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Fuzzy Inference System in Energy Demand Prediction

Thair Mahmoud, Daryoush Habibi,
Octavian Bass and Stefan Lachowics
School of Engineering, Edith Cowan University,
Australia

1. Introduction

Fuzzy Inference Systems (FIS) have been widely used in many applications including image processing, optimization, control and system identification. Among these applications, we would like to investigate energy demand modelling. Generally, developing an energy demand model is the challenge of interpreting the historical use of energy in an electric power network into equations which approximate the future use of energy. The developed model's equations are coded and embedded into a processor based system, which predicts the output when a certain type of input occurs. However, the range and quality of prediction is still limited within the knowledge supplied to the model. The major concern about the energy demand modelling is to categorize the type of prediction in short or long-term prediction. In addition, it is crucial to categorize the type of the power network to be modelled. Since identifying the useful historical operation data for setting the model parameters is crucial in modelling, the operation history of the modelled systems must to be analysed. In simple terms, modelling energy demand is the art of identifying the right modelling technique and system's operation parameters. The operation parameters differ based on the type and size of the modelled system. So, taking into consideration why the system is modelled will justify the selection of modelling techniques. Among the reasons for modelling energy demand is managing the use of energy through an Energy Management System (EMS).

For EMS, most of the Artificial Intelligence (AI) methods will lack robustness in terms of their programming and their required computation resources, especially when the EMS is designed to perform on-line quick response tasks. Artificial Neural Network (ANN) might be good candidate among modelling techniques, as there has to be a compromise between robustness of the method and its required computation resources for a specific type of modelling. However, there are a few reasons why ANNs are not suitable for our proposed discussion: their limited adaptability within limited computation resources, their training time and their models' complexity, especially when we deal with highly non-linear systems. Looking at our case study and the reasons this scenario is modelled, we have found that Fuzzy Inference Systems (FIS) are the most appropriate for modelling the energy demand in this specific system, since model development, model parameters, model adaptation capability and computation resources requirements are met. The reason behind choosing FIS

to model the energy demand is the flexibility to control the prediction performance and the complexity of the model. Fuzzy modelling and reasoning systems have been widely utilised in literature because of their applicability and modelling performance. The use of Adaptive Neuro Fuzzy Inference Systems (ANFIS) gives the fuzzy modelling two extra valuable advantages: the training time and prediction accuracy compared to other modelling techniques. Fuzzy modelling has been successfully applied in different types of applications including electricity and gas demands, economics and finance, weather and meteorology studies, health and population growth, geographic information systems, traffic and transport systems, etc.

In the recent years, energy demand prediction modelling has been widely investigated, especially when its smartgrid applications have been rapidly grown, and energy price change has been rapidly correlated to the energy demand prediction. Different smart prediction mechanisms have been introduced in literature. (McSharry 2007) has developed a day-ahead demand prediction models, and (Alireza Khotanzad 2002) has introduced a new short-term energy demand prediction modelling technique which integrates the real-time energy price change in the prediction models. (Amir-Hamed Mohsenian-Rad 2010) have also introduced the real-time price environment modelling to perform an optimised residential load control, where a fundamental bid-based stochastic model is presented to predict electricity hourly prices and average price in a given period by (Mazumdar 2008). Among the prediction mechanisms we aim at addressing the use of Fuzzy Inference systems in developing short-term demand prediction models, which can be applied in SmartGrid and electronic market applications.

The objective of this chapter is to review the use of fuzzy logic in modelling the energy demand in a specific electric network after analysing its demand characteristics. This chapter will also discuss the use of FIS to improve the prediction performance and adapt the prediction to the real time effects. We consider a real electric power system by modelling its energy demand and verifying the prediction output results. The next section will consider the system's operation data while selecting the most effective modelling parameters, highlighting the use of FIS in modelling, choosing the suitable data clustering method and detailing learning, training and verification for different type of demand patterns.

2. Fuzzy modelling

Fuzzy modelling is a widely utilised and targeted modelling method. It attracts attention from academic and industrial research sectors because of its applicability and flexibility in interpreting the human decision in many complex computer controlled applications. Despite that its complexity has been mainly considered in modelling, as the number of developed fuzzy rules affects the modelling performance, fuzzy modelling is still one of the most efficient modelling techniques. Its main modelling concept is the same as that used in other modelling techniques, which is building mathematical expressions based on historical operation data for the modelled system. It is considered an effective technique to establish an FIS from a given nonlinear input-output set of data, when in fuzzy modelling, the data is partitioned in the input space and an optimal fuzzy rule table and membership functions are developed.

The data partition is performed using data clustering methods. A data clustering method is applied to partition the input-output set of data into a set of clusters. Depending on the type of clustering method, different type and number of clusters can be identified.

A range of data clustering methods have been illustrated in literature such as the nearest neighbourhood clustering method (Wang 1994), Gustafson-Kessel clustering method(Donald and William 1978), Gath-Geva clustering method (Gath and Geva 1989), fuzzy c-means (FCM) clustering method (Frank Höppner 1999), the mountain clustering method (Yager and Filev 1994) (Yager and Filev 1994), and Fuzzy Subtractive Clustering Method (FSCM) (Chiu 1994). However, the main problem of fuzzy modelling comes from the difficulties of choosing the right range of parameters which leads to the number of rules. In other words, the inaccurate parameter settings would deteriorate the prediction accuracy. Good fuzzy modelling parameter settings come from a good understanding of the modelled system and its modelling problems. The main justification for this problem is that when the number of clusters is increased, the prediction output will have strong alignment with the modelled data. As when the number of clusters equals to the number of data, the developed clusters will specifically resemble the training data characteristics, and lose the generality of resembling the system operation characteristics. Consequently, the clusters will mostly resemble a part of the operation data. Therefore, the prediction will miss other kind of operation data that differ from data modelled despite their availability within the modelled data range, which will result in a high prediction error. In contrast, when the number of clusters is reasonable, the prediction will cover the training data regions, as well as any other types of operation data, as far as they are located within the range of the training data. The prediction however will result in an acceptable range of error, which is fairly accepted by all research communities.

In other terms, a suitable parameters choice is the key solution for a successful fuzzy modelling, which will be based on an optimized number of rules and prediction accuracy level. This problem can be solved by analysing the modelled system operation history and indentifying suitable modelling parameters. In addition, having experience about fuzzy modelling will help the modelling process. However, trial and error may be applied for output tuning in most of the modelling cases.

In comparing fuzzy modelling with ANN, it has been concluded that to select the right modelling method, it is crucial to consider the type and the size of the system, the amount of system's historical operation data and the required computation resources. Regarding the type and the size of our case study, it has been found that fuzzy modelling will suit the modelling process. More details about the case study and data analysis are explained in the case study section in this chapter. Full details about the fuzzy modelling process are also explained in modelling methodology section in this chapter. In this chapter we aim at discussing the use FIS as a tuner fuzzy system. The next section describes the main operation principles of Self-Tuning Fuzzy Systems STFS and the use of FIS to improve the prediction accuracy or to adapt the prediction to the external effects.

3. Self tuning fuzzy systems

In modern automation, adaptability has become crucial in implementing smart applications. In the way, that they resemble the human sense of adaptive thinking. Usually, ANN is highly utilised in implementing adaptive systems. However, self tuning and adaptive algorithms are not restricted to ANN, they can also be implemented through fuzzy logic and other optimization techniques. The specific tuning mechanism implementation is subject to the type of the problem or the system to be processed. The

tuner and main systems may share the same input parameters, or they may receive two different types of inputs from external sources depending on nature of operation. Self-tuning systems have practically unlimited applications, and they have been widely utilised in academic and industrial applications.

Basically, a STFS is an on-line adaptive output fuzzy system, where its output is changed depending on the type of input and the pre-defined knowledge in the fuzzy tuning system. Generally speaking, a fuzzy system is called tuneable when any of its parameters (input/output scaling factors, membership functions shape and type or fuzzy rules) are changed instantly. It is a combination of general and tuner fuzzy, where the tuner FIS tunes the general system' parameters. Although sometimes both systems have the same input parameters, but they still perform different independent jobs. The main reason using STFS in modelling is to perform a short term prediction and to add the safe prediction estimations to the predicted output. This can be achieved by adapting the prediction to the external effects through a pre-defined knowledge based system.

By looking at our modelled case study, it has been noticed that the model has highly non-linear characteristics. So, developing a model for a high precision prediction is a major challenge. Hence it is required to focus on the model prediction accuracy to consider its weak-points. By considering the energy demand in the targeted case study, modelling knowledge could be added regardless of its availability in the supplied operation data. Using the self-tuning fuzzy system will help in adding the missing knowledge to the operation history data. For such kind of systems, a possible design with external input parameters from external data sources to tune the main fuzzy model output based on a knowledge base could be implemented. In this chapter we aim at utilising the real-time demand change measure to investigate the FIS ability to adapt the prediction output to the actual demand change. Alternatively, in our modelling discussion we also use the main fuzzy system's input parameters to tune the prediction based on a knowledge base system. Similarly, the tuning part may use different mechanisms, e.g. rules, membership functions or output scale tuning. The Weights Adjusting Method (WAM), which is the method that adjusts the output of the main system, is derived from the process needs for adaptation. WAM is set to adjust the weights of the output of the main system and its tuner based on the needed amount of adaptation. Depending on the tuner's fuzzy rule base, a suitable WAM can be derived. Although even when different types of models are discussed in our modelled electric network, only one WAM is applied. For simplicity, we aim at utilising an output scale adaptation design. The full design details are explained in the Modelling Methodology section, whereas the results will be discussed from the prediction improvement point of view and the adaptation performance in the Summary section. In the next two sections, the details about modelling twelve-month load patterns in a real electric network are presented. Additionally, the twelve models are equipped with twelve different tuner fuzzy systems to improve their prediction accuracy or to adapt their prediction to the external effects, depending on the purpose of the modelling.

4. Case study

The electrical energy use of the power network of the Joondalup campus of Edith Cowan University (ECU) in Western Australia has been selected in this study to evaluate the robustness of the proposed modelling technique. Just like most commercial buildings that

the energy demand may depend on several independent variables, each having different weightings. Accept when it comes to a university type load profile, a few extra variables may affect the load change patterns. So, it is highly advantageous to analyse the historical operation data of the modelled system to indentify the effective variables. The ECU's electric network has nine substations serving 32 buildings. The minimum daily demand in this university does not drop below 500 kWh at any time, while the maximum daily demand may go up to 3500 kWh in summer daytime. Identifying the critical issues in the network is very important before proceeding in modelling. Fig. 1 shows Load changes in the ECU's Joondalup campus in January 2009.
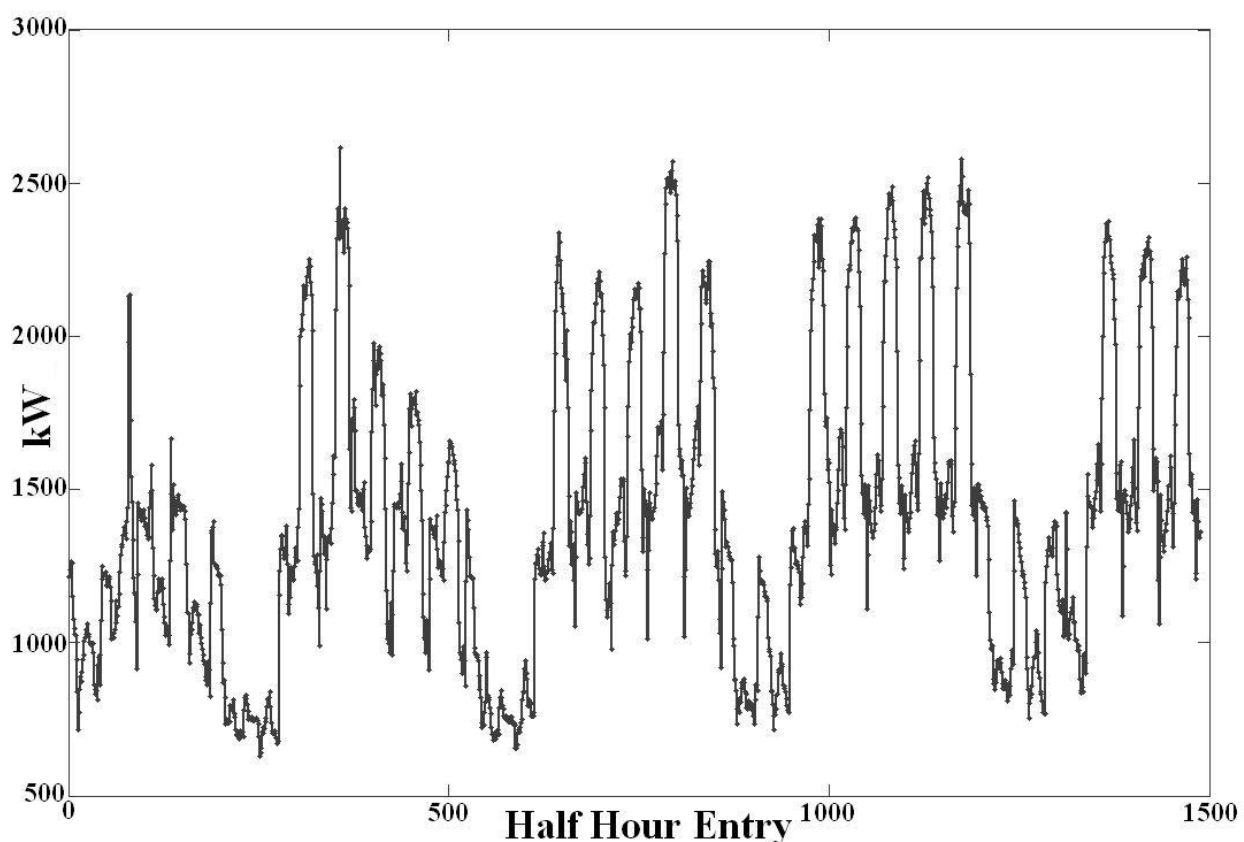
Fig. 1. Load changes in the ECU's Joondalup campus in January 2009.

By monitoring the load change in Fig.1, several load change patterns have been indentified including the weekdays, weekends and hours correlation. In addition, we can identify other important modelling factors e.g. weather, date, hours, order of the day (Monday, Tuesday,...,etc.) and type of the day (working day or weekends/holidays). It has also been noticed that big load changes are infrequent. In this modelling strategy, these big load change events are ignored. It is assumed that such big load changes need to be predefined or have warning settings assigned in order to avoid system overloads. From analysing these effective factors, we could draw a correlation picture about the load change in the ECU's Joondalup Campus and other effective parameters. For more details about load change analysis, Fig. 2 shows the correlation between a 30 minutes interval load change and other identified factors in the ECU's Joondalup campus in January 2009. Fig.2 includes 1500 entry of the correlated information data.
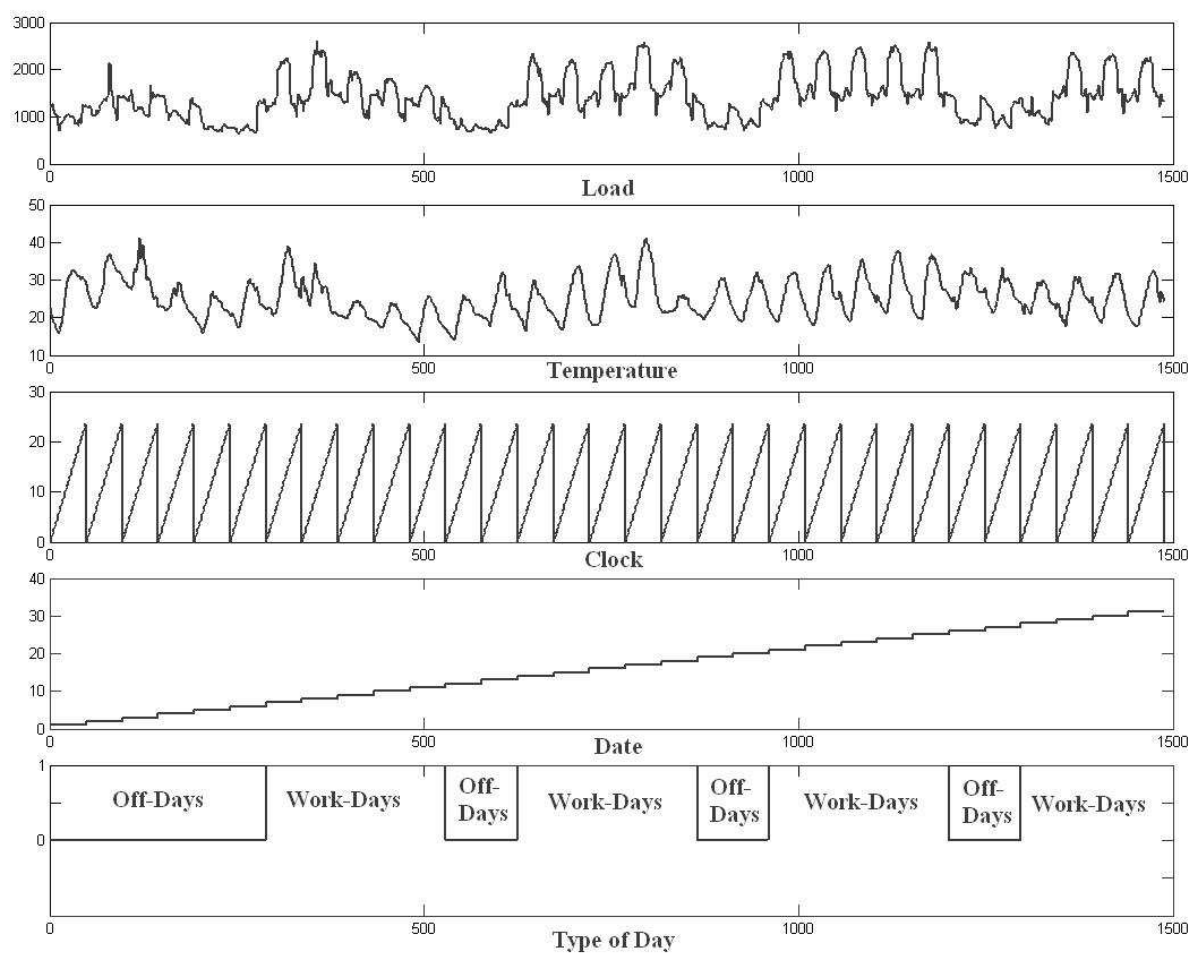
Fig. 2. Load change correlation with the effective factors for ECU's Joondalup campus in January 2009.

By spotting at the critical load change correlation among the identified parameters in Fig.2, several ideas about the energy use scenarios can be obtained. It is also noticeable that there is a big correlation between the daylight time, temperature, type of the day and the monthly order of the day. In Fig.2, only the effective load change parameters mentioned previously are illustrated. Theoretically, other load change parameters could be identified by analysing the university work hours, the nature of activities and the weekly time table in the university. From analysing the university weekly time-table, we could introduce another variable, which is the weekly order of the day. Although this parameter would have an effective load change contribution to the university's energy usage for a certain time of the year, namely the teaching period, but it rarely affects the load change in the remaining times of the year. On an average, it would require higher computation resources and would not indicate the load change effectively throughout the whole year. Therefore, it has been concluded not to consider this parameter among the modelling parameters. The next section details the modelling process and illustrates some hints about the fuzzy modelling.

5. Modelling methodology

This section covers the methodology to model the energy demand measured at 30 minute intervals in the ECU's Joondalup Campus. Basically, the model is developed by combining

two modelling systems: the main FIS which is developed from modelling the input-output data using FSCM and ANFIS, and the second FIS system which is either developed by using the correlation between the energy demand and the temperature throughout the day, or by using the knowledge about the real-time demand change with its ability to achieve safe adaptation to the main model's output.

To improve the prediction accuracy and reduce the model complexity, the annual energy demand of the ECU's Joondalup Campus has been proposed to be split into twelve monthly models, represented by twelve different demand pattern models. Each model represents a one month demand model. Fig. 3 illustrates the proposed annual energy demand prediction structure for ECU's Joondalup campus, it also illustrates the possible extra added input to improve the prediction accuracy when possible.
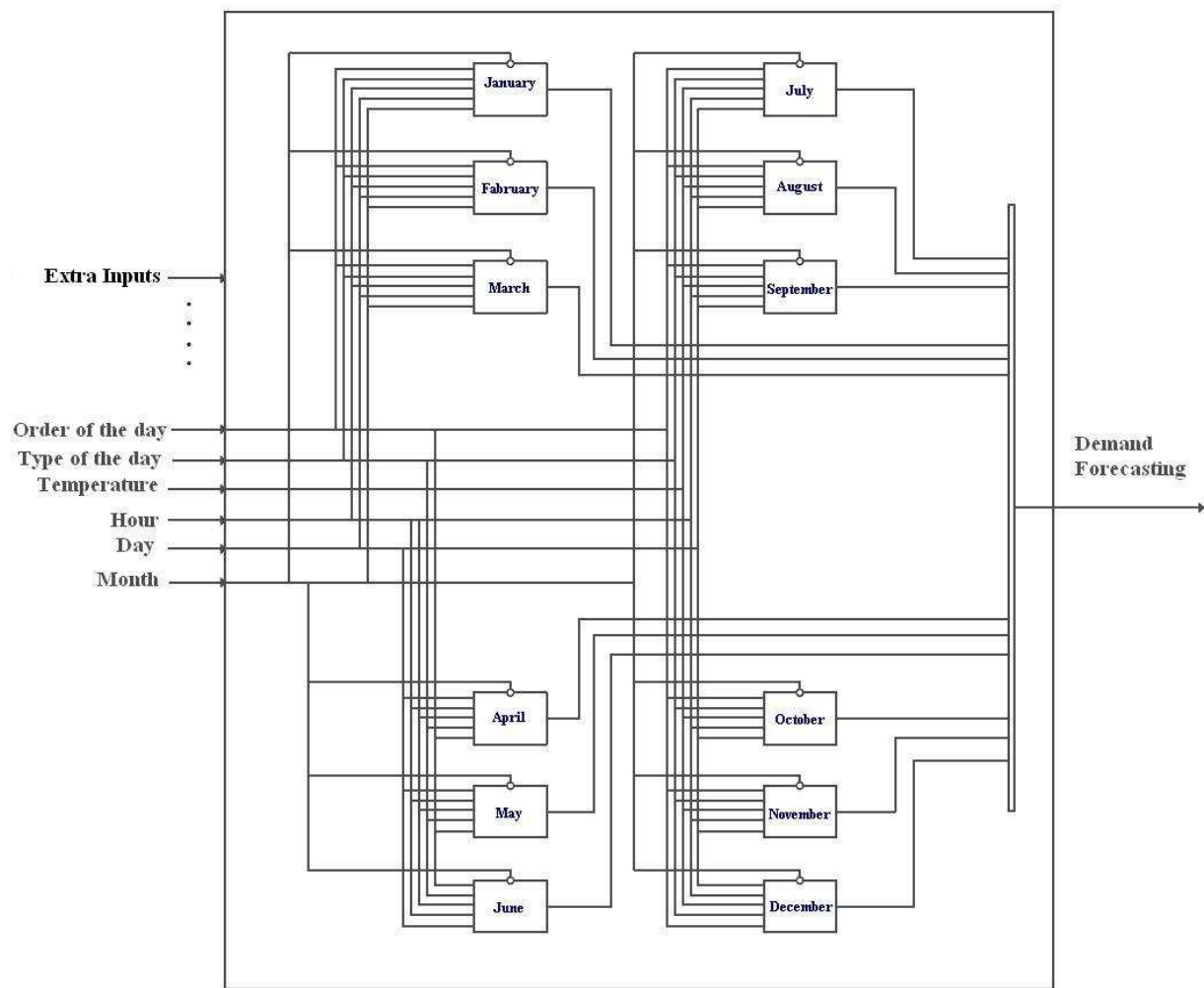
Fig. 3. The energy annual demand prediction structure of ECU's Joondalup campus

Splitting the annual demand model into twelve spilt sub-models gives the prediction the ability to cope with the twelve different load change patterns. In addition, it reduces the computation resources, when only one month model is active at a time. Thus the modelling uses twelve separate modelling methodologies depending on the load change analyses for the individual months. Regarding building the two FIS, their methodology is explained in the following subsections:

5.1 Main fuzzy system

In this subsection, we discuss the use of FIS in modelling. In this investigation, we aim at utilising data clustering methods to perform the fuzzy modelling. Data clustering methods divide the supplied data into different groups based on identified common characteristics in each group. However, these characteristics are identified based on the type of data clustering method. In literature, several types of data clustering methods have been discussed including the on-line and off-line methods. In our investigation, we aim at utilising off-line data clustering methods in modelling.

We aim at clustering the historical operation data of the targeted electric network to develop the demand prediction models. At the end of clustering, a fuzzy reasoning system will be developed. We aim at using ANFIS for developing our targeted fuzzy models. The complete modelling process is illustrated in Fig. 4.

In our modelling example, we use Fuzzy Subtractive Clustering Method (FSCM) (Chiu 1994). It is a method where each of the supplied data is tested under the condition that it has the highest density among the tested individuals. Every individual data is considered to be a candidate for the cluster centring. The individual density is evaluated as follow:

$$P_i = \sum_{j=1}^{n} e^{-\alpha \|x_i - x_j\|^2} \tag{1}$$

where

$$\alpha = \frac{4}{r_a^2} \tag{2}$$

The data density for a specific cluster centre candidate is evaluated from the number of nearer individuals that contribute to the cluster centre. The highest density is identified to become a first cluster centre. The cluster size is decided when FSCM parameters are set to cover a range of data individuals in the cluster's neighbourhood. The radius r_a , which is also referred by Range of Influence (ROI), defines the range of neighbourhood for the clusters extraction. Each of the developed clusters is a basis of a fuzzy rule that describes the system attitude, when the number of these clusters is the number of the fuzzy rules in the modelled network. When the first cluster centre is found, the next highest density is evaluated. Let the new investigated cluster centre to be x_i, and P_i be its density measure. When every data individuals is x_c, the next cluster centre is identified as follow:

$$P_i = P_i - P_{c1} e^{-\beta \|x_i - x_{c1}\|^2} \tag{3}$$

$$\beta = \frac{4}{r_b^2} \tag{4}$$

$$r_b = 1.5 r_a \tag{5}$$

Where P_{c1} is the next density point to be examined, and x_{c1} is the next data point to be examined. where r_b is a constant, which has the influence of reducing the density measure. r_b is defined based on the experience of data clustering. Usually, it is larger than r_a to avoid closely placed clusters. Sometimes, trial and error is used to select the best value of r_b. However, the value of r_b is set to $1.5 r_a$ as illustrated in literature (Chiu 1994), and r_a is set based on the experience about the data clustering. In our investigated cases different values were applied depending on the type of the problem. It is clearly noticed that ROI value decides the number of

membership functions, thus influencing the complexity of the developed network. Table 1 illustrates the full details about r_a settings for the investigated cases.
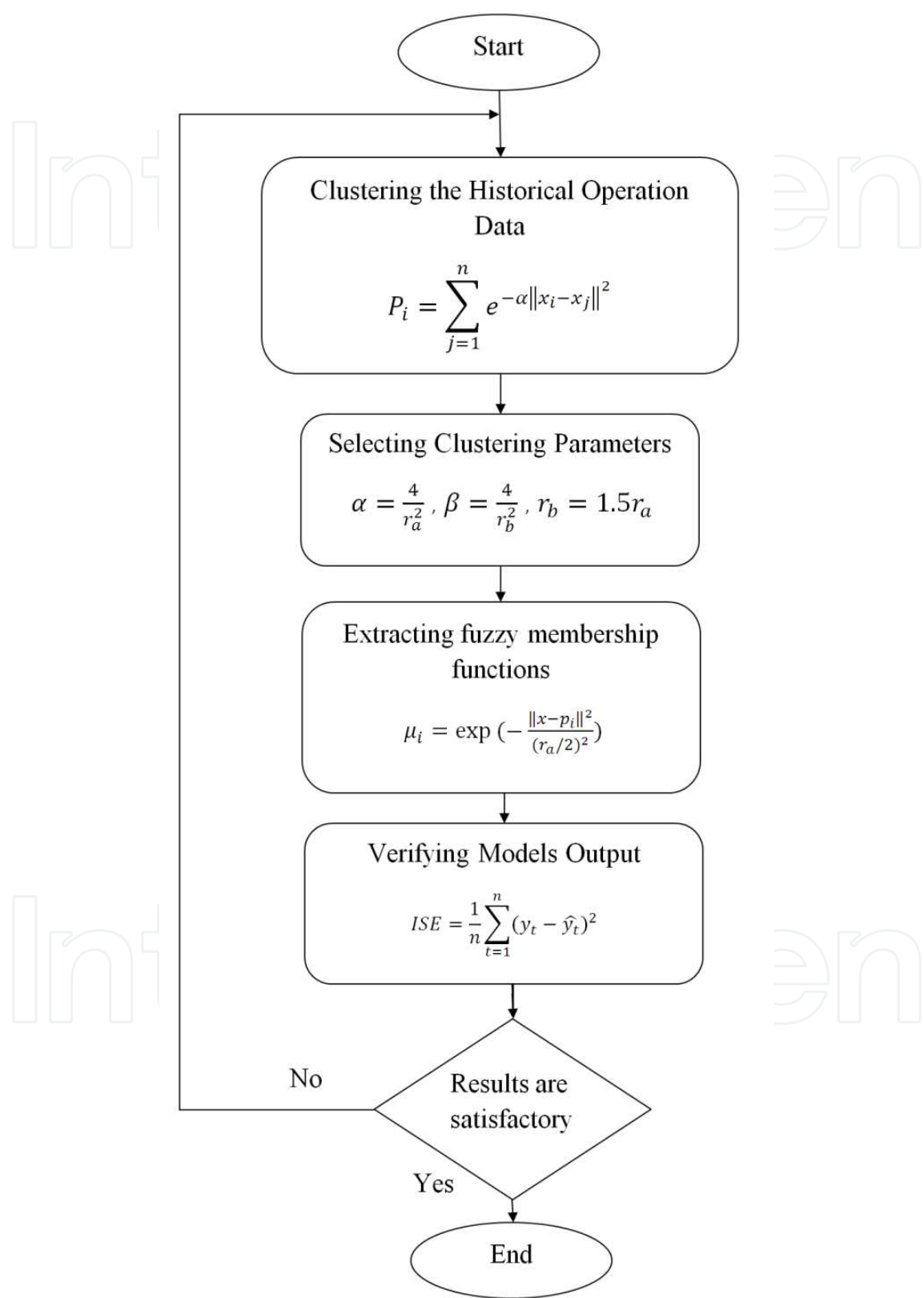

Fig. 4. Selecting suitable FSCM parameters in ANFIS modelling

The next stage is to repeat the above estimation process to identify other cluster centres. The process of indentifying clusters is repeated until the amount of new identified density is equal of less to 0.15 of the highest identified density. More information about FSCM parameters details is found in (Chiu 1994).

The identified data clusters can be easily utilised as fuzzy rules' centres in the zero-order Sugeno fuzzy models. When a data individual is located within the cluster range, a membership function between that particular data individual and its cluster centre is derived. Data affiliation to the cluster centres is derived as follow:

$$\mu_i = \exp(-\frac{\|x-p_i\|^2}{(r_a/2)^2}) \tag{6}$$

where x is the cluster centre and p_i is the input set of data.

By clustering temperature, hour, day and load change data, random FSCM parameters values e.g. Influence Range, Squash, Accept Ratio and Reject Ratio are applied.

These values selection may have strong effects on the complexity of the developed models. Table 1 shows the number of membership functions and the selected ROI values for each of the twelve month models.

Months\Membership Functions ranges	ROI	Rules	Membership Fctn.
January	0.35	28	112
February	0.4	23	92
March	0.5	14	56
April	0.33	40	160
May	0.44	17	68
June	0.4	25	100
July	0.45	20	80
August	0.48	19	76
September	0.43	18	72
October	0.5	11	44
November	0.5	16	64
December	0.41	20	80

Table 1. ROI Values and Complexity of the 12 Month Models

After clustering is made, the developed membership functions are trained. Then, when the developed network is being trained, a simple test will be carried to verify the prediction accuracy of the developed models. To increase the range of prediction in the developed models, the historical operation of three years set of data (2007, 2008 and 2009) is used. The three years data has been divided into three different groups. The first set of data is used to extract the clusters, which is taken as a 90% of the 2007 and 2008 historical data. The second set of data, which is used to train the developed fuzzy systems, has been taken as a whole set of 2007 and 2008 data. Finally, the third set of data, which is used to verify the success of the developed model, has been taken as the 2009 operation data. Fig. 5 shows the data utilization in developing the demand models in this work.
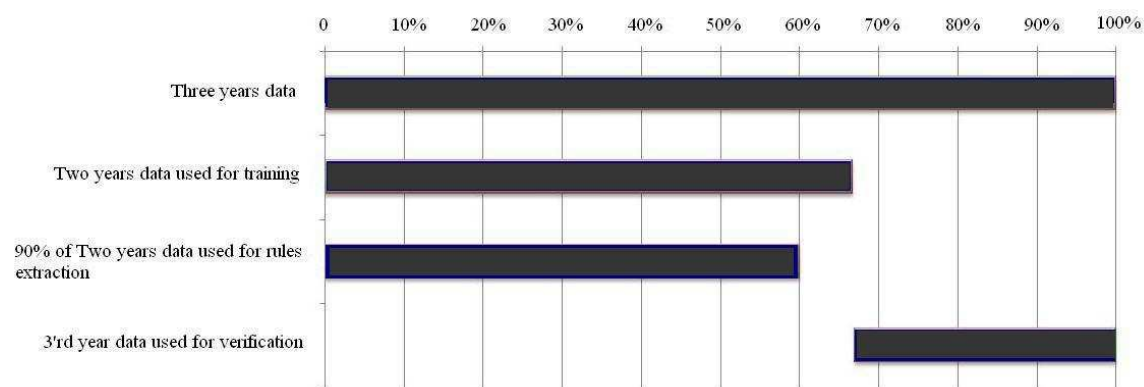
Fig. 5. Modelling data utilization for the ECU's Joondalup Campus energy consumption

After the rules which relate the input-output data have been developed, the developed clusters have been utilised in neuro-fuzzy networks to develop a zero-order Sugeno FIS, which will perform a 30 minutes ahead short-term prediction. In conventional fuzzy systems, trial and error is applied to tune the developed membership functions of the input-output universe of discourse of the fuzzy system. When ANN is used to tune the membership functions, an automated selection process based on the performance index is performed. The membership functions are trained to resemble the training data characteristics. In neuro-fuzzy networks, their networks structure is changed accordingly with the operation scenarios. Neuro-fuzzy networks however utilise the ability of learning of the neural networks to get the best tuning process with better performance and less time (Kandel 1993). Since the fuzzy systems have the property of universal approximation, it is expected that the equivalent neuro-fuzzy networks representation have the same property as well.

Adaptive Neuro Fuzzy Inference System (ANFIS) is another candidate to perform the fuzzy membership functions tuning. ANFIS structure was firstly proposed by (Jang 1993), where other models of ANFIS were proposed by (Chin-Teng Lin 1996) and (Wang and Mendel 1992). Fig. 6 illustrates the ANFIS structure with its learning mechanism.
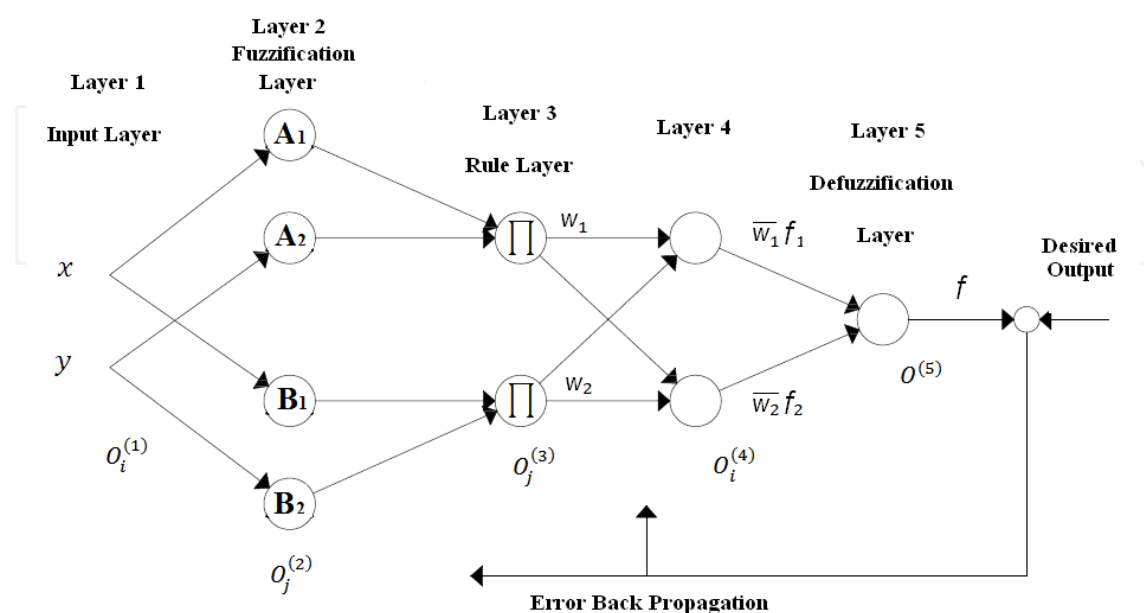

Fig. 6. ANFIS structure with its learning mechanism

where f is the output of the net, x and y are the inputs to this net. The weights of layer 3 are represented by ($\overline{w}_1, \overline{w}_2$), and the weights of layer 4 are represented by ($\overline{w}_1 f_1, \overline{w}_1 f_2$), where the used rules of Sugeno ANFIS in this model are expressed in the following form:

$$If \ x \ is \ A_1 \ and \ y \ is \ B_1 \quad THEN \ f_1 = p_1 x + q_1 y + r_1$$

$$If \ x \ is \ A_2 \ and \ y \ is \ B_2 \quad THEN \ f_2 = p_2 x + q_2 y + r_2$$

Where (p_i, q_i, r_i) are the parameters that are determined and referred to as the consequent parameters. More details about ANFIS parameters can be found in (Jang 1993).

In conventional neuro-fuzzy networks, back-propagation algorithm is used to adjust the network parameters, while in ANFIS the adjusting mechanism is performed by the Hybrid Learning Algorithm (HLA). HLA is basically combined of two identification methods, the least-squares method to identify consequent parameters for the forward pass in layer 4 and the back-propagation method for the backward pass to identify the premise parameters by the gradient descent in layer 2. This combination achieves faster convergence than that of the original back-propagation method. Table 2 illustrates the hybrid learning passes with their identified parameters:

Parameters\Direction	Forward pass	Backward Pass
Premise parameters	Fixed	Gradient descent
Consequent parameters	Least-square estimator	Fixed
Signals	Node outputs	Error signals

Table 2. Two passes in the hybrid learning procedure for ANFIS (J. S. R. Jang 1997).

Finally, when verification result is within an acceptable error bound, the modelling procedure is concluded. Fig. 7 illustrates the developed input membership functions for the four inputs zero-order Sugeno fuzzy system of January's operation of the ECU's Joondalup Campus power network.

From Fig 7, and from the developed Sugeno-fuzzy system for January demand prediction, the developed rules are explained as following:

If *(Temperature is Temperature in Cluster n) and (Hour is Hour in Cluster n) and (Day is Day in Cluster n) and (Day-type is Day-type in Cluster n)* **Then** *(Demand is Demand in Cluster n)*

Where $0 < n \leq$ number of developed rules.

Finally, for the other 11 months of the year, their developed models have different input-output ranges based on the pattern of operation and weather change throughout the four seasons of the year in city of Joondalup. Although other effective modelling parameters have been nominated for the proposed models, experimental investigations have been applied to use three-, four- and five-input modelling parameters for the demand prediction performance improvement, we stick to choosing the four-input modelling parameters, which has been successfully approved to be an optimal selection, from the prediction complexity and prediction improvement point of view, for the developing demand prediction models for the targeted power network.
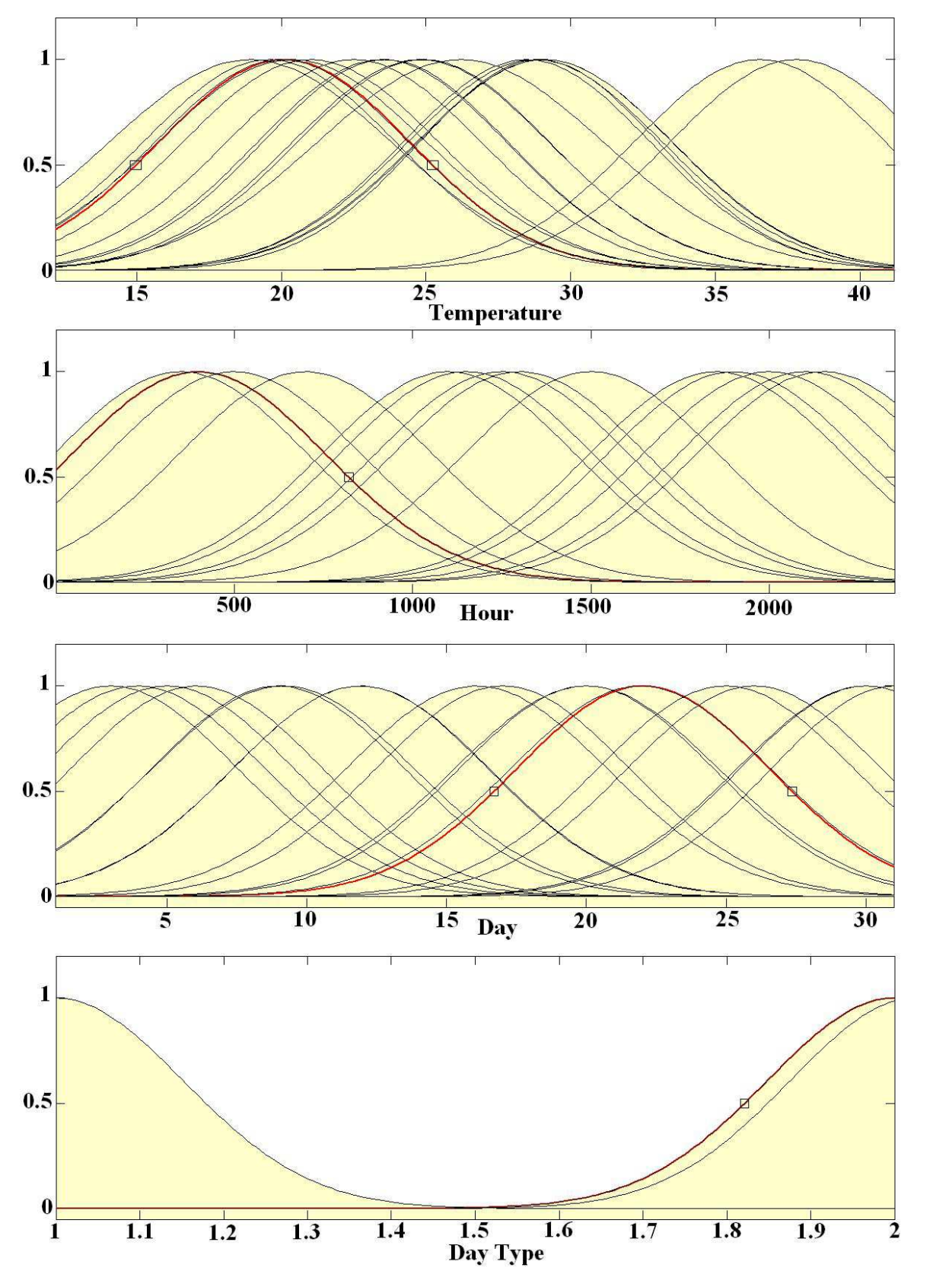
Fig. 7. The developed input membership functions for the four inputs zero-order Sugeno fuzzy system of January's operation of the ECU's Joondalup Campus power network.

5.2 The self-tuning fuzzy system

In this subsection, we aim at discussing two tuning mechanisms which have the ability to improve the prediction accuracy and adapt the prediction to the external effects such as the real-time demand change:

5.2.1 Parallel self tuning fuzzy system

First, we will look at improving our prediction results, based on our knowledge of the energy demand conditions, which could have been partially missed in the given historical operation data. We aim at using the self tuner fuzzy system to improve the prediction accuracy. Fig. 8 illustrates a main fuzzy system with its tuner fuzzy system combination.
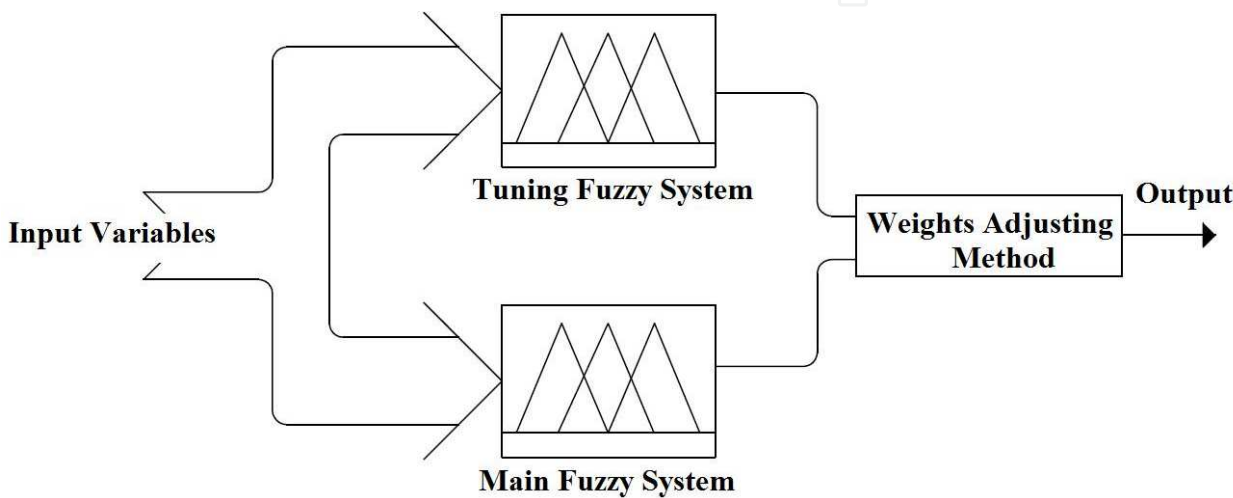
Fig. 8. Self-Tuning fuzzy system (self tuning fuzzy system)

For this system, it is required to enhance the performance of the prediction model by using the knowledge of the system performance, safe operation estimations and actual important needed decisions. In this work, two of the model inputs are selected to develop the fuzzy rule-based system. The rule-based system is developed to have a smooth transition between the specified operation cases in the decision making. In this work generally, we investigate the use of a one rule based system the twelve-month models. Table 3 illustrates the propose rule based system in this investigation.

Hour\Temperature	V. Cold	Cold	L. Warm	Room temp.	Warm	Hot	V. hot
Midnight	S. low	Normal	Normal	S. High	High	V. High	V. High
Dawn	Normal	S. High	High	V. High	V. High	Vv High	Vv High
Morning	Low	S. Low	Normal	Normal	S. High	High	V. High
Afternoon	V. Low	V. Low	Low	Low	S. Low	Normal	Normal
Sunset	V. Low	Low	S. Low	Normal	S. High	High	V. High
Evening	Low	S. Low	S. Low	Normal	S. High	High	V. High
Night	S. Low	Normal	S. High	High	V. High	V. High	Vv. High

Table 3. Self tuning fuzzy rule-based system

To cope with the operation pattern changes through the twelve months of the year, different membership functions are proposed for every month models: all twelve-month models

have the same membership functions shape, but with different input/output ranges. Fig. 9 shows the proposed membership function design for the tuning fuzzy system of the January prediction.
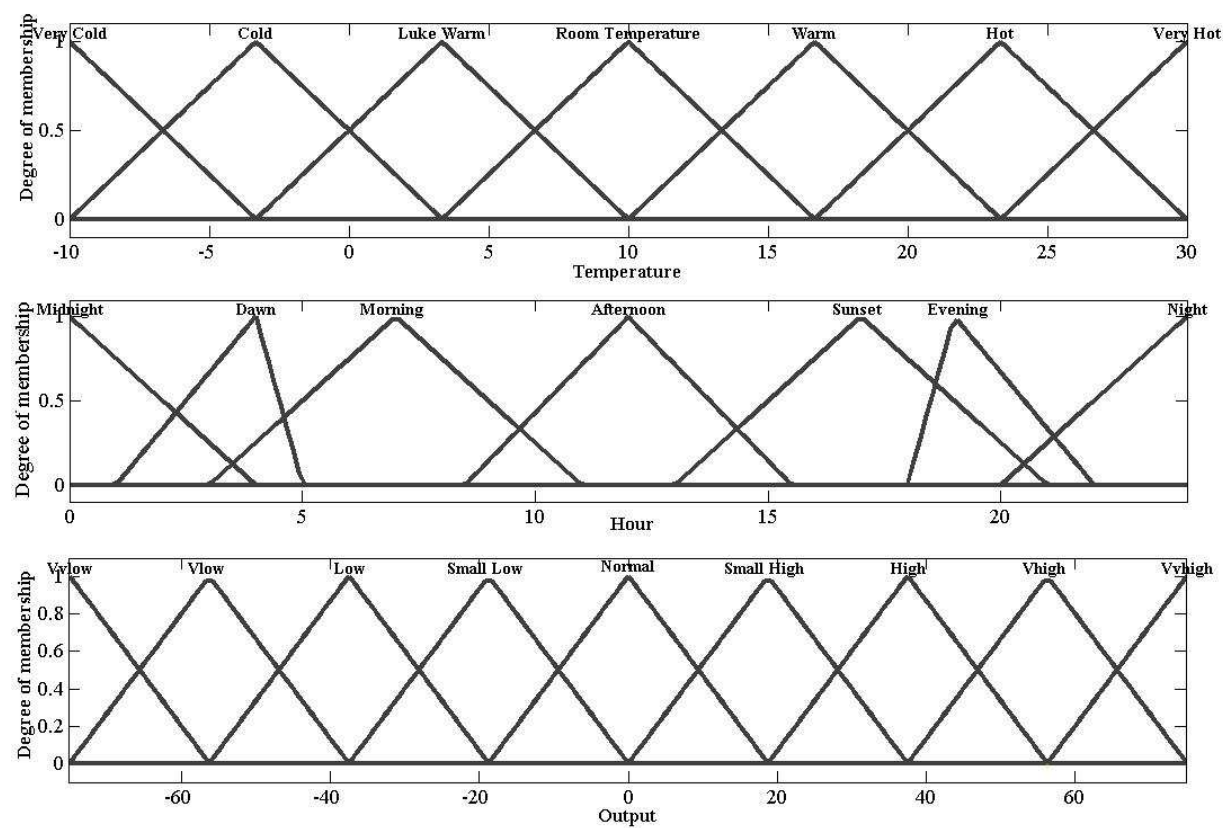

Fig. 9. Membership functions design for the tuning fuzzy system of January demand prediction model

Table 4 illustrates the membership function design for the twelve monthly prediction fuzzy systems.

Months\Membership Functions ranges	Temperature	Hour	Output
January	[-10 30]	[0 24]	[-75 75]
February	[-10 35]	[0 24]	[-75 75]
March	[-10 20]	[0 24]	[-50 50]
April	[15 35]	[0 24]	[-30 30]
May	[0 20]	[0 24]	[-40 40]
June	[0 25]	[0 24]	[-50 50]
July	[-20 20]	[0 24]	[-50 50]
August	[5 20]	[0 24]	[-30 30]
September	[-20 20]	[-4 24]	[-30 30]
October	[30 70]	[0 18]	[-200 200]
November	[10 50]	[-4 18]	[-100 100]
December	[-10 20]	[-4 18]	[-100 100]

Table 4. Membership function design ranges for the 12 monthly demand prediction tuning fuzzy systems

The twelve-month models have different self-tuning fuzzy designs. From the twelve designs, different prediction improvements are carried out. Conservatively, we would like to spot on the weakest prediction region throughout January in Fig. 10, which shows the demand prediction for the 17th to the 21st of January 2009 using ANFIS and Self-Tuning Fuzzy System. The amount of prediction improvement is calculated by evaluating the Integral Square of Error (ISE). ISE is evaluated as follow:

$$ISE = \frac{1}{n}\sum_{t=1}^{n}(y_t - \widehat{y_t})^2$$

where n is the number of entries, t is the time at each entry, y_t is the actual demand and $\widehat{y_t}$ is the predicted value. From the equation above, the results show that the self-tuning fuzzy system has an enhanced prediction accuracy error. Table 5 shows the amount of ISE in each month and the percentage of improvement achieved by the fuzzy tuning systems.
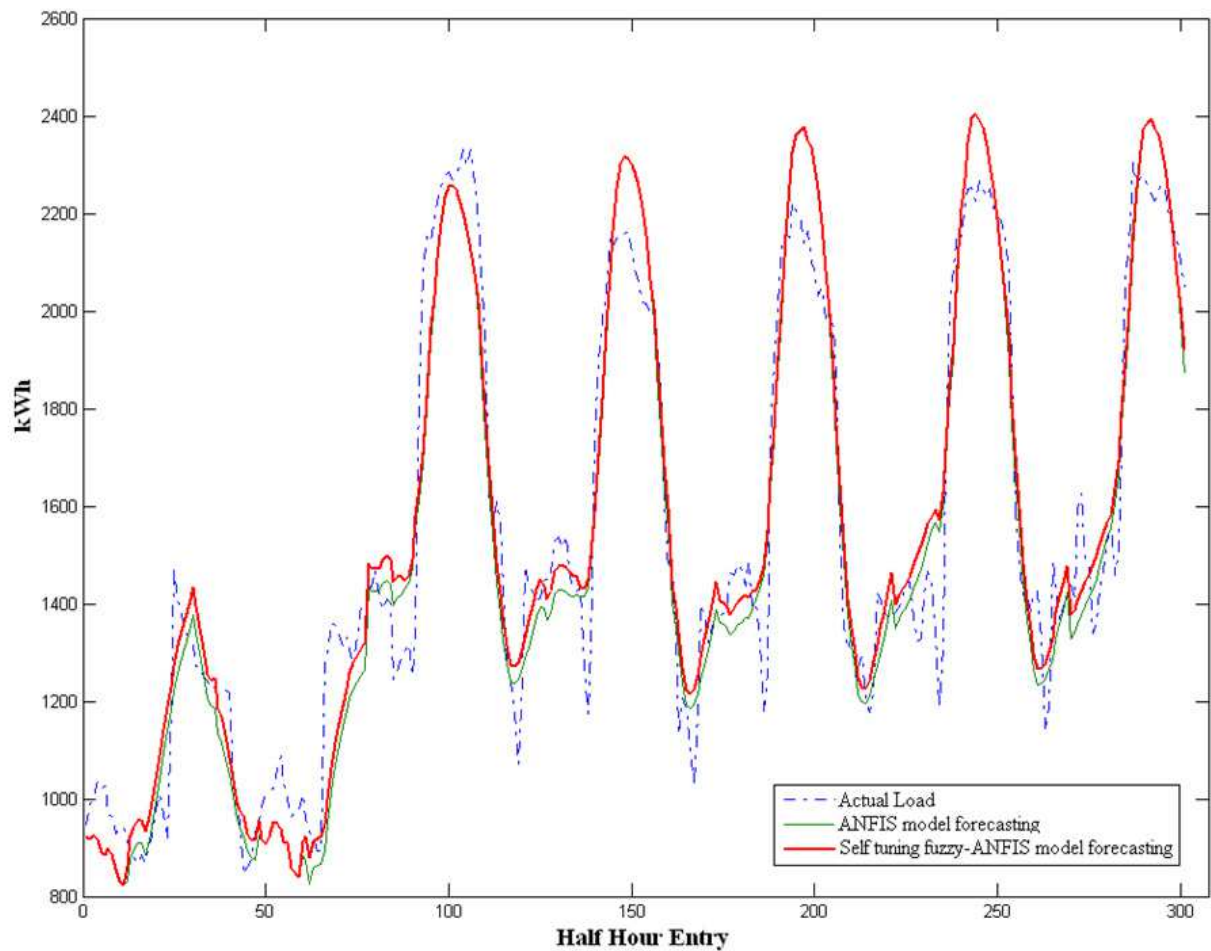

Fig. 10. Self tuning and ANFIS prediction for the 17th to the 21st of January 2009

Month\model	ANFIS ISE	Self-tuning fuzzy-ANFIS ISE	Improvement
January	29030	27230	6.2%
February	23590	22080	6.4%
March	42060	41040	2.5%
April	45300	45160	0.3%
May	27880	27760	0.4%
June	21660	21390	1.2%
July	19100	18760	1.7%
August	25030	24930	0.3%
September	24160	23760	1.6%
October	29260	28920	1.1%
November	27050	25060	7.3%
December	32890	30490	7.2%

Table 5. The amount of ISE in each month with improvement rate made by fuzzy tuning systems

5.2.2 Feedback Self-Tuning Fuzzy System

The Feedback Self-Tuning System FSTF is applied when any external effect variables such as the real load measures are fed to the model to adapt its prediction accuracy. With its adaptation mechanism, it adapts the model prediction to the external effects. The adaptation is developed based on an expert knowledge based system, which achieves successful and safe adaptation when the external effects are applied. The main principle of using this mechanism in our case study is to consider the actual instant demand change pattern change in the next subsequent prediction intervals, which provides flexibility to the model to correct its prediction path. The mechanism is built based on a feedback signal supply to allow the real demand change to enhance the prediction output.

Just like the parallel self-tuning fuzzy system, the adaptation may apply on the main fuzzy parameters e.g. membership function parameters, input-output universe of discourse or the output scale. For simplicity, we aim at utilising the output scale example in this chapter. Fig.11 illustrates the adaptation mechanism for the Feedback Self-Tuning System.

For the twelve different load change patterns in the targeted electric network, twelve different adaptation designs are required. For simplicity, one rule base system could be implemented to cope with twelve-month load change pattern. It is required therefore to tune the FSTFS input-output universe of discourse to fit its output with the load change patterns in every individual month. Out of this adaptation mechanism, different adaptation

ranges may come from the twelve-month models. Table 6 illustrates the used rule based system for the proposed FSTFS.
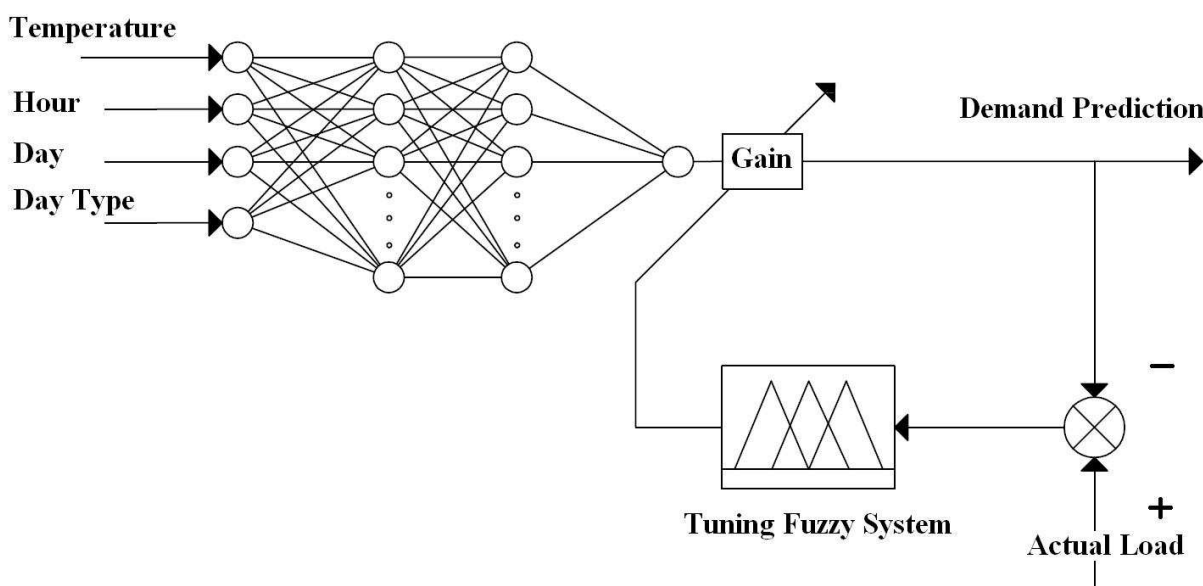

Fig. 11. Feedback Self-Tuning Fuzzy System

Error	Degree of Change
Vvery Low	Vvery High
Very Low	Very High
Low	High
Zero	Normal
High	Low
Very High	Very Low
Vvery High	Vvery Low

Table 6. FSTFS Rule Based System

Fig. 12 illustrates the FSTFS membership function design for the proposed demand prediction model.

The feedback prediction mechanism can be safely utilised in generation scheduling application or any other energy management system applications. For a safe use of prediction output, a safety margin value is added to the prediction results, which allows a flexible utilisation for the predicted demand.

To show the adaptation performance of the investigated systems, a conservative result is shown in Fig. 13, which illustrates the weakest prediction accuracy region throughout the year for the investigated electric power network.
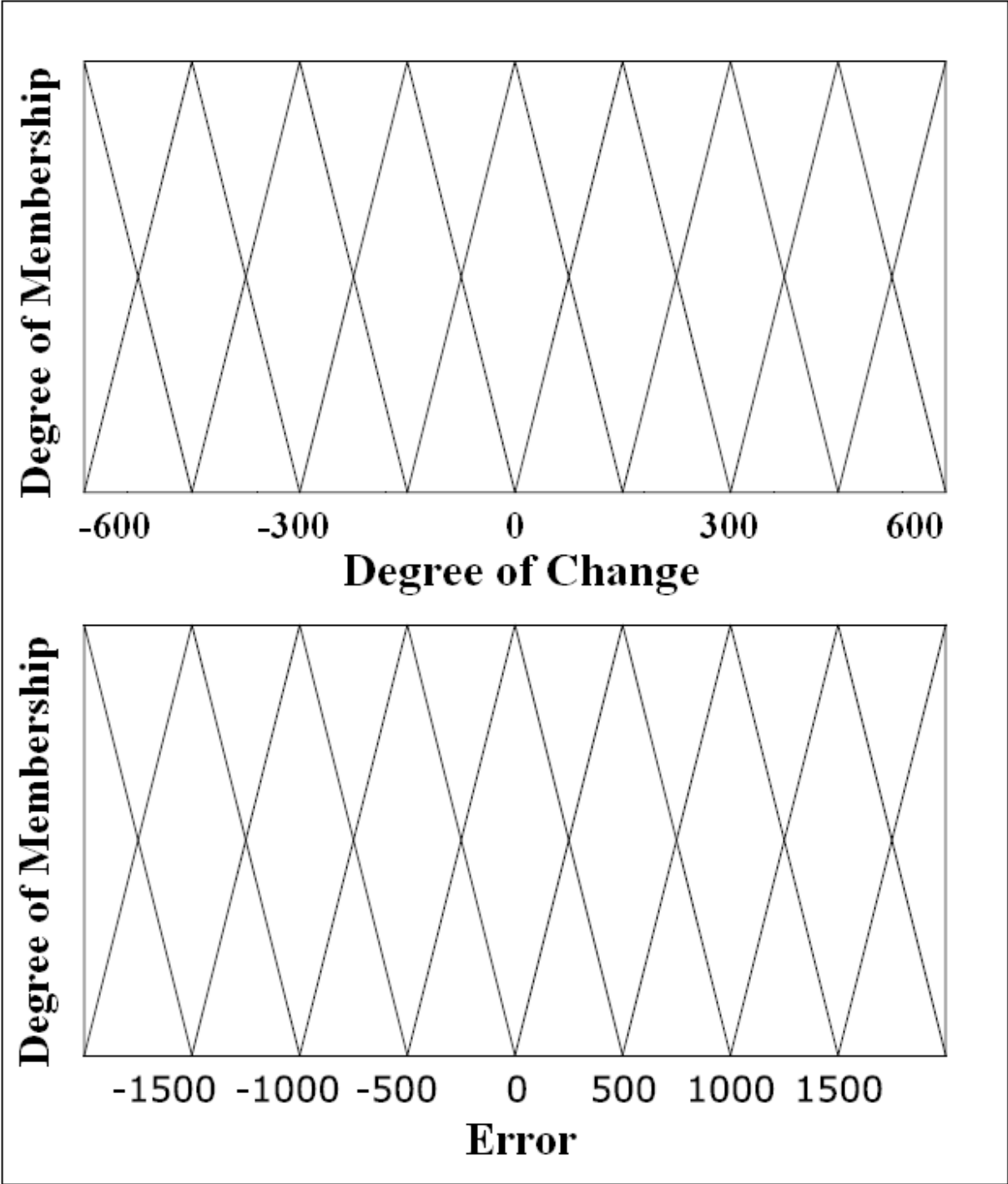

Fig. 12. FSTFS membership function design for the proposed demand prediction model
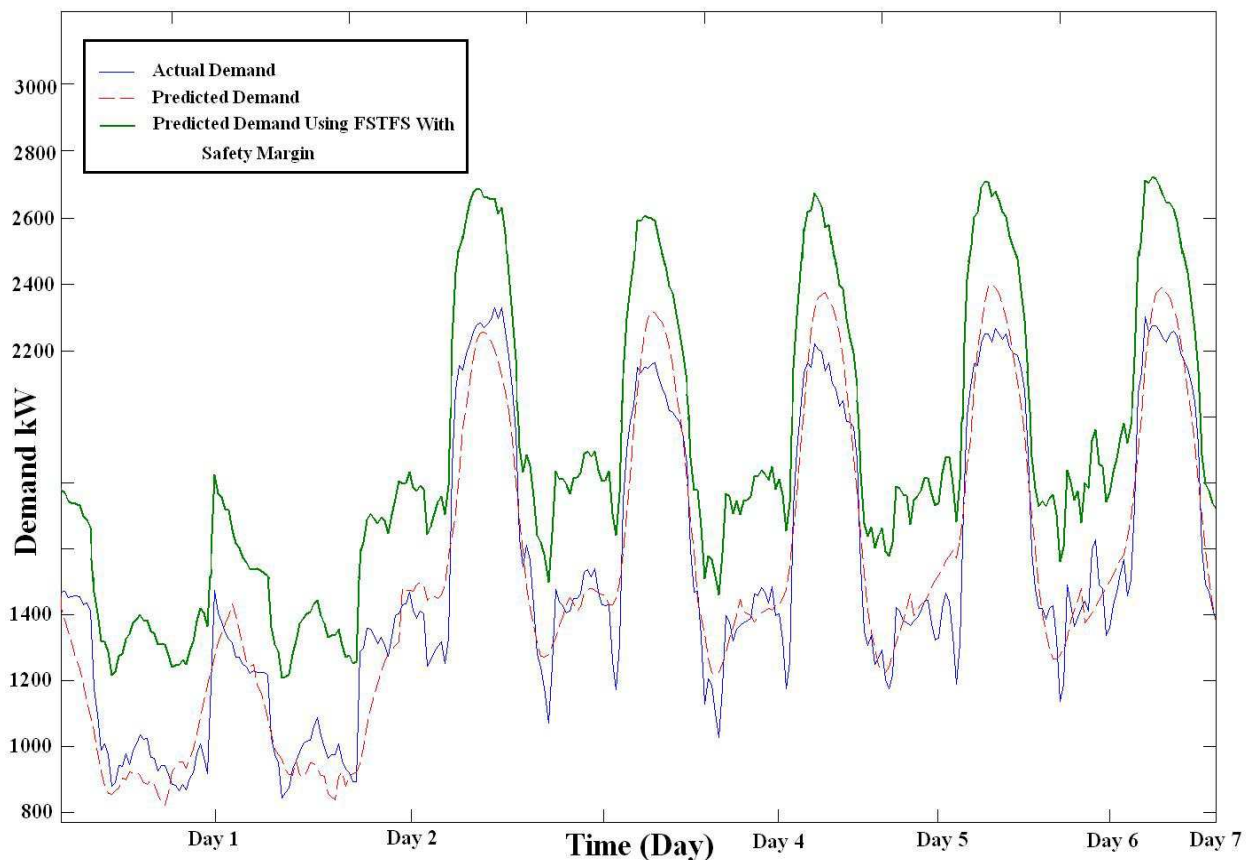
Fig. 13. Actual and Feedback Self-Tuning System Demand Prediction in the ECU Power Network for the 17th to the 21st of January 2009

6. Summary

In this chapter, the art of using FIS in modelling energy demand prediction for a specific electric network has been discussed. The type and the size of the modelled electric network has been comprehensively analysed in terms of the input-output identified effective parameters and their correlation in changing the pattern of the energy use. The identified parameters, however, were used in developing the energy demand prediction models. Fuzzy modelling process has been discussed by looking at its applications and limitations for the selected case study. In our modelling, we have utilised Fuzzy Subtractive Clustering Method to show the tips about its use in modelling, where ANFIS has been applied to develop the zero-order Sugeno fuzzy models. The annual energy demand model for the selected case study has been developed for an individual monthly basis with a specific design applied to deal with the twelve-month patterns. However, certain modifications had to be applied on each month to account for the peculiar conditions to that month.

In addition, two fuzzy tuning mechanisms have been used to improve the fuzzy models prediction accuracy. The first mechanism was used to add the safe operation assumptions to reduce the missing knowledge in the decision making for the developed models. The results from the first mechanism showed that the added fuzzy systems improved the prediction accuracy with different rates throughout the twelve months of the year. In case of the

second fuzzy tuning mechanism, a real-time demand change has been added to the main fuzzy models to adapt their prediction to the real-time demand change through tuner fuzzy systems. From the twelve different demand changes throughout the year, different prediction adaptation ranges have been found. As a conclusion for these discussions, the FIS has a wide range of applications in modelling, especially when we deal with highly non-linear multiple input-output systems we have also shown throughout this chapter that several simulation studies have proved the success of using FIS in modelling, which brightens wider its range of mathematical and engineering applications.

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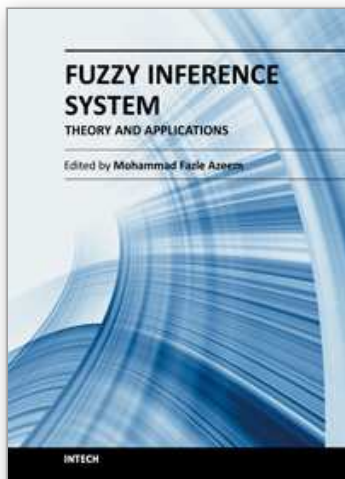
Fuzzy Inference System - Theory and Applications

Edited by Dr. Mohammad Fazle Azeem

This book is an attempt to accumulate the researches on diverse inter disciplinary field of engineering and management using Fuzzy Inference System (FIS). The book is organized in seven sections with twenty two chapters, covering a wide range of applications. Section I, caters theoretical aspects of FIS in chapter one. Section II, dealing with FIS applications to management related problems and consisting three chapters. Section III, accumulates six chapters to commemorate FIS application to mechanical and industrial engineering problems. Section IV, elaborates FIS application to image processing and cognition problems encompassing four chapters. Section V, describes FIS application to various power system engineering problem in three chapters. Section VI highlights the FIS application to system modeling and control problems and constitutes three chapters. Section VII accommodates two chapters and presents FIS application to civil engineering problem.

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