Intelligent Forecasting of Electricity Demand

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ABSTRACT

In this paper, a number of approaches to the modelling of electricity demand, on a variety of time-scales, are considered. These approaches fall under the category of 'intelligent' systems engineering, where techniques such as neural networks, fuzzy logic and genetic algorithms are employed. The paper attempts to give some motivation for the employment of such techniques, while also making some effort to be realistic about the limitations of such methods, in particular a number of important caveats that should be borne in mind when utilising these techniques within the current application domain. In general, the electricity demand data is modelled as a time series, but one application considered involves application of linguistic modelling to capture operator expertise.

1. INTRODUCTION

Over the past 10-15 years, there has been an explosion in the number of application of intelligent techniques. For the moment, a working definition of the word 'intelligent' will be taken to mean the utilisation of engineering techniques which have, to one extent or another, been born out of human reasoning, adaptation or learning, biological cognitive structures, or principles of evolution. Intelligent techniques have been widely applied to the modelling of industrial plants [1], utilised in model-based predictive controllers [2] and used to model and forecast time series [3], as well as providing a number of solutions to problems in classification [4], pattern recognition [5] and decision support systems [6].

This paper considers, in particular, the application of intelligent techniques to the modelling and forecasting of electricity demand, with reference to hourly, weekly and annual load data. With the continuing emergence of new deregulated electricity markets, forecasting of electricity unit price has also become an important application area for intelligent techniques [7], though price forecasting is not the focus of this paper. There have been many applications of intelligent techniques to electricity load forecasting in the literature. See [8-11] for a representative selection. Some papers focus on peak load forecasting, particularly in the consideration of daily demand forecasting [12], while others consider the full daily *profile* or weekly or annual time series of load [13,14]. Finally, the intelligent systems literature has also considered the electrical load forecasting problem on all its time scales: short-term (hourly/daily) [9,15], medium term (weekly) [8,16,17] and yearly [18,19].

All of this literature suggests that many of the problems arising in electricity demand forecasting may be effectively dealt with using intelligent techniques. One of the aims of this paper is to analyse why this is so and to provide some detail on how advantage can be taken of such techniques. A further objective is to look at the possible generalisation of particular techniques to different utilities and to admit some general conclusions regarding the development of effective modelling and forecasting tools for electrical load.

2. PROBLEM ANALYSIS

This section details the problem to be tackled and to look at why (and possibly why not !) intelligent systems techniques can be useful in a load forecasting context.

2.1 Problem Definition

The essential problem is to determine future values of electrical load, given past values of electrical load and some causal inputs. The causal inputs should be appropriate to the time scale of interest, for example:

Hourly: Weather inputs (temp., humidity, wind speed and direction, cloud cover, etc), special events (bank holidays, sporting events, etc)
Weekly: Weather inputs (heating degree days, cooling degree days), economic activity
Yearly: Economic inputs (GDP, average industrial wage, consumer price index, etc), demographic variables (population numbers, immigration, emigration, distribution, etc)

It is normal to construct a mathematical model based on the currently available data, from which future behaviour of the load variable can be extrapolated. Typically, such a model is of the form:

$$y_k = f(y_{k-1},\ldots,y_{k-n},u_k^1,\ldots u_{k-m1}^1,\ldots,u_k^p,\ldots u_{k-mp}^p) \qquad (1)$$

where:

y_k represents the electrical load in year k,
$u_k i$ represents causal input i in year k, and
f represents some mapping which may be linear or nonlinear.

Note that the mapping, f, can be synthesised by an 'intelligent' methodolody, if required. One important issue is that any load model relying on causal inputs must have future values of that input available (through some mechanism, possibly a further forecasting model) in order to produce a load forecast.

2.2 Intelligent Techniques for Load Forecasting

Why are intelligent techniques likely to be useful for the load forecasting problem ? The following presents a fairly rough list of characteristics of the problem which may merit the application of such methods:

- **The function, f, may be nonlinear**. Typically, intelligent methods such as neural networks, quantitative fuzzy models or genetic programming can be used to synthesise nonlinear functions.
- **Hard quantitative information is not available**. There are many cases where load forecasting knowledge is performed purely on operator experience, requiring the construction of an alternative framework (e.g. a fuzzy linguistic model) for knowledge formulation.
- **The problem structure lends itself to intuitive solution**. In some cases, intelligent tools can present structures which provide a good match to the problem. An example here would include fuzzy partitioning of data between, say, Summer and Winter.
- **Nonlinear problems generally lead to multi-modal performance surfaces.** When the nonlinear modelling tool falls into the 'intelligent' category (e.g. neural nets, fuzzy models, etc) or not (e.g. Volterra, bilinear or Hammerstein models), the performance surfaces that must be searched are usually multi-modal, with a plethora of local minima. 'Intelligent' stochastic search techniques, such as genetic algorithms, can be effective in finding a solution close to a global minimum.

A number of caveats must be highlighted at this point. Note that, while tools such as neural networks provide adaptive solutions to problems and require little *a priori* knowledge, many other linear adaptive structures have been in existence for some time (see [20] for example) and may provide a more parsimonious solution to the modelling problem. A test for nonlinearity should *always* be performed prior to using neural or fuzzy techniques. Finally, note that neural nets *do not* provide a linear solution by default!

A further caveat in the application of 'intelligent' techniques is the lack of requirement for *a priori* knowledge. While this is, at first glance, a clear advantage of the solution methodology, it does not provide any motivation for the practitioner to investigate the problem more closely, which might reveal some easy simplifications, or reveal a wealth of knowledge which is traditionally known about the problem of interest. Specifically, for the load forecasting problem:

- A vast body of knowledge is available in relation to linear time series modelling
- Some simple nonlinear transformations may possibly be utilised to bring the problem within the domain of linear adaptive techniques

The ultimate danger is that the naïve load forecasting practitioner may select a so-called 'intelligent' technique, with no knowledge of the time series tradition which has gone before and will, no doubt, get an answer. Given that we are dealing with a forecasting problem, there is no benchmark answer to compare with, other then possibly that provided by a more traditional linear approach (which we assume the practitioner has no knowledge of). It is with regard to this difficulty that this author believes that intelligent modelling techniques such as neural networks and fuzzy models be firmly regarded as a nonlinear extension of liner adaptive techniques, so that practitioners have access to the wealth of knowledge which has gone before. The following section documents a particular example, in this regard.

2.3 Naïve, Intelligent or Both ?

In this section, an example is presented of autoregressive forecasting of weekly electrical load. For clarity, no causal (exogenous) variables are included, with load models relying purely on past load values. Two models are proposed to forecast weekly electrical load 52 weeks ahead:

1. An intelligent neural network model, with little knowledge of traditional methods, and
2. A traditional, linear Box-Jenkins model

<u>Model 1</u>
Here, it may be deemed reasonable to base the model input vector (regressor) on the previous 52 weeks of data, while the weights and biases of the neural network are determined on the full 10 years of data available. Note that one year of data is reserved for testing of the model.

The model is of the form:

$$f(Y_t,\ldots,Y_{t-L}) \quad = \quad a_t \tag{2}$$

where the function f is synthesised by a feedforward MLP neural network, Y_t is the load value at week t and L the regressor length, in this case a full season equal to 52 weeks (1 year). a_t is an (unmodelled) white noise component (equivalent to the forecast error). A fully connected MLP was used with a 3-5-1 neuron configuration resulting from architecture optimisation. The network was trained with standard backpropagation (with momentum and adaptive learning rate) with stopping point determined at the minimum of a cross-validation set. The performance is evaluated in terms of the mean absolute percentage error (MAPE), with results given in Table 1.

<u>Model 2</u>
The univariate Box-Jenkins model is derived from the general SARI(p,d)(P,D) (seasonal autoregressive integrated) model which can be written as:

$$\Phi_p(B)\Phi_P(B^L)\nabla_L^D\nabla^d Y_t = a_t \tag{3}$$

where:

Y_t is the time series

$\nabla_L^D \nabla^d = (1-B^L)^D (1-B)^d$ is a differencing transformation required if the data is nonstationary. d is the degree of non seasonal differencing, D is the degree of seasonal differencing, and L is the number of seasons in a year,

a_t is the forecast error,

$\Phi_p(B) = (1-\phi_1 B - \phi_2 B^2 - ..... - \phi_p B^p)$ is the non seasonal autoregressive operator of order *p*,

$\Phi_P(B^L) = (1-\phi_{1,L} B^L - \phi_{2,L} B^{2L} - ..... - \phi_{P,L} B^{PL})$ is the seasonal autoregressive operator of order *P*.

The lags p and P are determined using correlation analysis, as are the degree of the differencing operators, d and D. The seasonality of the data, L, is usually known *a priori*, or may also be determined using correlation analysis. A variety of methods may be used to determine the model parameters in the Φ(B) polynomials, iterative least squares proving a popular approach. Following model construction, t-ratio tests may be used to assess the significance of the model.

Model type	**MAPE Linear**	**MAPE Neural Network**
Autoregressive (52 inputs)	3.96 %	4.45 % (Model 1)
Box-Jenkins	3.81 % (Model 2)	3.35 % NNBJ type 'A' 2.35 % NNBJ type 'B'
Structural State Space	2.74 %	2.57 %

Table 1: Comparative results for linear and neural models

Table 1 gives comparative results for linear and nonlinear (neural network) versions of models with different structures:

- 52 contiguous autoregressive inputs,
- A 'partitioned' input structure using the methodology of Box and Jenkins as described above, and
- A basic structural model [22] formulation, where different model segments focus on trend and seasonal components.

The neural network version of the structural state-space model utilises a neural network to model the residual (the regressor of which is structured using the Box-Jenkins methodology) remaining after linear structural state space modelling.

Clearly, Table 1 provides for some interesting conclusions ! The basic comparison between the results for Model 1 and Model 2 yield the following conclusions:

- The linear model constructed using traditional methods significantly outperforms the 'naïve' neural network model (3.81 % Vs 4.45 %),
- The ANN model (Model 1) is not able to resolve the most useful regressor inputs from the superset presented to it,
- A neural network model presented with a structured regressor significantly outperforms the linear version, and
- The linear structural model is very good, with a modest improvement when the residual is modelled by an ANN.

Hopefully the above provides a clear message: 'intelligent' techniques must be applied *intelligently* is a good solution is to be achieved. Use *a priori* knowledge and any transformations which can assist.

3. LINGUISTIC MODELLING OF SHORT-TERM LOAD

This section 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 [23].

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 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.

3.3 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 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.

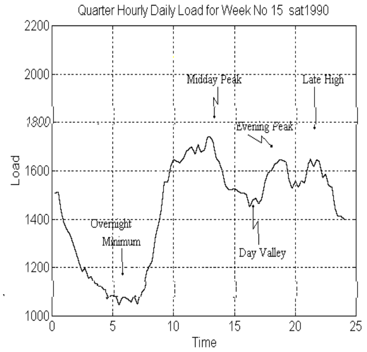


Fig.1: Sample 24-hour load profile

3.4 Output Variables

The output variables of this fuzzy model are the changes that the model recommends to 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)***.

3.5 Construction of Fuzzy Sets

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.2: Sample of Questionnaire

3.6 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"

Table 2:: Sample Extract of Questionnaire for Fuzzy Rule Base.

3.7 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.3. 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 [26][27]. Mamdani implication was implemented initially because critical analysis claimed that it was most suitable for application involving linguistic modelling [24][25].

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.

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.3: Schematic Representation of Fuzzy Model.

3.8 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 (illustrated in Fig.4) 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.

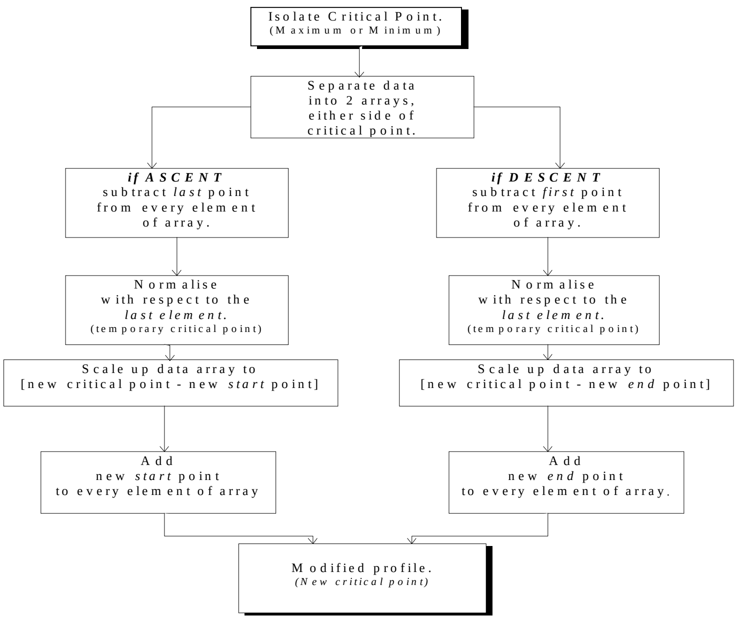


Fig.4: Interpolation Mechanism Flowchart.

3.8 Sample Results

Table 3 gives sample results for a single day. 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.

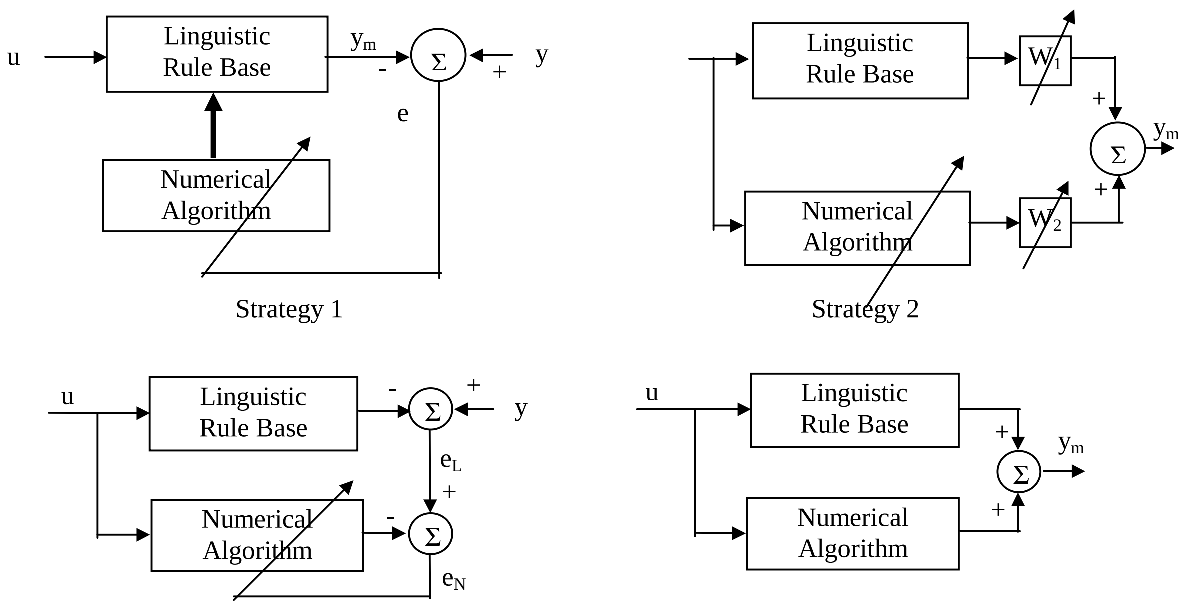
Forecast Statistics for a Thurs. 1990			
	Forecast [MWatts]	E.S.B. Load [MWatts]	Error [%]
Overnight min.	*1347*	*1314*	*2.50*
09.00 am	*2164*	*2226*	*2.78*
12.00 noon	*2213*	*2314*	*4.36*
Day valley	*2020*	*2112*	*4.36*
Evening peak	*2365*	*2415*	*2.07*
Late high	*1942*	*1974*	*1.62*

Table 3: Sample day performance from linguistic model

3.9 Linguistic Model Adaptation

Further to this work, a quantitative fuzzy model, utilising a neuro-fuzzy engine, was implemented to provide a data-based refinement to this linguistic model. The idea was to retain the intuitive nature of the model, while allowing the model to learn by its mistakes. In this sense, three strategies (illustrated in Fig.5) are possible:

1. Attempt to adapt the original linguistic model,
2. Adapt a numerical model and a set of combinatorial weights, and
3. Model the residual from the linguistic model



Strategy 3 in Training and Forecasting Modes

Fig.5: Possible strategies for adapting the linguistic model

The ultimate choice selected Strategy 3, since Strategy 2 would not, in any case, remedy intrinsic errors in the linguistic model and it was thought prudent to retain the good linguistic model intact (eliminating Straetgy 1). For further details, see [13] or [28]. One of the interesting points to emerge from this work is that all commonly held subjective beliefs are not always borne out by the data. The operators held that there was a significant correlation between rainfall and load, especially when rainfall was combined with cold (leading to the concept of 'misery'). However, this was not borne out by a multi-correlation analysis performed in the subsequent data-based analysis.

4. GENETIC OPTIMISATION OF A FUZZY WEEKLY LOAD MODEL

In this application, weekly load forecasting is considered, with a quantitative fuzzy (TSK) model used to interpolate between separate linear season models.

4.1 Model Construction

Separate linear Seasonal AutoRegressive (SAR) Winter and Summer models are identified on partitioned data which is segregated using triangular fuzzy sets. Following partitioning, data is preprocessed using the seasonal and non-seasonal operators,

$$\nabla_L^D \nabla^d = (1 - B^L)^D (1 - B)^d \tag{4}$$

which have been previously defined in Section 2.3. The parameters of the SAR models (i.e. the fuzzy consequence functions) are determined using least squares (unimodal performance surface), while the fuzzy parameters are determined using a genetic algorithm, given that the performance surface is significantly multimodal. A typical performance surface for a two set example (just Summer and Winter sets) is shown in Fig. 6.

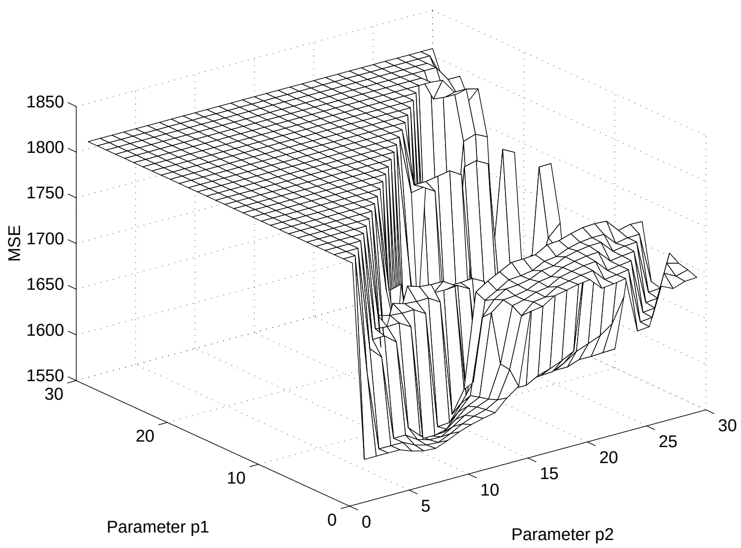


Fig.6: Example performance surface in fuzzy set parameters

In order to partition the data according to season, the raw data, shown in Fig.7, is detrended to give a zero-mean sequence. Following this operation, positive data, in general, corresponds to Winter time (larger heating and lighting loads), with the negative values corresponding to Summer. The transition region around the zero line roughly corresponds to Spring/Autumn, which can be further discriminated using trend (+ve going or -ve going). Therefore, in order to discriminate easily by season, universe of discourse is the previous weekly load value from the detrended data sequence.

4.1 Optimisation of Fuzzy Model

A simple genetic algorithm (SGA) with elitism [29] is employed to optimize the fuzzy set parameters, with the consequent function parameters evaluated at each step using a batch least squares algorithm. The complete optimisation procedure is outlined in Fig.7. A population of 60 is used with binary coded chromosomes and roulette wheel selection is used to select offspring. The fitness function is selected as a multi-step prediction criterion. For the two set case, Fig.8 shows the variation in the multi-step MSE, while Fig.9 shows the weekly prediction over a year obtained using the optimized fuzzy model, compared with the best linear model prediction. The final fuzzy parameters obtained are (5359.8 7024.1), indicating a

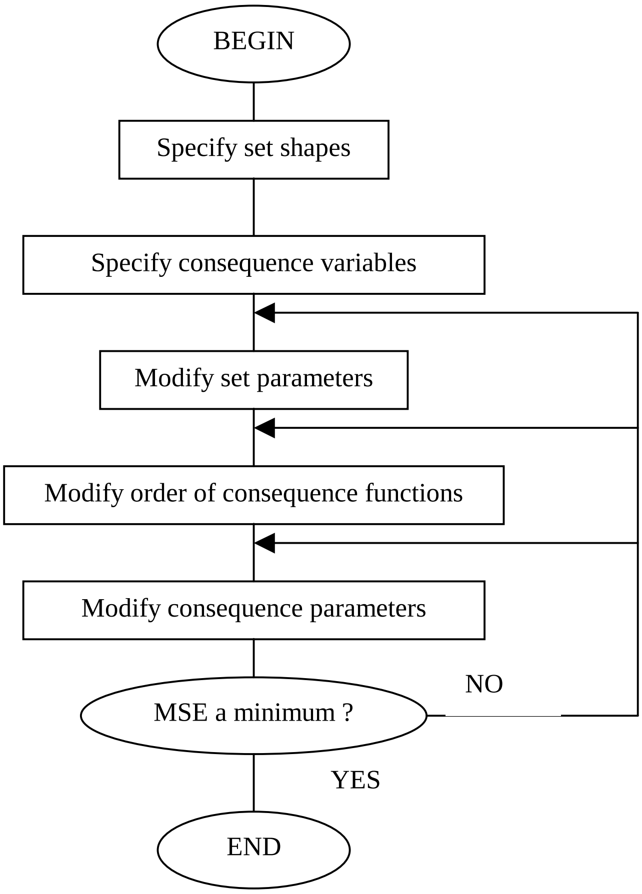


Fig.7: Model determination procedure

relatively small overlap in models in the transition region. For a quantitative comparison, the MSE for the optimised fuzzy model (1484) compares favourably with that for the single linear model.

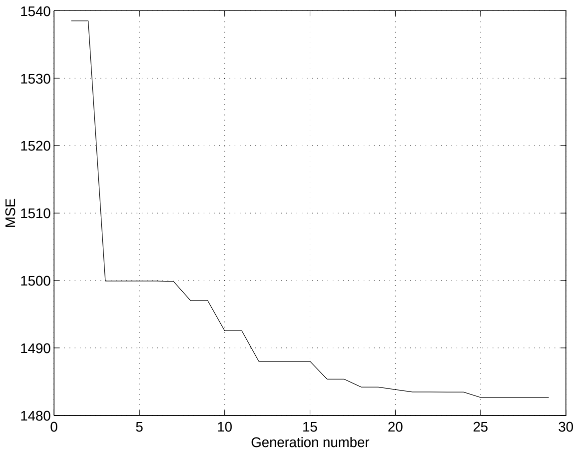


Fig.8: Variation in MSE for best candidate with generation number

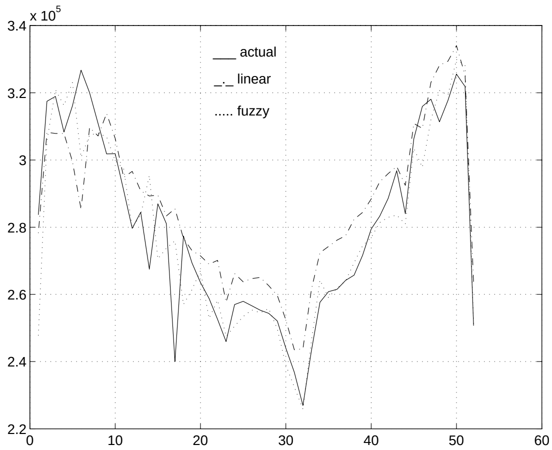


Fig.9: Sample results from fuzzy weekly model

CONCLUSIONS

This paper contains a number of applications of intelligent systems to electrical load forecasting. However, the main message is not that intelligent systems provide an improvement over conventional linear techniques, but rather that prudence is required in their application. Frequently, lessons and techniques learned in traditional analysis can serve us well as we try to harness the power of newer techniques. In addition, the absence of a requirement for a significant amount of *a priori* information is a double edged sword - lack of understanding of the problem may result in a solution that is non-parsimonious and sub-optimal, in many cases being significantly to that obtained from traditional methods. This is rarely more true than in forecasting, where we aim to determine what is unknown and therefore can be easily led to believe that the solution we have is a good one.

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