Linguistic Modelling of Short-Timescale Electricity Consumption Using Fuzzy Modelling Techniques.

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ABSTRACT

This paper presents a mathematical model for short-term (24 hour) electrical energy consumption in Ireland. The model is based on fuzzy logic and the parameters determined by drawing on the extensive intuitive knowledge of operators in the National Control Centre (NCC) in E.S.B., using a series of questionnaires to determine the shape and location of the fuzzy sets, and the fuzzy rules used to evaluate the model output. The performance of the computer-based fuzzy model is comparable to that obtained by E.S.B. experts.

1. INTRODUCTION

Load consumption is a non-linear varying parameter in the complex operation of an electrical supply board. It is both economically and environmentally sound to know the system load demand a priori. Therefore the production of a dedicated, accurate load forecasting mechanism would be an invaluable asset to any generating facility. At present expert operators can forecast to a very high degree of accuracy, using an immeasurable amount of intuition and experience. The motivation for this project came from the important role played by electricity load forecasting which led to a desire to produce a system capable of producing reliable, consistent and accurate short-term load forecasts.

Traditional approaches to electricity load forecasting include regression and interpolation techniques, but these may not yield the desired level of accuracy. Alternatively these are complex algorithm based approaches in the area of time-series analysis and artificial neural networks. This paper documents an attempt to incorporate the expert knowledge and actions of these experts into a mathematical model using fuzzy modelling techniques. Fuzzy linguistic modelling provides an appropriate means to capture such information. This knowledge based fuzzy logic expert system is used to forecast an electricity load profile.

Electricity consumption forecasting is performed by virtually every power board in an effort to optimise the scheduling of generating resources in an efficient and cost-effective manner. The position and magnitude of the consumption peaks, and troughs, must be identified accurately if provision is to be made for the maximum generating capacity, while reducing the spinning reserve requirements in slack periods. In the NCC forecasting of the following twenty four hours' electricity consumption is performed by a team of experienced operators, using only the consumption history and their intuitive understanding of the relationship between consumption and appropriate causal variables, such as temperature, rainfall and other weather, socio-economic and temporal factors.

2. FUZZY MODELLING

Fuzzy modelling, in this context, implies the application of fuzzy logic to the modelling of dynamical systems. The utilisation of fuzzy models has significant benefits for particular applications, including the intuitive (linguistic) nature of the model ‘equations’ (or rules) and the capacity of modelling significantly non-linear systems. In this application, fuzzy logic is applied to the modelling of causal time series models.

2.1 Fuzzy Logic.

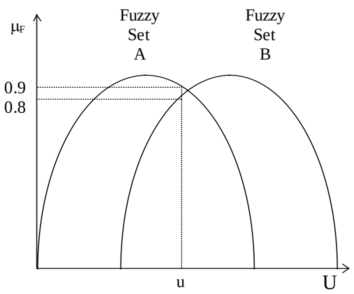

Fig.2.1 Example of Fuzzy Set Membership.

Fuzzy set theory, the generalisation of conventional set theory, proposed by Zadeh[1] as a revolutionary way of representing the vagueness associated with everyday life. Rather than events, or objects, belonging to a crisp set with clear boundaries, fuzzy set theory allows for events to exist in more than one set. The degree of ‘belonging’ that an element has in a set is called the membership function of the parameter for that fuzzy set. This means that the associated membership of an event in a fuzzy set can be multivalued. The possible range of all possible values a parameter may take on is called the 'universe of discourse' for that parameter. In classical set theory a function or variable is either a member of a set or not, it has a membership function of 1 or 0. A fuzzy set can be represented mathematically as, F, in a universe of discourse, U, is characterised by a membership function μ_F, which takes on values within the interval[0,1].

Example: If two fuzzy sets, A and B, were constructed, and an element, u, in the domain of discourse was isolated. the membership function of u in fuzzy set A would be μ_A, and μ_B for fuzzy set B, as shown above in Fig.2.1. Obviously the gradient of the lines constructing the fuzzy set is important and it is in this fact that the most information is held. Although, in so far as the author could see, this aspect of fuzzy set construction has not been dealt with in the literature. The condition of necessary overlap signifies the fuzzy models' capability to facilitate dual set membership. It is this characteristic of fuzzy sets that makes it possible to attempt to model common-sense reasoning. In so far as the author could ascertain, from a literature survey, trapezoidal fuzzy sets are the most widely used. This decision is strictly application dependent and very little, if any, justification for such choices have been documented. The general structure of the fuzzy set chosen to represent the system variables, however, can take on several different formats, including trapezoidal, triangular or Gaussian.

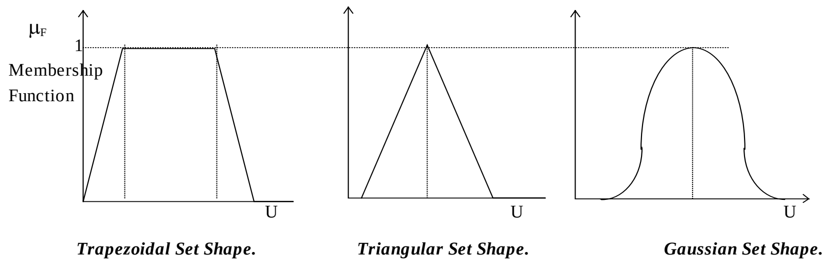

Fig.2.2. Typical Fuzzy Set Shapes.

This area of fuzzy logic modelling attempts to more accurately mimic the action of human reasoning. It makes more sense to use typical linguistic expressions, for example, small, medium and large, as variables of this fuzzy model, over strict quantitative numerical values. For example, one does not decide whether to carry an umbrella based on weather forecast information that yesterday's rainfall was 3.75 cm. The human rationale works on the basis that it decides 3.75 cm is considered to be ‘large’, and that ‘large’ justifies the carrying of an umbrella. This intuition, which is only available in the human mind, is what a fuzzy set attempts to capture.

A linguistic model is a model that is described using linguistic terms in the framework of fuzzy logic, instead of mathematical equations with numerical values, or conventional logical formulae with logical symbols [2]. Fuzzy linguistic modelling utilises the notions of normal commonplace language to label the fuzzy sets which represent quantitative variables. Another important component of any fuzzy model is the set of conditional statements, or rule base. The linguistic variables have and interdependent relationship with each other to produce the result of the decision. This is represented in an IF.. THEN .. statement structure. For example ...

if *temperature* = ‘high’ **then** *drink* something ‘cold’. or **if** *temperature* = ‘low’ **then** *drink* something ‘hot’.

The method by which the fuzzy model operates upon the fuzzy sets and proceeds to the completion of the model and applies the decision that has been arrived upon, is called the model algorithm. Within this there are many various options i.e. how the model arrives at a decision and how it decides which is the best decision to make, from those available.

2.2 Fuzzy Model Components.

There are three components to a fuzzy model - fuzzification, the fuzzy rule base and defuzzification. In E.S.B. context, fuzzification may be identified as the perception of variables by NCC operators, the rulebase considered as the symbolic representation of the load predicting process in the minds of the load forecasters, with the defuzzification constituting the determination of a crisp action as a result of the reasoning process.

2.2.1 Fuzzification.

There are many varying means of constructing the fuzzy sets from the available data and operator's experience. Although there are many applications utilising fuzzy logic and sets, the issue of how to build the sets is not well documented. Sugeno’s method [3], it has been noted, provides a more systematic method for the design of a fuzzy linguistic model. However some of the most important steps in this algorithm appear to depend very much on trial-and-error. There exists a substantial number of mathematical methods for constructing fuzzy sets from time series data, which are encompassed by the term ‘clustering algorithms’[4][5][6]. This investigation however deals with modelling the decision making routine of experienced system load managers.

2.2.2 Fuzzy Rule Base

The fuzzy engine or decision making process consists of a systematic structure made up of IF ...THEN... statements. These statements represent the rules of the system. The methodology for setting up the fuzzy inference engine was that of modelling the experts’ experience and knowledge. This is the least structured, of those available, but remains the most widely used. The rule base reflects the expert’s direct empirical knowledge of the operation.

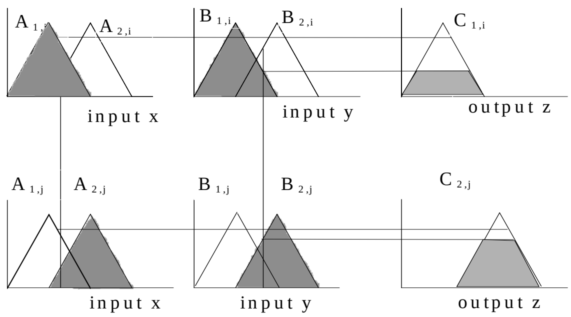

Fig.2.3. Fuzzy Set Implication.

Displayed in Fig.2.4, below, is a diagrammatic representation of a fuzzy rule, included is a display of how two fuzzy sets overlap and how more than one rule results. A fuzzy rule acts as a mapping from the input fuzzy sets to the output fuzzy sets. The method employed to express the effect of the connective *‘and’* in the decision rules is called the mode of implication. In this study two fuzzy implication algorithms were implemented, those by Mamdani[9] and Larson[10] respectively.

An example rule takes the form:

$$R_i : \ IF \ \ x_1(t) \ is \ A_{i,1} \ \ AND \ x_2(t) \ is \ A_{i,2} \ \ AND \ \ldots\ldots\ldots x_j(t) \ is \ A_{i,j} \ \ \ldots\ldots\ldots x_N(t) \ is \ A_{i,N} \ldots\ldots\ldots\ldots\ldots\ldots$$
$$THEN \ \ Z_1(t) \ is \ C_{i,1} \ldots\ldots\ldots Z_j(t) \ is \ C_{i,j} \ldots\ldots\ldots Z_M(t) \ is \ C_{i,M}$$

2.2.3 Defuzzification.

A defuzzification scheme is used to map the answers to the rules, which are scaled versions of the output fuzzy sets, to attain a solution. There are several defuzzification strategies available but by far the most widely employed is the centre of area method (COA). Previous research and studies have shown that COA yields superior results over other mean of maximum (MOM) techniques, on the basis COA gives a lower mean square error. The set $z_i(t)$ is computed by first evaluating the degree of satisfaction of each rule. The minimum membership values of x (t) in fuzzy set $A_{1,i}$ and $A_{2,i}$, then subsequently the memberships of y (t) in $B_{1,i}$ and $B_{2,i}$, all corresponding to the application of Rule[i], are computed. Finally, these values are propagated across the sets to the final set, to decide the conclusion to the rule. Computing the crisp value for $z_i(t)$, called defuzzification, is generally done by finding the *centroid* of the area covered by the overlapping conclusion fuzzy subsets and projecting the resultant point onto the domain of discourse.

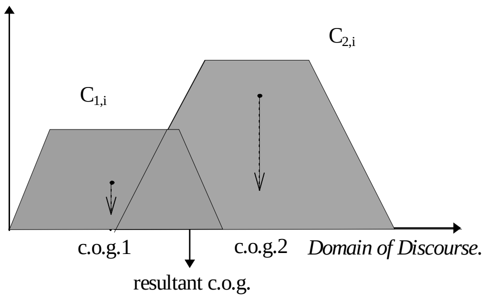

Fig.2.4. Centre of Gravity De-Fuzzification

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3. E.S.B. FORECASTING PROCEDURE

The data received from E.S.B. formed the data of this project. E.S.B. has a systems software package in operation which displays numerous load profiles on demand. The importance of this system to the operators forecasting mechanism deemed it necessary to replicate this system. The data is supplied on-line quarter hourly to the National Control Centre (NCC) terminals. The average maximum system load would be in the region of 2300 MWatts.

The data retrieval system used by E.S.B. National Control Centre runs off a large archive of data. The system runs on-line, so the operator forecasting for the forthcoming time period has the load figures, right up to fifteen minutes previously, readily available. In the forecasting environment, it was noted that Dublin accounts for approximately two-thirds of the national figure. Thus the operators frequently consider Dublin to be representative of the rest of the country.

Weather data was also made available for the corresponding dates. This included solar intensity, wind speed and direction, temperature and relative humidity. These are made available on-line from E.S.B.'s own weather station. No rainfall data is collected at this weather station so such data was collected from the Meteorological Service. However in the forecasting environment the forecasters have comprehensive weather forecasts available on demand from various different sources.

Forecasting within the NCC is done on a daily shift by shift basis. Before an expert finishes his shift he forecasts the next most critical point, in the next shift. Forecasts are generated by means of an intuitive differencing technique. The forecaster selects what he estimates to be the most suitable 'standard day' and then the standard day profile is 'adjusted' in line with the operators' experience and intuition so as to achieve the profile forecasted for the next period.

3.1 Standard Day Selection.

Inherent in this model is the load forecasting notion of a 'standard' day. The forecaster selects a shift profile from record that he considers will be a close approximation to that which is expected for the future period. This represents the idea of a standard day. The basis upon which a shift is chosen as standard is made by comparison of the characteristics for the two days in question. It is worth noting at this stage that the standard day and the day to be forecasted will, in virtually every case, have the same calendar 'dayname'. In the fuzzy model a mechanism was devised so that the load profile for the forecasted day was developed on a shift by shift basis, which was then adapted according to the experts fuzzy advice, hopefully, to within the accepted tolerance of the expected daily characteristics and parameters.

3.2 Unpredictable Load Changes

The system load data received, and utilised in this project, has a ±25 MWatt pseudo-random variation. The prefix "pseudo" is used to describe this fluctuation because it depends entirely on the demands made by a large Arc Furnace load which utilises this much energy over a very short time scale, 15-30 minutes, at random intervals, which are impossible to forecast.

4. STANDARD DAY AND SYSTEM INPUT SELECTION

The ‘standard’ day concept, as utilised by NCC staff, is also followed in the current investigation. The fuzzy model developed is a variational one, in that the model is driven with differences between the inputs associated with the standard day and those forecast for the day in question. The outputs produced by the model describe the predicted deviation from the standard day load profile. To assist in the selection of an appropriate ‘standard’ day, it was necessary to construct a data retrieval system akin to that which E.S.B. have at their disposal. The previous three days and the same day last week, also the same day, within the same week the previous year, were all made available to the system. The data is presented on a quarter-hourly basis.

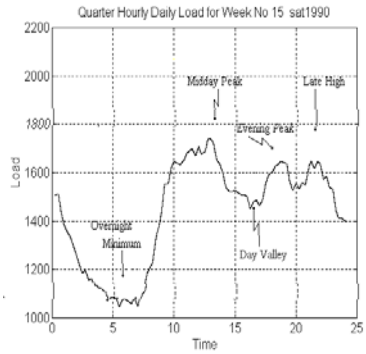
4.1 Input Variables.

The most important input variable is outdoor temperature, although the other weather variables also make a significant contribution. Subsequent to several meetings with the operators, fuzzy variable input spaces were generated. As an example, for ambient temperature the most suitable linguistic terminology was decided upon as *(freezing, very cold, cold, comfortable, warm and hot).* These represent the various thresholds and watersheds that this variable could pass through, utilising the commonplace terminology used by the experts concerning daily weather forecasts.

For quantifying wind speed, the application of a modified Beaufort scale type system was considered the best option. This resulted in the terms .. *(calm, light/gentle breeze, moderate/fresh breeze, moderate/strong breeze, storm force).* Wind direction was represented, in a crisp set manner, by the eight cardinal compass points.

The selected terminology for the fuzzy linguistic variable representing the sun’s heating ability or brightness was... *(dull, overcast, cloudy, clear, bright, sunny).* Due to an inability to find any suitable person in either E.S.B. or the Met. Office who could quantify this parameter, the range was divided proportionately and crisp decisions made as a result.

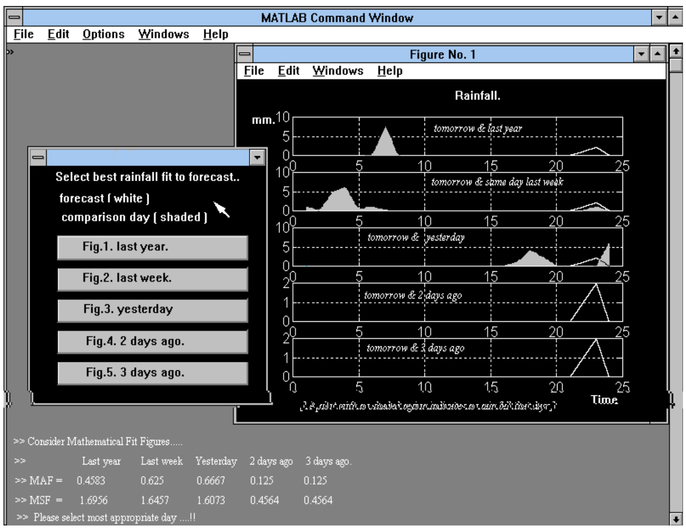
The rainfall data came from the Met. Office, since E.S.B. weather station was unable to provide this information. It was considered appropriate to adopt the system utilised by them. The resulting terminology that was implemented was...*(dryday, wetday, rainday) but a* rainday *can be(light, moderate, heavy).* It was deemed unnecessary to try and find a correlation between relative air humidity and electrical demand in this set of data, since the expert operators did not consider it to be of any relevance or significance in the forecasting process.



4.2 Output Variables.

The output variables of this fuzzy model are the changes that the model recommends be applied to the standard day selected. The most important points on the daily load profile plot are the overnight minimum, the load at 9.00 a.m.,and the midday peak. The magnitude of the load demand at this latter point would typically be the largest over the entire day. Later the load falls into day valley, and later still the ascent to the evening peak. In Summer, however, there is frequently another peak in the profile, much smaller than the evening high and usually before midnight. Its presence is significant and was duly included into the set of output variables, called the late high. The full set of basis points, upon which the forecast is constructed, is therefore ***(Overnight min., 09.00 a.m., 12.00 noon, Day valley min., Evening peak, Late high)***.

4.3 Matlab Environment.



Matlab®, a mathematical macro package, offered the necessary top quality plotting ability and eliminated debugging at the expense of marginally longer execution time. Matlab® proved adequately capable of the task and the data retrieval system operates at a level that is comparable to that of the NCC package, with the ability to select any day within any week from the data set. Once the historical data has been analysed it is made available to the software environment where it is utilised to build the standard day selection routines. An appropriate ‘standard’ day is selected by the program, then offering the operator a graphical display of five plots of the forecasted rainfall against the rainfall for five other days on record, namely the same day last year and last week, yesterday, two days ago and three days ago, as shown in Fig.4.1. However, the operator also has the option to override this decision and can choose a day that he may think is more appropriate. This retains control of the procedure in the hands of the operator, but the default settings on these options hand selection back to the program. There are numerous windows similar to the one displayed above during program execution, culminating in the selection of the standard day from those offered.

The inclusion of the plots for two and three days ago enables the operator to see if a prolonged period of bad weather is being displayed. This is only pertinent to the case of bad weather and this leads to a notion called ‘misery’ by the expert operators.

Misery amongst the consuming public is displayed in system profiles as higher loads than the weather, or other conditions, invoke particularly in Winter. The author found this particularly hard to define in quantitative terms, but in fuzzy linguistic variables it became clearer. Misery = (Cold and Wet and Dull and Windy) . Although the operators gave a definition of misery and the conditions that induce it, they were still unhappy with the manner in which it was being dealt with. The experts said that they found the approach of misery difficult to predict and that often it arises under less severe conditions than outlined above.

5. DETERMINATION OF FUZZY CONSUMPTION MODEL PARAMETERS

5.1 Collection of Fuzzy Information.

It was decided that a questionnaire be constructed so as to collect the information on the fuzzy set boundaries, from the experts, in a structured and systematic manner. This information determined the fuzzy sets and associated fuzzy values. The questionnaire was then constructed with the purpose of gaining three very important fields of information from the operators:

- Intuitive linguistic parameter names.
- Specification of the quantitative ranges, thresholds and watersheds of data.
- Systematic decision criterion and rule base.

Furthermore, it confirmed that in reality, the operators forecast procedure, or at least the reasoning behind the decisions, is intuitively the same as the structure of the fuzzy logic rule based mechanism.

	Freezing	V.Cold	Cold	Comfort	Warm	Hot	V.Hot
-5°C							
-4°C							
11°C							
12°C							
13°C							
14°C							
15°C							
16°C							
17°C							
18°C							
19°C							
39°C							
40°C							

Fig.5.1 Sample Extract of Questionnaire

5.2 Resulting Input Fuzzy Sets.

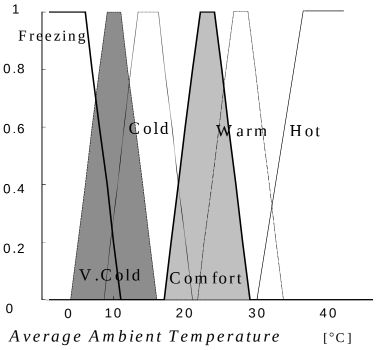


Fig.5.2 Temperature Fuzzy Sets.

Initially the temperature sets were generated by taking the averages of all opinions. Surprisingly, several of the operators provided answers, which were different to that of the general option. As a result, some of the sets were disjointed and did not achieve a membership value of unity. Such a lack of smoothness would lead to quick, sharp decisions as a variable passes through the region of discontinuity. Both these characteristics were deemed unacceptable. It was decided that taking the most often selected set would be sufficiently accurate and maintain continuity.

The solar intensity parameter was incorporated not as a fuzzy variable but in the form of a crisp linguistic parameter due to an inability to get the data quantified or benchmarked. During program execution the model asks the operator various questions pertaining to his perception of the previous day's sunshine.

The entire model is separated by the seasonal division of the day and week concerned existing within the bounds that the experts would consider to be Summer or Winter. As a result of this Summer and Winter fuzzy sets were constructed and implemented. This caters for the fact that there are vastly differing reactions to very similar conditions occurring from one period of the year to the other.

5.3 Resulting Output Fuzzy Sets.

There is primarily only one fuzzy output space and that is possibly the most important group of fuzzy sets in the model. These sets are build around the system load changes, namely v.small, small, med-small, med, med-large, large. Their application and quantification in relation to electricity load changes is very significant. Initially, when averaged answers were used, the fuzzy sets were disjointed and discontinuous due to the outlying opinions of several experts. Therefore, for the same reasons as outlined above, the most popular fuzzy set for each fuzzy variable was chosen from those available.

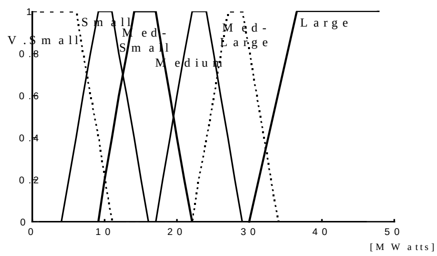


Fig.5.3 Continuous System Load Change Fuzzy Sets

5.4 Fuzzy Rule Base Construction.

The modelling of the decision making process of the operators is encapsulated within the fuzzy rule base. An array type of mechanism is the most systematic and structured method of representing such a complex process. When all the arrays had been completed by as many experts as was possible, the most popular opinions regarding the degree of influence each weather parameter had on a particular profile point was selected. Special attention was also applied when a parameter has an especially large or smaller effect than normal, in an effort to model special day (e.g. World Cup match day) characteristics.

Name: *A. N. Other.* ***Temperature***

Wind	FREEZING	V.COLD	COLD	COF'T	WARM	HOT	V. HOT
CALM	+ML	+M	+MS	NIL	-S	-M	-ML
LIGHT AIR	+ML	+M	+MS	NIL	-S	-MS	-M
LIGHT / GENTLE	+ML	+M	+MS	NIL	-S	-MS	-M
MOD.FRESH BREEZE	+ML	+ML	+MS	NIL	-S	-MS	-M
STGBREZ /MODGALE	+ML	+ML	+MS	NIL	-VS	-S	-MS
FRESH/STG GALE	+L	+ML	+MS	NIL	-VS	-S	-S
STORM	+VL	+L	+MS	NIL	-VS	-S	-S

LEGEND: ± : Increase or Decrease. VS : "Very small" S : "Small" MS : "Medium small"
M : "Medium" ML : "Medium large" L : "Large" VL : "Very large"

Fig.5.4 Sample Extract of Questionnaire for Fuzzy Rule Base.

5.5 Fuzzy Inference Engine.

Once the input and output fuzzy sets were selected and the rule base constructed then systematic coding of these rules in the IF...THEN...structure took the format outlined in Fig.5.5.

IF MODEL is [SUMMER, WINTER].
& TEMPERATURE is [FREEZING, V.COLD, COLD , COMFORT, WARM, HOT, V. HOT].
& HISTORIC TEMPERATURE is [FREEZING, V.COLD, COLD ,COMFORT, WARM, HOT,V. HOT]
& RAIN is [DRYDAY, RAINDAY, WETDAY].
& WETDAY is [LIGHT, MODERATE, HEAVY].
& HISTORIC RAIN is [DRYDAY, RAINDAY, WETDAY].
& WETDAY is [LIGHT, MODERATE, HEAVY].
& WIND is [CALM, LIGHT BREEZE, MODERATE/FRESH BREEZE,STRONG BREEZE/ MODERATE GALE, FRESH/STRONG GALE, STORM].
& DIRECTION is[NORTHERLY, SOUTHERLY, EASTERLY, WESTERLY].
& SOLAR INTENSITY is [DULL, OVERCAST, CLOUDY, CLEAR, BRIGHT, SUNNY]

THEN DELTA LOAD is [0.00 A.M., OVERNIGHT MINIMUM, 9.00 A.M. , MIDDAY PEAK, DAY VALLEY, EVENING PEAK, LATEHIGH , MIDNIGHT]

each element of DELTA LOAD has a corresponding element of LOAD CHANGE associated with it, where
LOAD CHANGE = [VERY SMALL, SMALL, MEDIUM SMALL, MEDIUM, MEDIUM LARGE, LARGE, VERY LARGE]

Fig.5.5 Schematic Representation of Fuzzy Model.

There exist many various different mechanisms to model this type of fuzzy reasoning which occurs naturally in the human mind. The most notably successful of these are those accredited to Mamdani and Larson [9][10]. Mamdani implication was implemented initially because critical analysis claimed that it was most suitable for application involving linguistic modelling [7][8]. However rudimentary application of Larson reasoning showed no improvement in load forecast accuracy, so it was not fully encoded as a model option. One can never tell how many rules might be fired by a particular day selection, without in-depth study. An algorithm was developed whereby the COA's of the fuzzy output load change sets were calculated prior to program execution. In the de-fuzzification strategy the degree to which any particular rule is relevant is measured by the maximum membership function of the output load change set.

5.6 Interpolation Mechanism.

Of primary importance at the output of the fuzzy model is the presentation of the daily profile in quarter-hourly form. A straightforward, albeit intricate, linear interpolation mechanism was devised, whereby the forecasted critical points are joined together, maintaining the characteristic curves of the 'standard' day. These characteristics include ascent and descent rates of the 'standard' day profile.

The interpolation technique employed in this study involves isolating the 'standard' day either side of the critical minimum, or maximum, point and application of the algorithm to either side in turn.

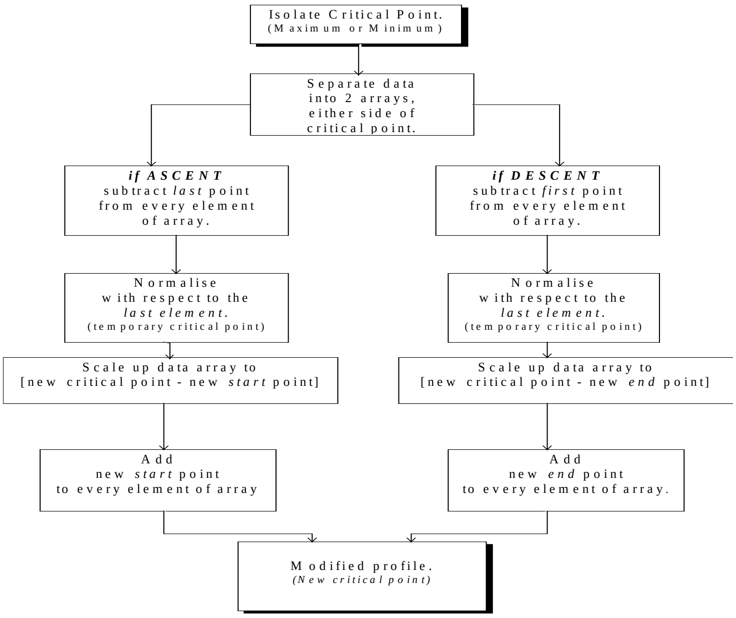


Fig.5.6 Interpolation Mechanism Flowchart.

6. LOAD FORECASTING EXAMPLES

6.1 Forecasts and Model Performance.

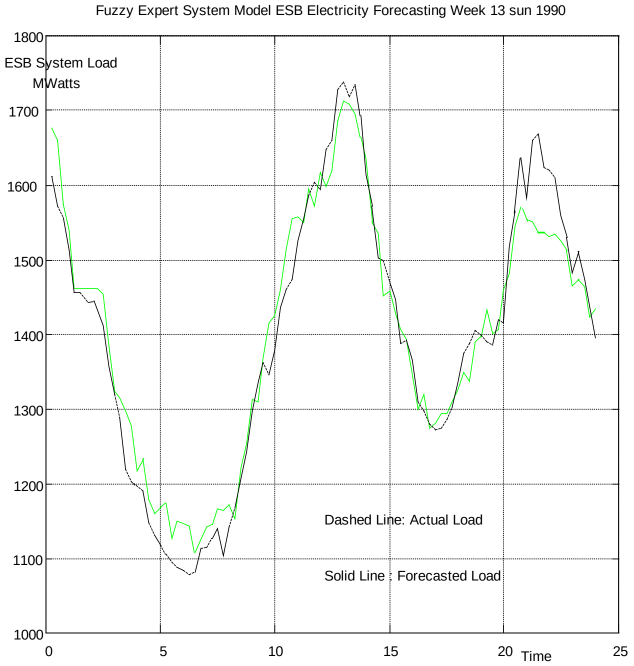
The forecasts generated by the fuzzy model were represented by the new values are the critical points of load profile. This investigation is primarily concerned with the generation of an entire 24 hour load forecast. It was on this basis that the interpolation mechanism was deemed necessary. The forecasted load profiles are generated and plotted against that which actually occurred at the end of the program's execution.

An evaluation the model's performance is measured and quantified by the mean absolute fit(MAF) and mean squared fit(MSF), calculated with the differences between the forecasted and actual demand. The mean absolute fit is defined as the sum of the absolute differences between the two data sets divided by the number of data points involved. Alternatively the mean squared fit is calculated by squaring the absolute value of the differences and averaging the resultant data over the number of data points involved. The mean squared fit penalises isolated large differences more than the absolute fit. Another parameter of the system performance is the maximum error in the forecast.

$$Error\ signal\ ....e_t = y - \hat{y}_t \qquad M.A.F. = \frac{\sum_{t=1}^{n} |e_t|}{n} \qquad M.S.F. = \frac{\sum_{t=1}^{n} (e_t)^2}{n}$$

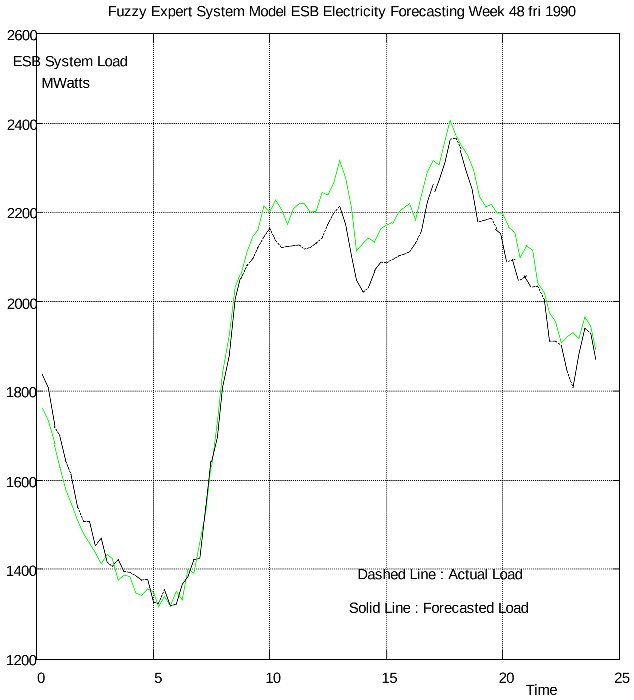
Generally, he fuzzy model produces a consistent forecast within the 50 MWatt acceptable tolerance and, on occasions, achieves a surprisingly high degree of accuracy, with MAF's of the order of 10 MWatts or less. However, it has to be accepted that the model does encounter days that it cannot forecast to any substantial degree of accuracy. A mitigating factor, however, is that experts admit that certain kinds of day are very often, in their minds, impossible to forecast to within ±100 MWatts.

6.1 Forecast Modelling Examples



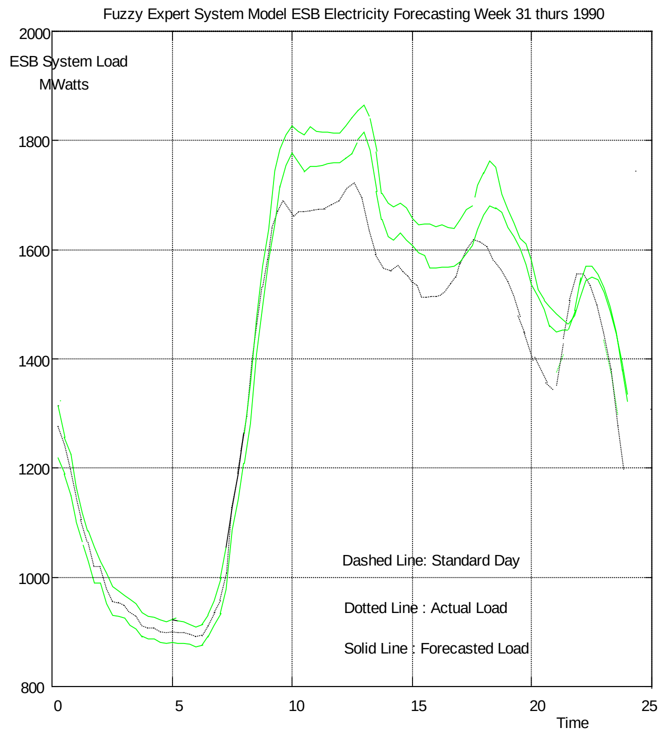
Forecast Statistics for Week 13 Sun 1990			
	Forecast [MWatts]	E.S.B. Load [MWatts]	Error [%]
Overnight min.	*1079*	*1103*	*2.17*
09.00 am	*1298*	*1311*	*1.00*
12.00 noon	*1738*	*1710*	*1.64*
Day valley	*1273*	*1272*	*0.08*
Evening peak	*1669*	*1569*	*6.37*
Late high	*1534*	*1474*	*4.07*

Week 13	M.A.F. [MWatts]	M.S.F. [$Mwatts^2$]
Sunday	*4.8761*	*41.5723*
Monday	*4.0839*	*244.0755*
Tuesday	*56.7886*	*129.0462*
Wednesday	*5.4534*	*100.6567*
Thursday	*24.1435*	*99.0687*
Friday	*17.341*	*107.33*
Saturday	*2.959*	*65.9250*



Forecast Statistics for Week 31 Thurs. 1990			
	Forecast [MWatts]	E.S.B. Load [MWatts]	Error [%]
Overnight min.	*1347*	*1314*	*2.50*
09.00 am	*2164*	*2226*	*2.78*
12.00 noon	*2213*	*2314*	*4.36*
Day valley	*2020*	*2112*	*4.36*
Evening peak	*2365*	*2415*	*2.07*
Late high	*1942*	*1974*	*1.62*

Week 31	M.A.F. [MWatts]	M.S.F. [$Mwatts^2$]
Sunday	*3.0226*	*38.1968*
Monday	*56.4771*	*60.3053*
Tuesday	*59.1557*	*61.8644*
Wednesday	*59.678*	*62.1476*
Thursday	*47.7897*	*54.4534*
Friday	*54.1846*	*66.2142*
Saturday	*56.2901*	*73.81*



Forecast Statistics for Week 48 Fri. 1990			
	Forecast [MWatts]	E.S.B. Load [MWatts]	Error [%]
Overnight min.	*873*	*900*	*3.00*
09.00 am	*1581*	*1636*	*3.36*
12.00 noon	*1815*	*1863*	*2.57*
Day valley	*1567*	*1638*	*4.33*
Evening peak	*1681*	*1763*	*4.65*
Late high	*1570*	*1549*	*1.35*

Week 48	M.A.F. [MWatts]	M.S.F. [$Mwatts^2$]
Sunday	*72.0908*	*83.6483*
Monday	*48.3864*	*53.4578*
Tuesday	*42.6273*	*52.4199*
Wednesday	*53.7689*	*64.8862*
Thursday	*23.478*	*48.0795*
Friday	*33.8218*	*59.6568*
Saturday	*8.4395*	*36.2367*

7. CONCLUSION.

From a reasonably wide range of tests, it would appear that the accuracy of the forecasts from the fuzzy model are generally in line with those produced by operators in the NCC and other non-linear black-box modelling approaches [11]. In this respect, the project is a success, since the quality of the modelling package output is constrained by the knowledge base contained within it. It is highly unlikely that the package would produce forecasts of an accuracy which exceeds that of the NCC operators. The software package however, offers a permanent storage base for operator knowledge and, given the intuitive linguistic nature of the model, may easily be refined based on further operational experience with the package.

Other possibilities include automatic adaptation of the model in response to measured modelling errors. The adaptation in a *self organising fuzzy controller* may be performed on the input fuzzy set shapes and positions, the rulebase or the defuzzification mechanism used. These characteristics of the fuzzy model may be altered individually, or in any combination, the latter incurring significantly more complex adaptation mechanisms. However, in spite of the possible use of complex adaptation algorithms, the fuzzy model still retains its basic intuitive appeal, which is of paramount importance in the current application.

8.ACKNOWLEDGEMENT.

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