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Load Demand Forecasting: Model Inputs Selection

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Abstract—Developing a good demand forecasting model is the art of identifying the best modelling parameters. Improving the forecasting performance needs to study the input/output parameters of the system to identify the effective forecasting variables. In this paper, the energy demand of Joondalup Campus of Edith Cowan University (ECU) in Western Australia has been selected as a case study for the design and verification of a suitable forecasting model. Fuzzy Subtractive Clustering Method (FSCM) based Adaptive Neuro Fuzzy Inference System (ANFIS) is used as a proposed modelling network in this paper. Basically, three-input forecasting models have been developed based on 12-month models to perform ECU energy demand forecasting. The input/output parameters selection was made after analysing the historical demand pattern in ECU energy system. Generally, increasing the number inputs in model network may have wider training scope and better forecasting accuracy. However, the wrong choice of the additional input would deteriorate the forecasting accuracy. From analysing the historical operation of ECU energy system, four and five-input variables could be identified and modelling has been performed. The result show that four-input models were the best in the prediction performance among 12-month models of the annual demand predicion of ECU.

I. Introduction

ENERGY Management System (EMS) is key to achieving secure, reliable, efficient and low cost energy supply. The main objective of EMS is to make optimized use of the energy to achieve a cleaner and economic energy supply. By anticipating future energy demand, a suitable mix of energy sources may be identified, including renewable sources, with substantial economic and environmental benefits.

Among many roles of EMS, demand forecasting is considered as a key function for achieving green and economic generation. The use of soft computing and artificial intelligence can aid in developing demand prediction models. A number of artificial intelligence methods have been applied to achieve accurate forecasting models. ANFIS based on the data field was proposed by [1] to develop a demand forecasting model. This method was proposed to solve the drawbacks of the general fuzzy neural network, and to optimize fuzzy rules. This method has shown superiority in performance to that of the artificial neural network in terms of time of learning and accuracy of forecasting. A model of short term forecasting based on previous day features has been developed using adaptive neural fuzzy system. Many variables have been considered in the modelling procedure e.g. temperature maximum and minimum, climate change and the previous days consumed load [2]. Short term forecasting model has been

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developed using neuro fuzzy system *Locally Liner Model Tree (LoLiMoT) learning algorithm* [3]. The model performance has been compared with a multilayer preceptron and *Kohonen Classification and Intervention Analysis.* Next day demand forecasting in electrical power generation has been developed using ANFIS [4]. The purpose was to improve the power system as an application of artificial neural networks and fuzzy logic based hourly load demand forecasting with linear polynomial and exponential equation. Multivariate inputs for electrical load forecasting on hybrid neuro-fuzzy and fuzzy C-Means forecaster has been proposed by [5]. The neuro-fuzzy approach was used with additional fuzzy C-Means clustering method before the input enters the network. An intelligent method for medium and long-term energy demand forecasting of a complicated electrical systems has been provided. The demand forecasting using time series modelling and ANFIS estimator has been developed [6]. A clustering based genetic fuzzy expert system for electrical energy demand forecasting has been presented. A novel load forecasting approach has been developed by integration of genetic fuzzy systems and data clustering for extracting a load forecaster expert system [7]. A new approach to short-term load forecasting in a deregulated and price-sensitive environment has been presented. A real-time pricing type scenario is envisioned where energy prices could change on an hourly basis with the consumer having the ability to react to the price signal through shifting electricity usage from expensive periods to cheaper periods when possible[8]. ANFIS modelling has been proven as a reliable forecasting method as compared to other forecasting methods. The number and type of the input variables is playing a big role in increasing or decreasing the forecasting accuracy. As a case study for this investigation, energy demand and load curve data from the Joondalup Campus of ECU is used.

II. Load Curve in Edith Cowan University

The load curve for the selected power system has several pattern changes which are dependent on several variables. From the load curve changes, it has been identified that the major factors that affect the load changes are weather, date, time, order of the day (Monday, Tuesday,...,etc.) and type of the day (working day or weekends and holidays). In this study, infrequent university events which results in abnormal load demands are neglected, as it is assumed that these abnormal load changes will have warning notifications or predefined settings to avoid system overloads. Figure 1 shows January 2008 energy demand for ECU.

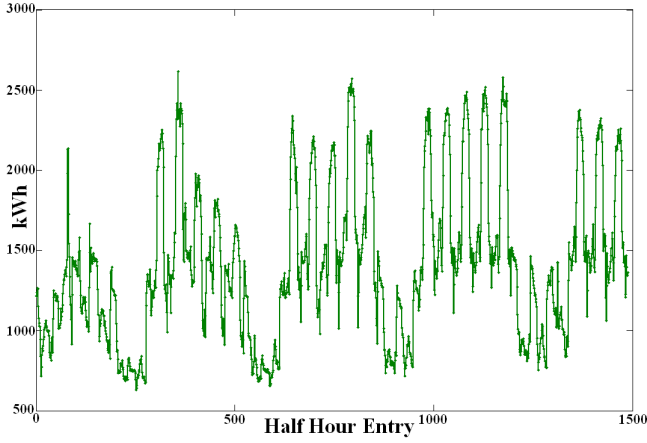The load curve is used to estimate the range and pattern of data for forecasting. The other accessible important factor,

Figure 1. January 2008 demand curve for Joondalup Campus of ECU
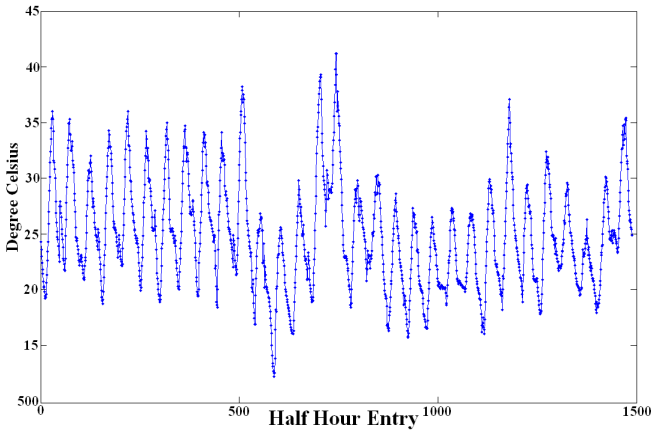
Figure 2. January 2008 Temperature data for the City of Joondalup

Figure 3. Different load patterns for Joondalup campus of ECU in 2008 and 2009

Figure 4. ANFIS learning structure

which can greatly influence the forecasting, is temperature changes. Figure 2 shows the daily temperature change in the city of Joondalup in January 2008.

To identify suitable parameters that can improve forecasting accuracy, previous years' demand has been analysed. It has been found, as shown in Figure 3, that the type of the day (working day or weekends and holidays) has a large bearing on the demand pattern. It may be observed that for the same variable values, different demand can be obtained as shown in Figure 3. It is therefore necessary to look for another variable that accounts for the differences in demand. It is known that there are many unmeasured factors that may affect the demand, e.g. the number of students on campus, number of occupied rooms, nature of students and staff activities, etc.. However, there are still some simpler factors that may substantially influence the demand, e.g. the order of the day in the week. It is hypothesised that the type of the day will have more influence than the order. This is simply because in holidays or weekends the demand drops to nearly half, whereas there is no substantial difference between the working days of the week.
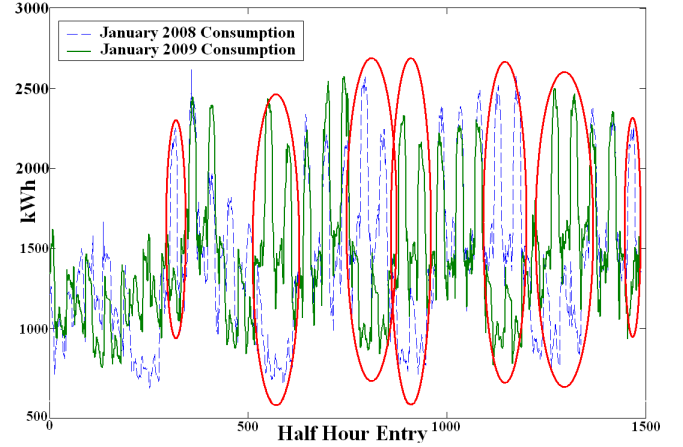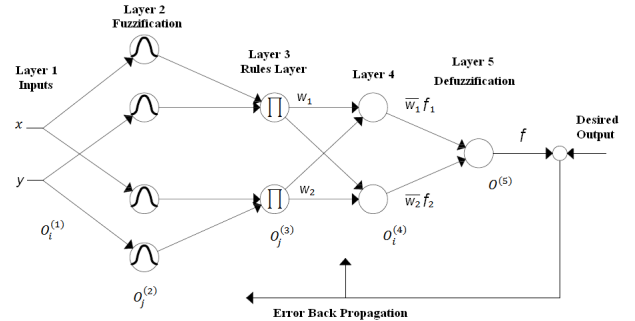
III. ADAPTIVE NEURO FUZZY INFERENCE SYSTEM

In order to use neural networks for fuzzy inference, it is necessary to study the structure of this system along with its training algorithm. Adaptive Neuro-Fuzzy Systems (ANFIS) were first introduced in [9], with further models proposed in [10], [11]. These structures proved to be useful for control purposes and many other different applications. The simple diagram of Figure 4 shows the structure of ANFIS, where f is the output of the net, and x_1 and x_2 are the inputs to this net. The weights of layer 3 are represented by (w_1, w_2), and the weights of layer 4 are represented by ($w_1 f$, $w_2 f$). The type of algorithm that ANFIS uses to identify fuzzy parameters is either hybrid learning or back-propagation algorithm type. In this work, ANFIS learning and adjusting depend on Hybrid Learning Algorithm (HLA). In the forward pass the algorithm uses least-squares method to identify the consequent parameters on layer 4. In the backward pass the errors are propagated backward and the premise parameters are updated by gradient descent. Table I summarizes the actions in each pass.

Accordingly, the hybrid approach converges much faster since it reduces the search space dimensions of the original pure backpropagation method [9].

Table I
HYBRID LEARNING ALGORITHM PROCEDURE FOR ANFIS [12]

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

IV. FUZZY SUBTRACTIVE CLUSTERING METHOD

Fuzzy Subtractive Clustering Method (FSCM) is a method, that extracts rules from supplied input-output training data. It is a statistical classification technique, which is used for discovering whether the individuals of a population fall into different groups by making quantitative comparison of multiple characteristics. FSCM was firstly proposed by [13]. The computation simply depends on the number of data points, and is independent from the dimension of the problem. Rules extraction is made based on:

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

where

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

and r_a is a positive constant that represents the radius of data neighbourhood. In (1), p_i is the density of each examined point. X_i is the point, that is examined at time of measuring density p_i of this point, and x_i is other data within the neighbourhood. After finding the density for each data point, the highest density point will be selected to be the first cluster centre. The other cluster centres will be chosen according to the following formulas:

$$p_i = p_i - p_{c1} e^{-\beta \|x_i - x_c\|^2} \tag{3}$$

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

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

where p_{c1} is the next density point to be examined, and x_{c1} is the next data point to be examined. Data point with highest remaining potential is selected as the second cluster centre. The process is repeated until the amount of the remaining potential data becomes less than a fractional value of that in the first cluster potential. For this work, the value is selected to be 0.15, relating this work to [14][15].

V. MODELLING METHODOLOGY

The system operation historical data constitute the input to the FSCM based ANFIS. This data stream consisting of the half-hourly readings of the power consumption is structured by dividing it into 12 separate monthly sets used to derive separate monthly models, thus simplifying the models and reducing the required computational resources. Figure 5 presents the structure of the annual energy consumption demand model.
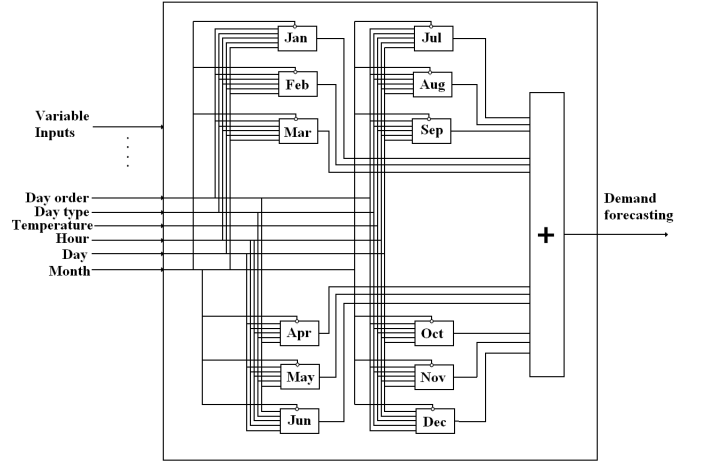

Figure 5.   Demand forecasting model of every half hour load in the year
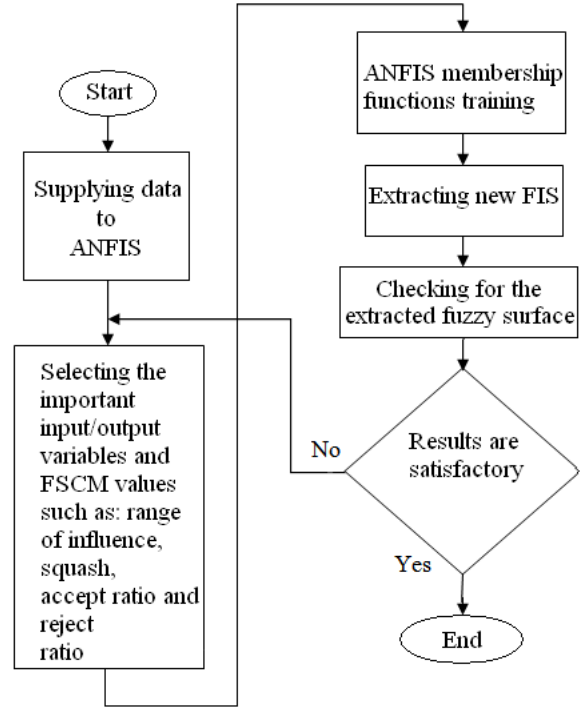
Figure 6.   Fuzzy Subtractive Clustering Method modelling procedure

Each of the monthly models has been developed by supplying order of the day, type of the day, temperature, hour, date, and consumption data to ANFIS framework. Random values are utilised to initiate clustering of the supplied data using FSCM. In Figure 6, clustering and rule extraction procedure is presented. The choices of the number of input/output variables and FSCM parameters, such as Range Of Influence (ROI), squash, accept ratio, and reject ratio values, are made based on trial and error. Tuning is applied to improve the modelling performance.

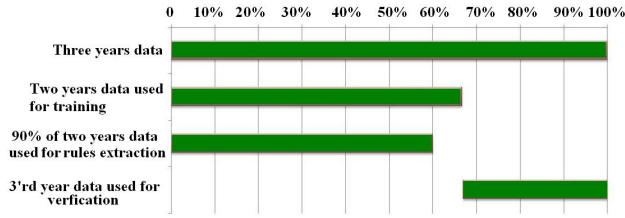Figure 7. Data utilisation in developing demand forecasting model

To increase the range of learning, the historical data are organised into three groups. The first group is used to develop ANFIS rules, and it consists of 90% of the two years of the historical data. The second group, used to train the developed ANFIS system, contains full two years of the historical data. Finally, the third group, used to verify the validity of the developed model, consists of the third year of historical operation data. Figure 7 illustrates the utilisation of the original data in the modelling process.

A sufficient number of training epochs is applied at each modelling step to ensure having heavy training process. The developed fuzzy model surfaces are monitored to ensure having suffecient coverage for the prediction range. When the prediction is achieved with an acceptable error ratio, then the modelling procedure is complete. Otherwise, if the resultant surface has incorrect shape, or not covering all the prediction ranges, new values for the range of influence and number of epochs are applied. Figure 6 depicts the modelling procedure decisions. Figure 8 presents the surfaces of the developed fuzzy systems for the three, four and five input variables.

VI. RESULTS

The obtained results demonstrate the dependence of the forecasting accuracy on the number of inputs. Figure 9 illustrates different forecasting accuracy for the three-, four- and five-input systems. In order to evaluate the degree of forecasting enhancement, the Mean Absolute Error (MAE) is used.

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|(y_t - \hat{y}_t)| \qquad (6)$$

Where n is the number of entries, t is the time at each entry, y_t is the actual demand and $\hat{y}_t$ is the forecasted value. Table II presents MAE results with modelling complexity for all investigated cases. Modelling complexity is shown in terms of used number of membership functions (MMFcn) and the value of (ROI). It is clear that the fourth input significantly reduced the forecasting error, while it is shown that in case of five inputs system, the range of forecasting accuracy improvement may change from negative 30% to positive 50%; depending on the load change patterns in each month. However, the complexity of the models has been raised to double or triple in most cases. It simply tells that this input does not have
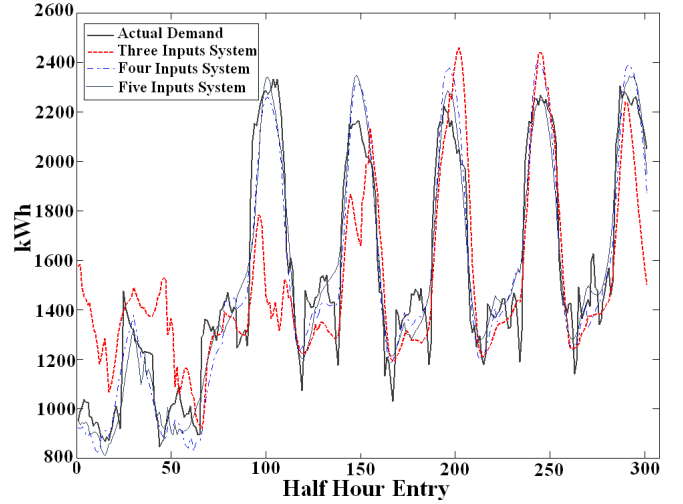

Figure 9. Forecasting results comparison for demand in ECU from 17'th till 21'st of January, 2009

big influence on the load changes in ECU. Thus considering it as a fifth input to the models will not have significant prediction improvement, or it may even work negatively. Figure 9 shows the forecasting results for the three-, four- and five-input systems. For safety consideration, a spot on the period from 17'th till 21'st of January 2009, which shows the worst forecasting accuracy in that month, is shown.

Studying system operation conditions e.g. the operation times, the number of people and the amount of consumed energy during the day or night may help in developing supportive variables to improve the forecasting accuracy, as long as the significance of the input is assessed prior to its use in the model development.

VII. CONCLUSIONS

In this paper, load demand forecasting method was developed based on realistic data using FSCM based ANFIS. Selection of the important factors (inputs) in modelling is crucial in order to achieve best forecasting outcomes. 12-month demand forecasting models were developed based on historical operation data of ECU power consumption. Selection of significantly effecting factors (inputs) has been investigated. It has been found that for the specified power system, the four-input ANFIS could achieve the best forecasting accuracy. The results illustrate the forecasting accuracy across the twelve-month span. However, adding an improper input to the model structure may affect modelling complexity and error reduction ratios.

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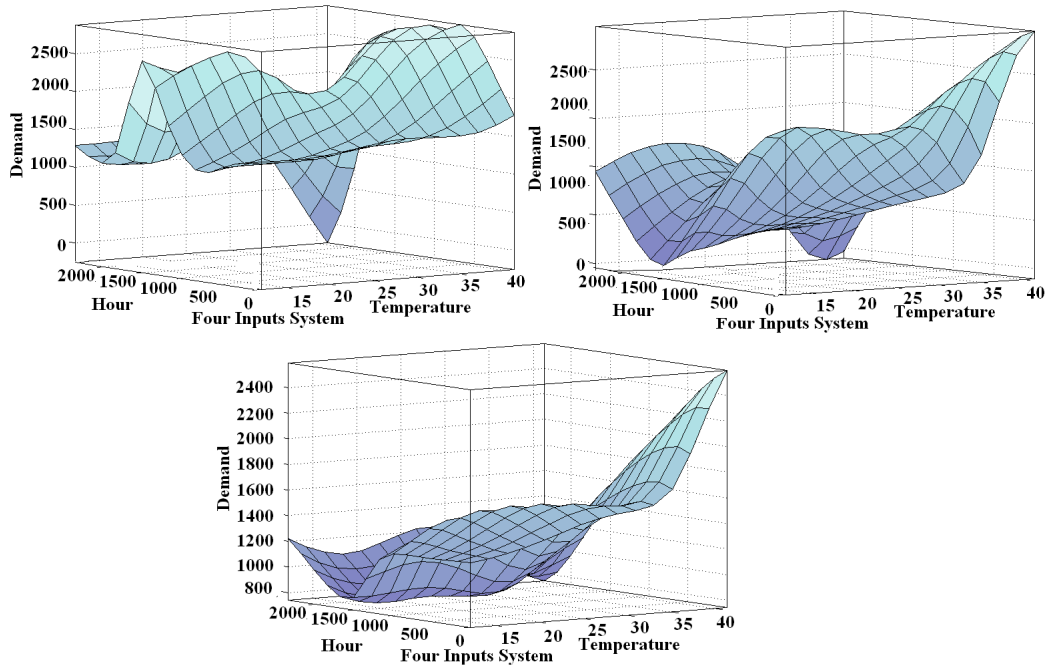
Figure 8. Fuzzy surface for the developed fuzzy models of the three-, four- and five-input system

Table II
THREE-, FOUR- AND FIVE-INPUT SYSTEMS FORECASTING ACCURACY

Month\Inputs	Three inputs			Four inputs			Five inputs		
	MAE	MMFcns	ROI	MAE	MMFcns	ROI	MAE	MMFcns	ROI
January	75360	63	0.35	29030	76	0.43	14540	150	0.5
February	146600	69	0.38	23580	72	0.4	15920	150	0.5
March	164800	33	0.45	42060	56	0.5	53940	145	0.5
April	99800	78	0.33	45300	160	0.33	24480	140	0.5
May	70550	39	0.44	27880	68	0.44	35950	145	0.5
June	68940	45	0.48	21660	100	0.4	21990	320	0.4
July	61000	36	0.5	19100	80	0.45	29140	145	0.5
August	96980	36	0.5	25030	76	0.48	31070	145	0.5
September	148600	54	0.45	55780	76	0.43	43872	120	0.55
October	86490	24	0.5	29260	44	0.5	33820	125	0.5
November	95110	33	0.48	27050	64	0.5	41120	135	0.5
December	73850	45	0.41	32920	60	0.41	22680	182	0.45

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