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POWER DEMAND PREDICTION USING FUZZY LOGIC

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Abstract: The paper discusses the implementation of a fuzzy-logic approach to provide a structural framework for the representation, manipulation and utilization of data and information concerning the prediction of power commitments. A neural network would then be implemented to accommodate and manipulate the large amount of sensor data involved. A training facility could allow the system to replace the requirement for skilled dispatchers in scheduling the generators. An algorithm has been implemented and trained to predict the total power demand on an hourly basis. The parameters taken into consideration cover environmental and weather-related conditions. Prediction of the power demand at each geographical load point, and hence the country-wide demand, has been tested in Jordan. Results concerning the daily prediction have been obtained. It is found to be very promising, especially in that the prediction is evaluated in a fuzzy environment.

Key words: Fuzzy Systems, Unit Commitment, Power management, Load forecasting.

1 INTRODUCTION

Predicting the optimal number of generators to be committed to meet a regional power demand, is an intractable task. This is due to numerous factors that affect an operator's decision. The fact that some of these factors, such as climate, are considered as fuzzy variables adds to the complexity of the problem. Even the highly predictable factors have various variables that need to be considered. For example, day-time power consumption is different from night-time power consumption; besides, the length of day and night also varies from season to season. It is also true that in weekends and holidays power consumption is different from that of weekdays.

Dynamic programming and Lagragian relaxation methods are traditional analysis techniques that are used to minimize the operation cost, subject to various constraints such as power balance, generation limits, etc. These methods are mathematically rigorous and need considerable computational efforts to execute the iteration procedures, and it was found that they have some conflicting expectations in real-time analysis (Zhang, *et al*, 1989; Wang, *et al*, 1990). Furthermore, in spite of the sophistication of modern unit commitment programs, they often require modifications by human dispatchers to meet a commitment schedule that is compatible to the real-world need.

In general, power systems' operation requires experienced operators who are familiar with the system characteristics and use their own intuition to schedule the power generation rather economically and within a short period of time. That is, an operator uses certain algorithms for ordinary days, and in the case of special days the operator looks up past records which have similar conditions to the current one. This helps him/her to determine the power demand and what is the best combination of the available generators to be committed (Park and Park, 1989; Lambert, *et al*, 1991). Hence, the use of artificial intelligence (AI) tools to mimic the action of a skilled dispatcher has already been implemented in handling such a problem. The technique requires a significant amount of training and experience to use the tools effectively (Wang, *et al* 1990; Lambert, *et al*, 1989; Hammertstrom, 1993a; Lambert - Torres, *et al*, 1991; Tomsovic, 1992).

Computational neural networks (CNN) are essentially low-level computational algorithms that, sometimes, offer a good performance in dealing with data sensors used in pattern recognition and control. On the other hand, fuzzy logic is a means of representing, manipulating and utilizing data and information that possess non-statistical uncertainty. Fuzzy methods often deal with issues such as reasoning at a higher semantic or linguistic level than CNN's. Consequently, the two techniques complement each other (Bezdek, 1993). The CNN's supply the brute force necessary to accommodate and interpret large amounts of data sensor. Fuzzy logic provides a structural frame-work that utilizes and exploits these low-level results.

This paper presents a fuzzy model that can be used efficiently to predict an area's power demand. The area can be as large as a whole country. Jordan has been taken as a case study, and is a good example for several reasons: The uneven distribution of the population of Jordan, the country's steady growth and modernization process, and the region's political situation have resulted in mass movements of people which, in turn, greatly disturb the resources and requirements and daily life. To deal with such a situation where sophisticated parameters influence the power demand, various measures proposed in the literature were reviewed (Park and Park, 1989; Lambert, *et al*, 1989; Lambert-Torres, *et al*, 1991). A more accurate measure is the system developed in this paper. It is noteworthy to mention that although the system shows encouraging results for Jordan, it is applicable for various regions and countries with more or less disturbance than that of Jordan.

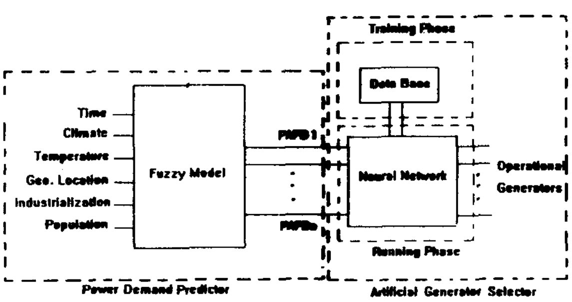

Fig. 1 System Block Diagram.

The paper is organized as follows: Section two gives a general description of the system development. The fuzzy model is presented in the third section in two phases: system analysis and methodology. The application and system evaluation are discussed in the fourth section. Further work and a brief description of the second part of this project are presented in the fifth section. Finally, the paper concludes in section six.

2 SYSTEM DEVELOPMENT

In this work the fuzzy logic concepts have been exploited to predict the total power demand in an efficient way to help optimize the number of generator units to be committed.

As shown in Fig.1, the suggested model consists of two subsystems: the computational unit (fuzzy model) and the artificial neural network. The fuzzy model is used to predict the total power demand, based on past records and expert knowledge. The input variables to the fuzzy model are the geographical location, population, climate, temperature, time and the industrial factor. The output of the fuzzy model is the current predicted area power demand (PAPD) at each of the n load points. Information concerning the predicted power demands from the fuzzy model is then processed through a neural network to compute the target generators to be committed.

The model is used to predict the total power demand in the days ahead. The architectural characteristics of the model are designed in such a way as to evolve the information flowing at each load point, and then execute all the necessary rules combining the input values to the output values of the model.

Computation of the predicted power demand has been implemented using an algorithm based on fuzzy logic. The algorithm computes the power demand individually at each load point and on an hourly basis. As shown in Fig. 8 the input data fed into the model concerning each state variable is fuzzified in such a way as to compose the system's possible rules. Each activated rule will emit a weighted fuzzy output variable. The summation of all the weighted fuzzy outputs is then defuzzified to produce the power demanded by each load point and at every hour. The system is trained on data given by the Jordan Supervisory and Control Center (JSCC) to predict the national load diagram.

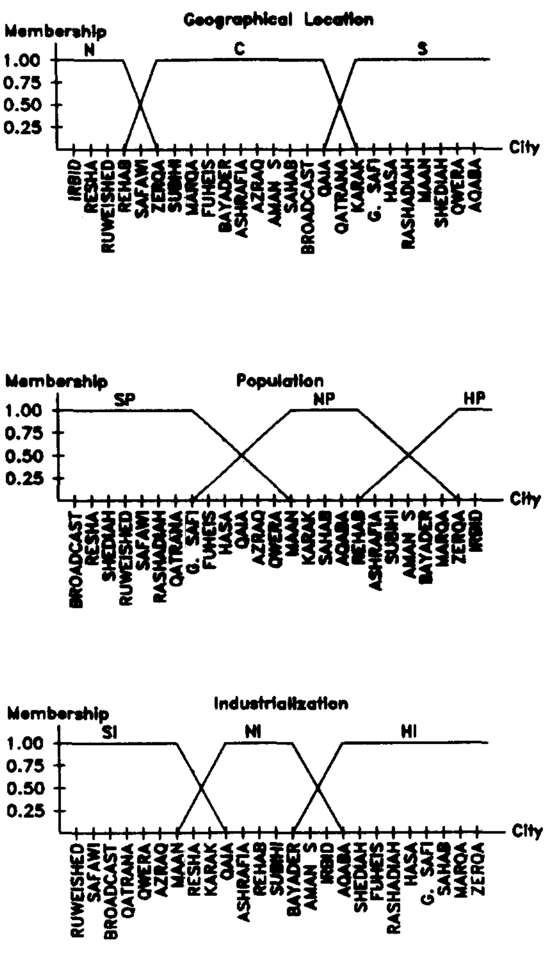

Fig. 2 Fuzzification of System State Variables: Geographical, Location, Population and Industrialization.

3 POWER DEMAND PREDICTION MODEL

3.1 System analysis

In this section, the fuzzy model is presented. The model is used to predict the total power demand. The system variables that have been taken into consideration as inputs to the fuzzy model, as shown in Fig. 1 are: time of the day (T), geographical location (L), temperature (K), climate (C), population (P) and industrialization (I). These variables are treated as the state fuzzy variables. As shown in Fig. 1, the output of the fuzzy model is the predicted area power demands. The PAPD's are functions of the fuzzy variables which comprise the inputs of the fuzzy model. Therefore, the amount of power consumption varies in accordance with the variation of the system's state fuzzy variables. In determining the PAPD, each load point in the area is treated individually. So, the algorithm determines the power demand of each load point in that specific area, and the PAPD is the aggregate sum of the predicted power demand at each load point.

The time of the day factor inherently imbeds human requirements for electricity as related to the day and night activities, weekdays, weekends, holidays and finally seasonal requirements. The temperature factor supports energy requirements related to the weather conditions. The location factor involves special requirements, and people's habits that may influence energy needs. The climate also reflects the reaction of humans to energy needs as a response to rainy, snowy and cloudy weather conditions. Finally, the population and industrialization factors have a significant effect on power consumption. For example, it could be expected that a certain load point which is lightly populated, highly industrial, and under cold and cloudy weather conditions, will have a medium power demand. Meanwhile, another load point under the same other conditions would have a high power demand, if it were highly populated. It should be noted that the model's main objective is to predict the total power demand within considerable bounds of uncertainty. The prediction of power demand is dependent on the system variables that may vary from time to time. Fuzzification of variables involves a trade off of precision in prediction and computation time. Increasing the number of fuzzy regions would improve the precision of power prediction but, on the other hand, would increase the computational time, and hence the time between two adjustments becomes larger. For example, the fuzzy variable, temperature, may have three labels: Cold(C), Warm(W) and Hot(H), and in a more precise identification it may have five labels: Very Cold(VC), Cold(C), Warm(W), Hot(H), and Very Hot(VH). Then a $0C^{o}$ may be cold (the first case) or very cold (the second case). As a matter of fact, consumption of power is considerably dependent on temperature. That is, a decision is taken in favor of low power demand when the combination includes cold in the first case and in favor of very low power demand when the combination includes very cold in the second case. In summary, decomposing a certain fuzzy variable into large number of fuzzy regions leads to a more precise prediction of the power demand. However, the cost of better precision is a large processing time, large memory needed to absorb all data and temporal results, and large step size between two consecutive adjustments.

In the algorithm described in this paper, each of the system state fuzzy variables is decomposed into a reasonable number of fuzzy regions following the rules of thumb (Cox, 1992), that is by choosing an odd number of labels associated with a variable. Each label should overlap between 10 and 50 percent of the neighboring space; finally the density of fuzzy sets should be highest around the optimal control point of the

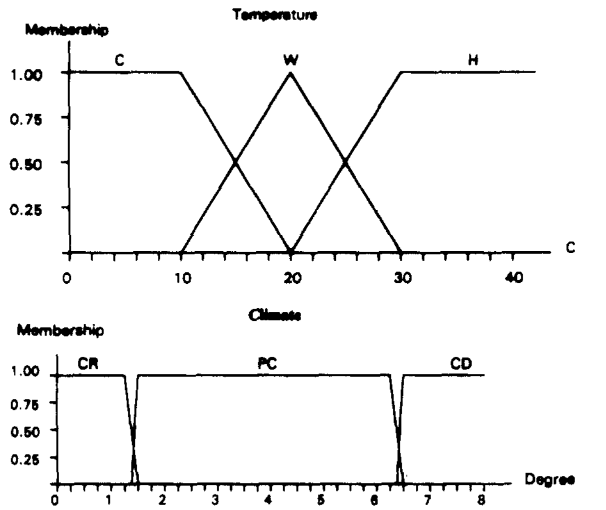

Fig. 3 Fuzzification of System State Variables: Temperature and Climate of the day.

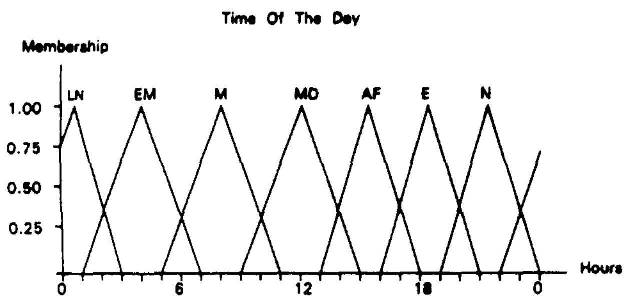

Fig. 4 Fuzzification of the Time Variable.

system and should thin out as the distance from that point increases. Fuzzification of the location, population and industrialization variables are shown in Fig. 2. Since temperature, climate, time and area power demand variables are of discrete abscissas, they are associated using ramp functions as shown in Figs 3, 4, and 5.

3.2 Methodology

The fuzzy system constructed here is a fuzzy associative memory (FAM) system, (Kosko, 1992). The fuzzy associative memories (FAMs) are transformations that map fuzzy sets to fuzzy sets. They encode a bank of compound FAM rules that associate multiple outputs with multiple inputs.

In this case, the FAM bank is a *6-dimensional* space with $7 \times (3)^5 = 1701$ possible fuzzy set entries. Let the domain of time (T), geographical location (L), temperature (K), climate (CL), population (P) and industrialization (I) be quantified to n points such that:

$$
\begin{aligned}
T &= t_1, t_2, \ldots, t_n \\
L &= l_1, l_2, \ldots, l_n \\
K &= k_1, k_2, \ldots, k_n \\
CL &= c_1, c_2, \ldots, c_n \\
P &= p_1, p_2, \ldots, p_n \\
I &= i_1, i_2, \ldots, i_n
\end{aligned}
$$

and the range of $PAPD$ to p variables such that

$$PAPD = d_1, d_2, \ldots, d_p$$

Let the subsets A^i, B^i, C^i, D^i and E^i represent the i^{th} fuzzy region in the state variable T,L,K,CL,P and I respectively. Finally, let G^i represent the i^{th} fuzzy region in the output variable $PAPD$, i=7 for T and $PAPD$, and i=3 for the rest of the variables. The subsets $A^i, B^i, C^i, D^i, E^i, F^i$ and G^i define the membership functions $m_{A^i}, m_{B^i}, m_{C^i}, m_{D^i}, m_{E^i}, m_{F^i}$ *and* m_{G^i} that map the elements of t_j of T, l_j of L, k_j of K, c_j of CL, p_j of P, i_j of I and d_j of $PAPD$ to degrees of membership in [0,1]. The membership value indicates how much t_j belongs to the subset A^i and how much l_j belongs to the subset B^i, etc. Each of the subsets described above, except the climate fuzzy variable subsets, can be represented by a fit vector such that:

$$
\begin{aligned}
A^i &= (a_{i1} \ldots a_{in}) \\
B^i &= (b_{i1} \ldots b_{in}) \\
C^i &= (c_{i1} \ldots c_{in}) \\
E^i &= (e_{i1} \ldots e_{in}) \\
F^i &= (f_{i1} \ldots f_{in}) \\
G^i &= (g_{i1} \ldots g_{in})
\end{aligned}
$$

where i=1,...,k. k is the number of fuzzy regions in a particular fuzzy variable, and is equal to 7 for the fuzzy variable T and $PAPD$, and 3 for the rest of the fuzzy variables.

As an illustrative example, let the fuzzy sets $A^3, B^1, C^1, D^3, E^2, F^3$ and G^5 encode the area power demand-prediction association (Morning, North, Cold, Cloudy, Normally populated, Heavily industrial; High) that can be interpreted linguistically as

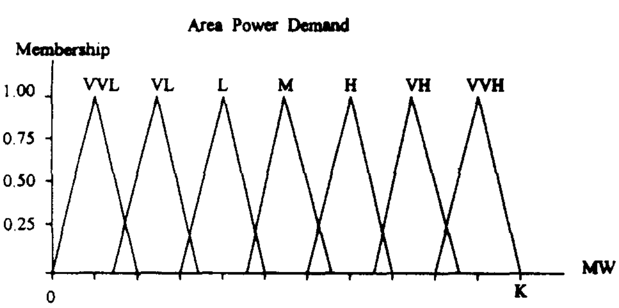

Fig. 5 Fuzzification of system output variable: Area Power Demand.

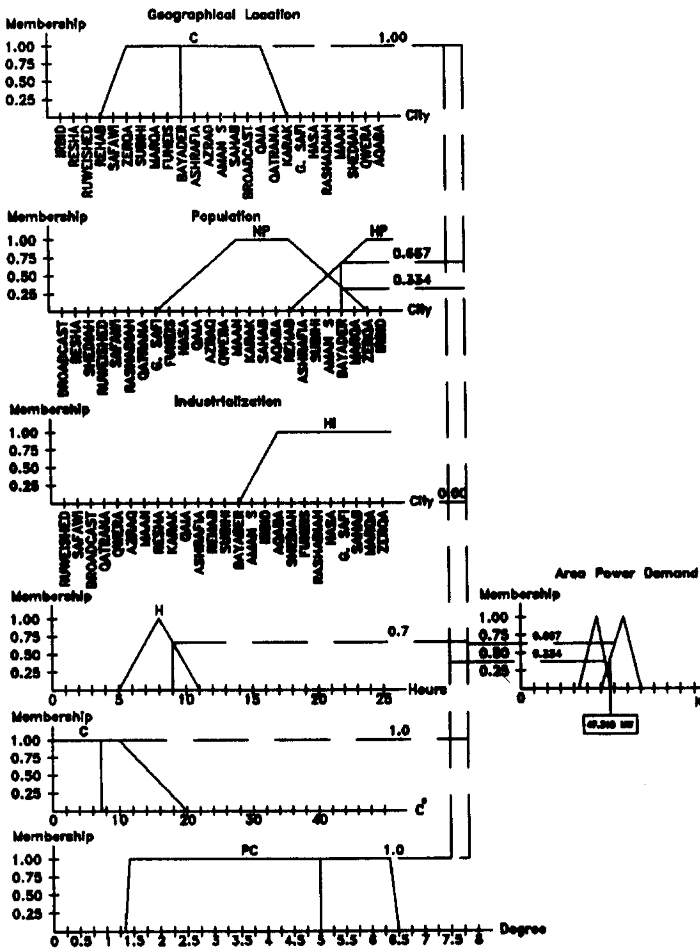

Fig. 6 An Example of Power Prediction.

" IF T is A^3 AND L is B^1 AND K is C^1 AND CL is D^3 AND P is E^2 AND I is F^3 ; THEN PAPD is G^5"

The association combining the state variables with the output variable are the FAM system rules that define the behavior of the system. The number of these rules or associations is dependent on the system state variables each of which is divided into fuzzy regions. When a set of input values is read, one or multiple rules will be activated in parallel but to a different degree, as shown in Fig. 6. The k^{th} activated rule will produce a non-null output G^k with a nonnegative weight w_k depending on its minimum membership value such that (Kosko, 1992):

$$w_k = min(m_A^{\,i}(t_j), m_B^{\,i}(l_j), m_C^{\,j}(k_j), m_D^{\,i}(c_j), m_E^{\,j}(p_j), m_F^{\,j}(i_j)) \tag{2}$$

Then the resultant output vector GG equals the individual weighted outputs B_k, such that:

$$GG = (w_1G^1, ..., w_kG^k, ..., w_mG^m) \tag{3}$$

where m is the number of the activated rules.

In the defuzzification process, to produce a single numerical output corresponding to the predicted area power demand, a (fuzzy centroid defuzzification process) is encountered. The fuzzy centroid GGG of the output vector GG is:

$$GGG = \frac{\sum_{k=1}^{m} d_k w_k)}{\sum_{k=1}^{m} w_k} \tag{4}$$

where d_k is the centroid of G^k. Fig. 6 shows the architecture of the FAM system, where the input data are received through A and are being processed to activate the rules associated to produce a weighted output B_k. Those individual weighted outputs are then defuzzified to emit the numerical evaluation of the predicted area power demand.

4 APPLICATION & SYSTEM EVALUATION

As mentioned earlier, Jordan has been taken as a case study for the proposed model. There are 35 load points, geographically distributed all over the country and connected together by 132KV and 400KV national grid lines. Each load point experiences both different weather conditions and distinct variations of power demand. The implemented algorithm shown in Fig. 7 scans over all the load points on an hourly basis. At each load point the related data describing the system fuzzy variables are manipulated by calling the associated fuzzy variable function in such a way as to compose all the possible rules. A weighted output fuzzy label is then searched to satisfy an activated rule. Different rules may be activated at the same time, and the combination of their outputs is then defuzzified to compute the predicted area power demand at that hour. The defuzzification process is done, bearing in mind the related minimum and maximum power demand. This is due to the fact that the power consumed by most load points varies extremely within different ranges. Finally, the numerical value of the computed area power demand is added successively to the total power demand.

For example, consider the forecasting for the Bayader load point for an ordinary day (April 11 1993) and under the following conditions: 1) Degree of cloudiness is five. 2) Dry bulb temperature of 7.8. 3) Time of the day is 9 o'clock. This may be worked out using the input data set (Bayader, 5, 7.8, 9) which activates two rules:

1. (M, C, C, PC, NP, NI; M) rule which is interpreted as:
" IF time T is morning (M) AND location L is center (C) AND temperature K is cold (C) AND climate CL is partly cloudy (PC) AND population P is normally populated (NP) AND industrialization I is normally industrial (NI) THEN area power demand (PAPD) should be medium (M) "

The output PAPD is then set to high but to a degree of membership given by :

$$min(m_M(9), m_C(Bayader), m_C(7.8), m_{PC}(5), m_{NP}(Bayader), m_{NI}(Bayader)) = min(0.7,1,1,1,0.334,1) = 0.334$$

2. (M, C, C, PC, HP, NI; H) rule which is interpreted as:
" IF time T is morning (M) AND location L is center (C) AND temperature K is cold (C) AND climate CL is patly cloudy (PC) AND population P is highly populated (HP) AND industrialization I is normally industrial (NI) THEN area power demand (PAPD) should be high (H) "

The output PAPD is then set to high but to a degree of membership given by :

$$min(m_M(9), m_C(Bayader), m_C(7.8), m_{PC}(5), m_{HP}(Bayader), m_{NI}(Bayader))$$
$$min(0.7,1,1,1,0.667,1) = 0.667$$

The above two rules describe the area power demand for the observed values of the system state variables. The resulting outputs are combined, and the fuzzy centroid is computed. The training parameter K has been assigned a value of 80 MW for the Bayader load point. Fig. 8 illustrates the computational procedure for the above example. In this case the fuzzy centriodal area power demand value equals 47.315 MW.

As stated earlier, the fuzzy model that has been suggested for power demand prediction is based on the fuzzy variables time, temperature, climate, location, population, and industrialization. Some of these variables have been considered to have more effect than others on the amount of power demand. For instance, the time of the day variable has a high effect, and this is due to the fact that there are fixed working hours in government offices and some other industrial areas. On the other hand, some highly industrial areas such as Rashadia and Shediah prefer heavy-working time hours between 0 and 7 o'clock, because at these hours consumers get price discount per kilowatt

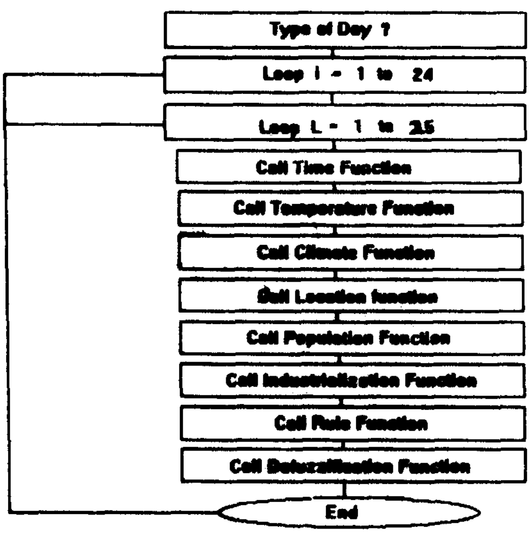

Fig. 7 Flowchart of the Algorithm

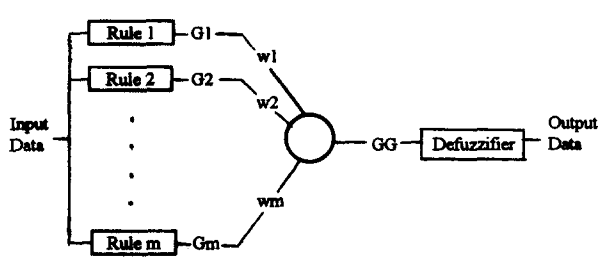

Fig. 8 Fuzzy System Architecture.

hour. Hence, power consumption varies in accordance with time; for example, at the Irbid load point on a certain day, the power demand at 7 a.m. was 29.87 MW and at 8 p.m. it was 98.52 MW. However, temperature and climate variables also have strong effects. This can be noticed from the example given in the previous section, where a change of 2 MW at the Bayader load point is due to a change of $14C^o$ in temperature and 5 degrees in cloudiness. Location, population, and industrialization are also relevant variables, but they are fixed for each load point in the short-term load forecasting computations. Hence, these variables can be frozen for short-term power-demand predictions. This, in turn, will facilitate prediction processing concerning the time, temperature, and climate variables. This has been attempted in the model, where each load point was denoted with a fixed variable covering its location, population, and industrialization, and has shown encouraging results. The system has been trained on the data concerning actual temperatures, actual degree of cloudiness, and actual power demand at each hour and at each load point. Data covers April 1 to May 15 1993. Data concerning power demand has been taken from the JSCC, and weather-related data has been taken from the Meterological Department in Jordan.

As an application example, the load curve has been estimated for Tuesday April 6 1993 during the 24 hours, and with the actual weather readings as inputs to the system. Fig. 9 shows the actual load curve (solid line), and the predicted load curve (dotted line) given by the model. The two curves have been compared for the indices: average error (e_{avg}), maximum error (e_{max}), minimum error (e_{min}), root mean square error (e_{rms}), and standard deviation error (e_{std}), where:

$$e_i = \frac{\text{Predicted value - Actual value}}{\text{Actual value}} \times 100\% \quad (5)$$

$$e_{evg} = \frac{\sum_{i=1}^{N} e_i}{N} \quad (6)$$

$$e_{max} = \text{maximum } (e_i) \text{ and } e_{min} = \text{minimum } (e_i) \quad (7)$$

$$e_{rms} = \sqrt{\frac{\sum_{i=1}^{N} e_i^2}{N}} \quad (8)$$

$$e_{std} = \sqrt{\frac{\sum_{i=1}^{N} (e_i - e_{avg})^2}{N}} \quad (9)$$

N is the number of hourly predictions, which is equal to 24. The above indices were evaluated for the data obtained using the fzstat.m program and their values are: $e_{avg} = 0.5219\%$, $e_{max} = 9.8799\%$, $e_{min} = 0.1115\%$, $e_{rms} = 4.4338\%$, and finally an $e_{std} = 4.4977\%$.

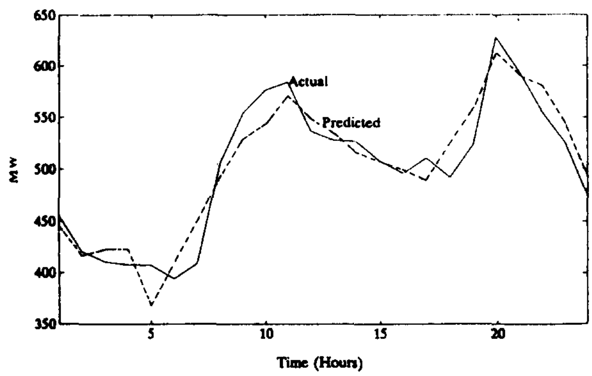

Fig. 9 The Actual Load Diagram (solid line) and the Predicted Load Diagram (dotted line) for Tuesday April 6 1993.

The above indices indicate that the system is qualified to replace the work of an operator. This is an interesting result, as it opens the door to industrial automation in a fuzzy environment. It is worth mentioning that one should not view the actual values, (solid line) in Figure 9 as optimal values. On the contrary, the results (dotted line) are closer to the optimal values. The fact that a computer has a greater ability to compare, remember, and correlate the conditions for different times, faster and more accurately than humans, reinforces this belief. Moreover, for more accurate power demand prediction, the system can be trained on scientific simulated data that represents an optimal load, given a specific fuzzy set for the input variable.

5 FUTURE DIRECTION

An on-going research is to design, train, and test the neural network. The neural network, the second subsystem of the research project, takes as inputs the predicted power demand generated by the fuzzy model and outputs the unit commitment schedule. The unit commitment problem involves determining an operational schedule for the available generating units over a period of time to meet the forecast load demand at minimum cost.

The modern unit commitment methods, such as dynamic programming, relaxation methods, etc., are mathematical optimization techniques (White, 1989). Those methods are known to be sophisticated and need to be modified in order to meet the requirements of the real world. However, the use of artificial neural networks as expert systems which reflect the human expert's thought processes has emerged as a powerful technique in solving unit commitment problems in the last few years (White, 1989; Salam, *et al*, 1991; Zhang, *et al*, 1989).

Neural networks are trainable dynamic systems that can recognize a complex input / output relation without definition. Several learning algorithms have been developed for neural networks. A backpropagation technique using the I/O mapping method has been chosen for this stage. Backpropagation neural networks are popular networks. Their main feature appears in their ability to realize complicated input-output mappings through learning. Although backpropagation networks are relatively slow, they can give good results in system recognition such as the case under study. The values of the weights are continuously changed in response to errors during training (Hammerstrom, 1993b). The net consists of nodes (neurons) arranged in layers, and each node is a single processing element that acts on data to produce a result. The layers are the input layer, the output layer and at least one hidden layer. All nodes in different layers are connected together with associated weights.

6 CONCLUSION

The paper presents an adaptive approach based on the use of fuzzy logic for predicting hourly power demand. An initial evaluation of the approach has reflected reasonable results that are compatible with the actual needs. Further evaluation will be gained through the implementation of sufficient teaching of the model. The implemented algorithm has shown little divergence in realizing the system performance and computational time. Meanwhile, it can still provide the control center operator with indications of load fluctuations, due to any inevitable conditions. The total predicted power demand, to help decide on an optimum number of generators to be committed, has also been investigated. Training a neural network will help in scheduling weekly, monthly and yearly maintenance for all the available generators. In other words, the model proposed here provides the user with a continuous optimization of the number of running power units based on expert knowledge and past history related to the area concerned. This will result in a considerable saving in power consumption, and give an efficient utilization of the available power units. Moreover, the algorithm could be made portable through the capability to freeze and activate the system state variables.

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