Qualitative and Quantitative Fuzzy Modelling of a 24-hour Electricity Consumption Profile.

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ABSTRACT

This paper presents a fuzzy model suite for short-term (24 hour) electrical energy consumption in Ireland. The model has both qualitative (linguistic) and quantitative (numerical) sections. For the linguistic model, the parameters are 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 quantitative model is used to model the error in the linguistic model and is completely data-based. The performance of the computer-based fuzzy model is comparable to that obtained by E.S.B. experts.

1. INTRODUCTION

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. At present, expert operators forecast the national consumption profile up to eight hours n advance using intuition and experience. The objective of the current research is to produce a model 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 the E.S.B. experts into a mathematical model using fuzzy modelling techniques, which is further supplemented by data-based techniques.

2. E.S.B. FORECASTING PROCEDURE

The data received from E.S.B. formed the data for 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.

2.1 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

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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 model, the standard day is always chosen as the same day the previous week. This guarantees that the same day of the week is used and that the underlying long-term increase in consumption magnitude is contained in the standard day profile.

2.2 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.

3. 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.

3.1 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.

3.2 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).***

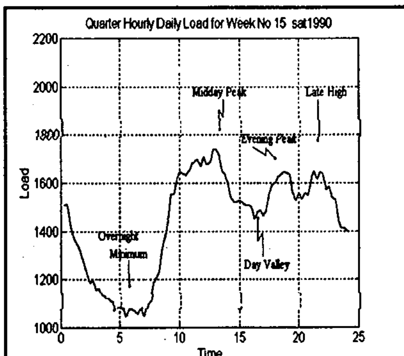

Fig.1: Typical Daily Profile

4. DETERMINATION OF LINGUISTIC MODEL PARAMETERS

4.1 Collection of Fuzzy Information.

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.

	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.2: Sample Extract of Questionnaire

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.

4.2 Resulting Input Fuzzy Sets.

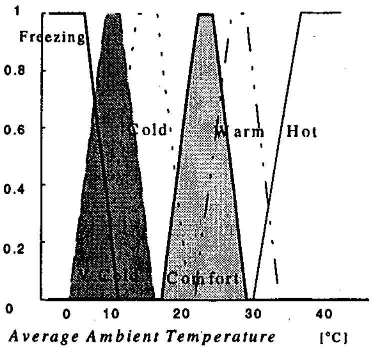

Fig.3: Temperature Fuzzy Sets.

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.

4.3 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.

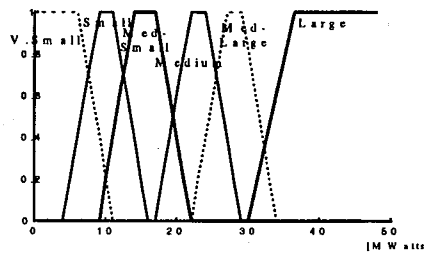

Fig.4: Continuous System Load Change Fuzzy Sets

4.4 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: Sample Extract of Questionnaire for Fuzzy Rule Base.

5.5 Fuzzy Inference Engine.

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 [1][2]. Mamdani implication was implemented initially because critical analysis claimed that it was most suitable for application involving linguistic modelling [3][4]. However rudimentary application of Larson reasoning showed no improvement in load forecast accuracy, so it was not fully encoded as a model option.

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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
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Fig.6: Schematic Representation of Fuzzy Model.

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.

4.6 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, as shown in Fig.7.

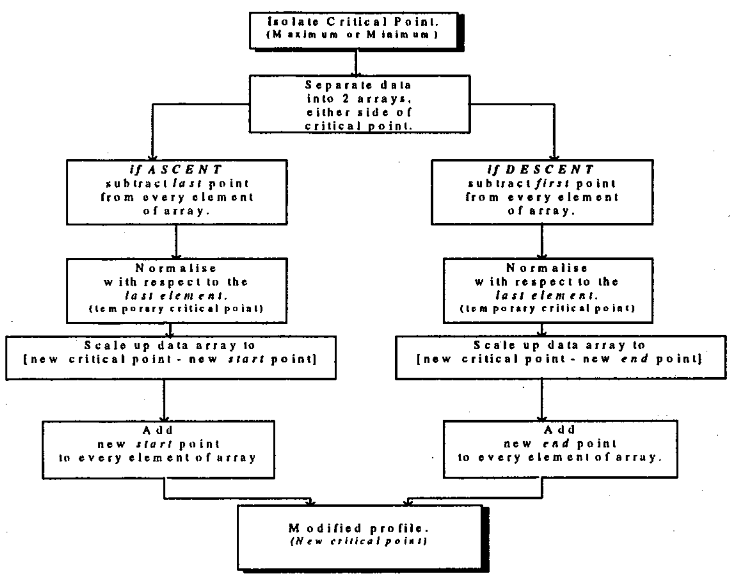

Fig.7: Interpolation Mechanism Flowchart.

5. FUZZY QUANTITATIVE MODEL

The addition of a further (quantitative) fuzzy model was motivated by the fact that the expert knowledge contained in the linguistic model may not be utilising all the information contained in the data. This applies to the selection of inputs, the determination of input sets and the rules used to determine the model output. In addition, there is no obvious way in which to update or improve the linguistic model in response to measured modelling errors. In contrast to the linguistic model, which is based on the 'Mamdani' [1] fuzzy modelling approach, the quantitative model is more closely associated with the Takagi-Sugeno-Kung [5] type models. There are several methods of including data-based information in the composite fuzzy model, but the one chosen has the attraction that the original linguistic model (which has been shown to perform adequately [6]) is retained in its original form, with the quantitative model used to forecast the *error* in the linguistic model, as shown in the configuration of Fig.8.

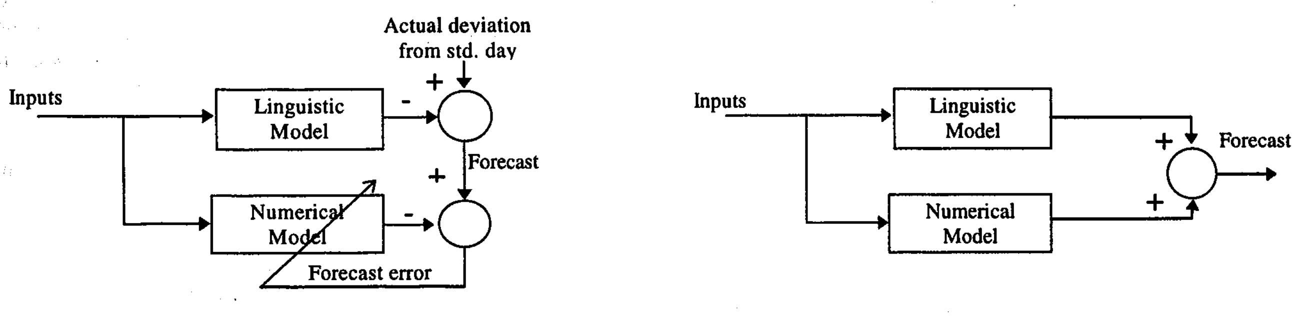

Fig.8: Training [Left] and forecasting [Right] modes for composite model

Correlation techniques were used to determine the effective inputs with a clustering algorithm used to determine the fuzzy input sets. In general, there was reasonable agreement with the structure of the linguistic model, with the exception that rainfall was found to be ineffective as a causal input. The numerical modelling was performed using the adaptive neuro-fuzzy inference system as detailed by Jang [7], which utilises a combination of gradient and least squares techniques for parameter determination.

6. LOAD FORECASTING EXAMPLES

6.1 Forecasts and Model Performance.

The composite fuzzy model generates forecasts for the next 24-hour period for the cardinal points on the daily load profile. The forecast is in the form of differences from the standard day and these are summed with the std. day profile and then interpolation performed to give the full 24-hour profile. An evaluation the model's performance is measured and quantified by the mean absolute error (MAF) and mean squared error (MSF), calculated with the differences between the forecasted and actual demand. The mean squared error penalises isolated large differences more than the absolute error. Another parameter of the system performance which could be used is the maximum error in the forecast.

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

6.1 Forecast Modelling Example

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*

Some comparative figures for the linguistic and numerical models over a number of representative days:

Forecast day	MAE / RMSE Linguistic	MAE / RMSE Linguistic + Numerical
Week 19 Thur. '90	*46.34 / 57.08*	*32.35 / 40.55*
Week 26 Wed. '90	*32.31 / 40.70*	*32.31 / 36.15*
Week 31 Tues. '89	*73.59 / 82.10*	*55.33 / 66.21*
Week 43 Thur. '90	*25.62 / 30.93*	*19.66 / 26.75*
Week 51 Mon. '90	*27.69 / 37.40*	*23.44 / 30.59*

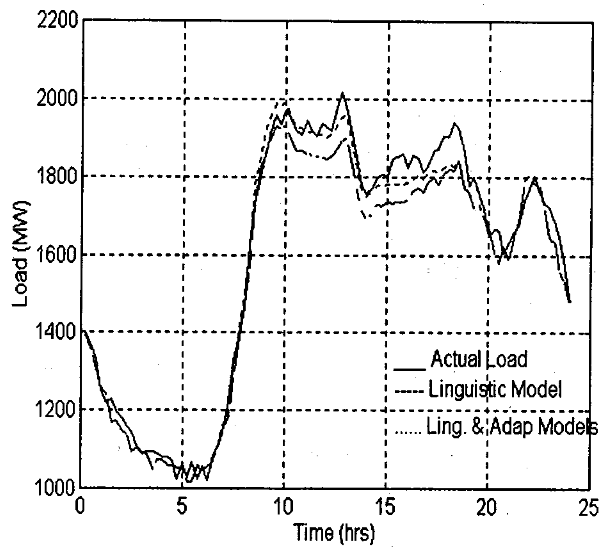

Fig.9: Forecast for Week 19 Thurs. 1990

7. CONCLUSION.

The main emphasis of the work has been to produce an intuitive and easy-to-understand model which also has a powerful and adaptable modelling capability. 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 [8]. 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.

8.ACKNOWLEDGEMENT.

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