuzzy system in modeling and managing uncertainty.

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