A fuzzy inference model for short-term load forecasting

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Abstract

This paper is concerned with the short-term load forecasting (STLF) in power system operations. It provides load prediction for generation scheduling and unit commitment decisions, and therefore precise load forecasting plays an important role in reducing the generation cost and the spinning reserve capacity./[1] Forecasting is a significant element in economic system performance and its impact on network power control. Load forecasting with the uses of fuzzy implementation is faster and more accurate than conventional load forecasting methods that deal with huge amount of data and the long time needed to be processed/ [1].

The accuracy of the dispatching system, which is derived from the accuracy of the forecasting algorithm used, will determine the economics of the operation of the power system. The inaccuracy or large error in the forecast simply means that load matching is not optimized and consequently the generation and transmission systems are not being operated in an efficient manner. In the present study, a proposed methodology has been introduced to decrease the forecasted error and the processing time by using fuzzy logic controller on an hourly base. The proposed fuzzy-based STLF method is applied on a real case study, and the results showed that the STLF of the fuzzy implementation have more accuracy and better outcomes.

Keywords: fuzzy logic; short term load forecasting

1. Introduction

Among all types of energy in the world, electrical energy has a specific characteristic, that is, the unavailability of wide storage. The efficiency of investment in electrical energy is time consuming (especially indeveloping countries that provide most of their required equipment from developed countries). In short-term load forecasting (STLF), the network load is estimated by extrapolating the relationship between load and variables that are strongly tied to the load, such as temperature, time, and etc.

Determining this relationship is a two-stage process that requires: a) identifying the relationship between the load and the related variables, and b) quantifying this relationship through the use of a suitable parameter estimation technique/ [2].

The requirement for improving and developing the precision of a load forecasting model is deep penetration to the relationship between load and its related quantities. Thus, the model should be presented so that the requirements are met.

Obviously STLF plays an important role in non-competitive to renewable energy systems. In power system restructuring, GENCO (Generation of Company) should be predict the demand of the system, and its corresponding prices should be predicted in order to make appropriate decisions in the market. Various models have been utilized to increase the accuracy of predictions in power system. Regression, statistical and state space models are among these models. Moreover, intelligent algorithms based on expert systems, evolutionaryprogramming, fuzzy system, artificial neural networks and a combination of them have been presented. Short-term forecasting is intended for short periods of time, in this case, the prediction horizon might be hourly, daily, weekly or monthly.

Short-term load forecasting plays a fundamental role in the operation of power systems. Generally, forecasting is considered in two major aspects: 1) forecasting overshadows long-term planning in generation and transmission, and 2) forecasting will result in an optimal design in distribution networks. The optimal design of a distribution network is obtained through considering both technical and economical issues, simultaneously.System planner must determine the pattern of generation so that the spinning and constant reserve capacities are supplied as well as the consumed load. Therefore the load forecasting error and the effect of possible exit of one or more generator units is compensated. In case the forecasted load is below the actual value and the necessary reserve capacity is not provided, the overall cost will increase.

Forecasting is a significant element in economic system performance and its impact on network power control. The aim of load forecasting in short periods of time is the prediction of system load, that is, the total load of all subscribers at a time. Forecasting below actual amounts, leads to insufficient provision of reserve capacity which is a threat to network security. On the other hand, forecasting above actual amounts, leads to excess reserve capacity which consequently results in higher provision costs.

The climate, time, past data, and random disturbance factors clarify the relationship between electricity consumption variations. Nature of these parameters is unknown. Fuzzy logic is a generalization of classical logic for reasoning in nonlinear cases and uncertain terms. Therefore it is a very suitable method for describing human knowledge, which is a vague concept and involves a lot of data. Load forecasting with the uses of fuzzy implementation is faster and more accurate than conventional load forecasting methods that deal with difficult data and the long time needed to be processed.

Regression analysis is one of the common methods used to estimate the load demand. The method is based on the relationship between daily load and temperature. Nowadays, statistical methods based on mathematical techniques, are widely applied to load forecasting. These methods are limited by unusual climate change or sudden changes in temperature. Electric distribution companies need accurate values in the load forecasting process. However, fuzzy method uses the distance between values, for example "high or low temperature". The issue leads to use fuzzy method instead of statistical methods.

Here fuzzy inference is used for the STLF, and to clarify the proposal methodology, Sanandaj power network in Kurdistan of Iran is consider as a case study.

2. Case Study: Sanandaj Power Network
2.1. Load Attribute

Good understanding of the system load characteristics helps to design a reasonable forecasting model to achieve accurate results in different conditions.

A typical daily load pattern curve in Sanandaj during summer season is depicted in Fig. 1. As can be seen from Fig. 2, the highest consumption rate in summer occurs when the energy demand for cooling and air conditioning is high, while the high consumption in winter is due to the usage of heating systems. The load pattern curve undergoes different changes due to unstable conditional factors; these factors that should be considered during the load-forecasting process are as follow:

• Weather
• Time
• Economy, and
• Random disturbance

Each parameter will be explained to show its influence on the consumption variation.

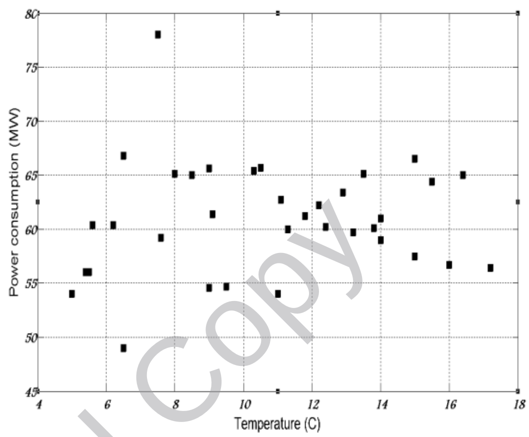

Fig. 1.Temperature at midday peak load

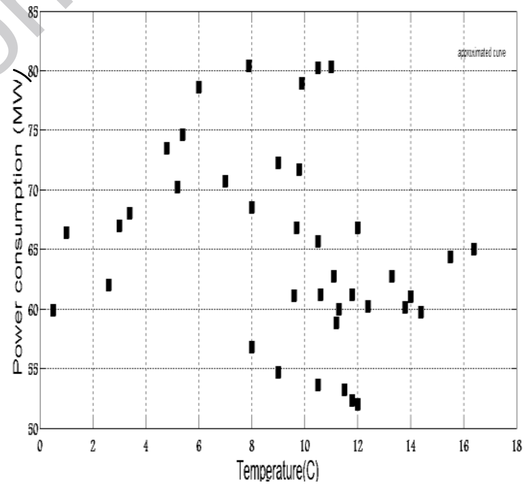

Fig. 2.Temperature at evening peak load

2.2. Weather

Temperature is considered to be the most important component in the dynamic of load, and many efforts have been made to obtain the exact relationship between this component and load. Temperature changes can affect the heating and cooling power demand in winter and summer, respectively. Temperature changes the affect of load pattern, directly. However, this changes do not happen so fast, but in any case can cause delays of heat storage in the buildings. The effect of temperature is different in various seasons. Low temperatures in winter can force the consumers to use heating appliances.

Also due to the hot weather in summer, the increasing demands for chilling and cooling equipment, affect the consumption pattern, dramatically.Accordingly, distribution Company with attention to the importance of temperature in predicting the load, adjust the time with bases temperature, and will be make change from the normal position cause to changing load pattern.

Humidity as one of the weather variables influences on air conditioning systems and cooling device in summer. The effect of moisture is like effect of air temperature value and causes to increase the room temperature. Humidity effect in variant models is different and may have affected directly or indirectly in the STLF.

2.3. Time

This factor includes the effects of season, working and vacation days. For example, the effect of day light hours in each season can be appeared in the load pattern.

2.4. Economy

The economic situation also affects the utilization of electricity. Cycle times daily, resulting in similar daily with subscribers of activities. Lowest demand is times are in the early morning hours andhigher demand is at the beginning of night. Industrial loads in the week are much more in comparison than the weekends. The vacation time have more effect of load pattern and the consumption than usual.

2.5. Random disturbance

Large industrial customers such as rolled steel, are may cause sudden load changes. The natural factors such as earthquakes, floods and civil war and migration from one area to another area which causes unrests or economic inactivity in region and other causes like these factors are change the load pattern in any area.

3. Proposed Methodology

Over the past two decades, there has been a tremendous growth in the use of fuzzy logic controllers in power systems applications. Since precise load forecasting remains a great challenge, the main objective of the fuzzy methodology in the current study is to develop a practical model that can achieve an accurate forecasting result.

The main advantages of using fuzzy logic in load forecasting applications are as follows:

- Fuzzy logic can implement design objectives that are difficult to express mathematically, in linguistic or descriptive rules.

Fuzzy logic uses fuzzy sets that enable us to condense large amount of data into smaller set of variable rule.
The fuzzy inputs used in the present research are listed as follows:

- Last day consumption (MWh).
- Last week consumption (MWh).
- Forecasted temperature(^{o}C)
- Last day temperature (^{o}C).
- Weather.
- Day (binary sets determine whether it is a normal work day or holiday).

The fuzzy input/output combination is shown in Fig.3. The well-known four steps for a fuzzy implementation are explained in the following: subsections.

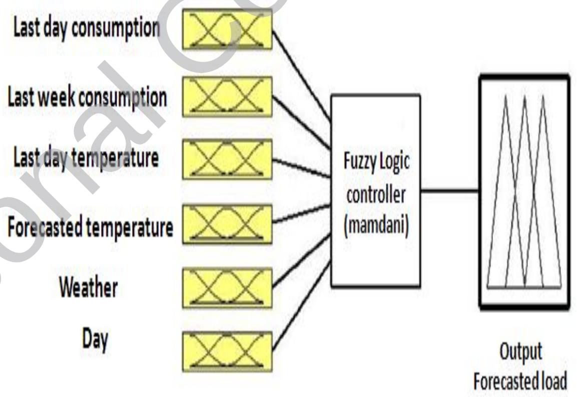

Fig. 3. Fuzzy input/output combination

3.1. Linguistic variables and fuzzy sets

Each input and output of the proposed fuzzy system is divided into number of fuzzy sets as shown in Figs. 4 to 11.The output is divided into seven fuzzy sets; it shows the degree of consumption for the forecasted load with respect to the inputs situation, the fuzzy output sets are as follows:

- Extremely low consumption (VVL),
- Very low consumption (VL),
- Low consumption (L),
- Normal consumption (N),
- High consumption (H),
- Very high consumption (VH), and
- Extremely high consumption (VVH).

The output consumption intervals were divided into seven Gaussian sets is shown in Fig.4. In this paper, a quiet better result is achieved by changing the amount of load maximum for “last day consumption”, “last week consumption”, and “output” in first hours of days and other times. In the first hours of day (1to 8 AM) we have got a variable range between 42 to 70 MW and in other hours (9-24 O'clock) between 42 to 90 MW.

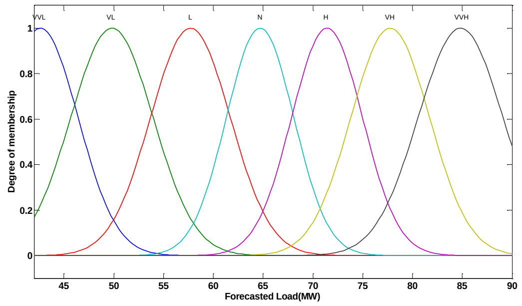

Fig. 4. Membership functions for the forecasted load in Megawatt (MW).

The intervals for “Last day consumption” and the “Last week consumption” inputs have been divided into seven membership function as follows:

- Very very low consumption (VVL),
- Very low consumption (VL),
- Low consumption (L),
- Normal consumption (N),
- High consumption (H),
- Very high consumption (VH), and
- Very very high consumption (VVH).

The membership functions for the historical data input are shown in Figs. 5 to 6 as follows:
“Last day consumption” and “Last week consumption”

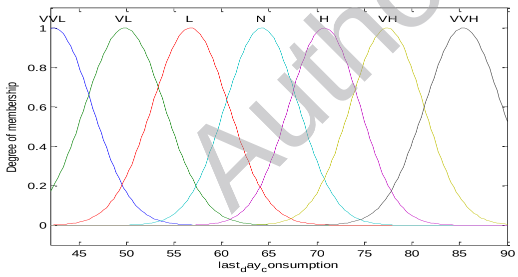

Fig. 5. Membership functions for the last day consumption in Megawatt (MW)

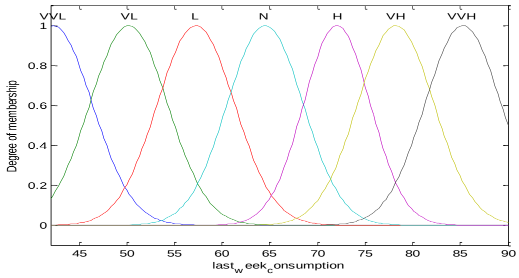

Fig. 6. Membership functions for the last week consumption in Megawatt (MW).

inputs are included in the fuzzy implementation to determine the behaviour of the consumption during the last day and the average last week, respectively.

As shown in Figs. 7 to 8, the intervals for the “Last day temperature” and “Forecasted temperature” have been divided into three membership functions as follow:

- Low temperature (L),
- Normal temperature (N),and
- High temperature (H).

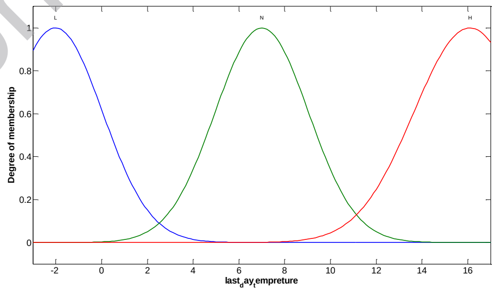

Fig. 7. Membership functions for the last day temperature in degree Celsius (^{o}C).

The average temperature values in Fig. 7 are occurring between -2 ^{o}C and 20^{o}C which represent the low and high average temperatures, respectively.

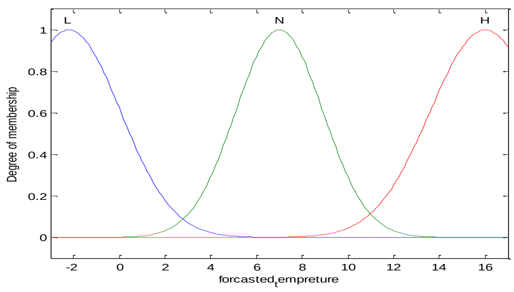

Fig. 8. Memberships function for the forecasted temperature in degree Celsius (^{o}C).

The weather interval inputs have been divided into four membership functions (full cloud, half cloud, cloud, clear) as shown in Fig. 9.

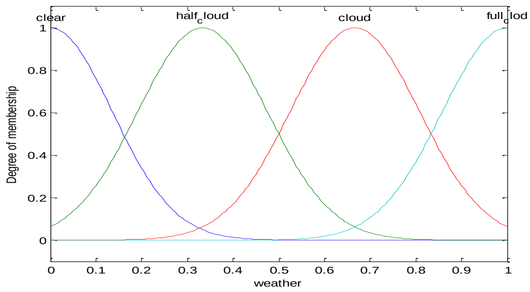

Fig. 9. Membership functions for the Weather.

The "Weather" inputs in the fuzzy implementation are used to determine which weather condition (i.e., full cloud, half cloud, cloud, clear) is dominant (Fig. 9).

As illustrated in Fig. 10, "Day" is an input with binary boundaries which determines if the day is a normal workday or holiday.

The "Day" input is used to determine the day duty (holiday or workday) within 0-1 range.

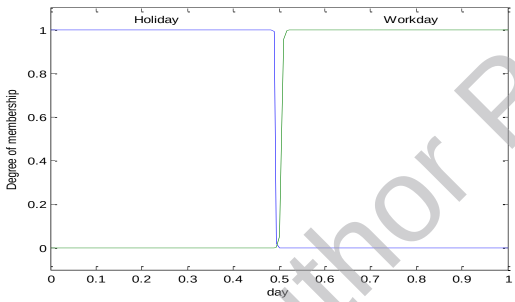

Fig. 10. Membership functions for the "Day".

3.2. Performing fuzzy inference

The process of fuzzy inference involves membership function, fuzzy logic operators, and if-then rules. This procedure is used to compute the mapping from the input values to the output values, and it consist of three sub-processes, fuzzificatin, aggregation, and defuzzification (Fig. 11). For example, rule 6 shown in Fig. 11. shows that the "Last day consumption" was 50MW and "Day" equal to 1 is a "workday", the degree of activation for the output set at rule six carries the same minimum input set "last day consumption" degree because the operator of "and" used. The activated sets due to fuzzification sub-process will be aggregated in the next step to form the combined shape shown in Fig. 11. After that, it will be defuzzified to get a crisp number (forecasted load= 64.6 MW).

If the day is holiday, then the (last day consumption) will be ignored and "last week consumption" value should be considered as a last holiday.

4. Case study

In this work the Sanandaj power network in Kurdistan of Iran is considered as the case study. The data used here have been taken from the Sanandaj Distribution of Company in. The capacity portfolio includes fuel oil-fired steam generating system, gas fired combustion turbine. The rules in the fuzzy logic were made based on the historical system load data sheet of the years 2008 to 2011. The fuzzy sets were tuned to get the right response based on the variation of different parameters. Tables 1 to 2, compare between the actual loads and the fuzzy forecasting results. The mean absolute percentage error (MAPE) is used to measure the error for the proposed method.

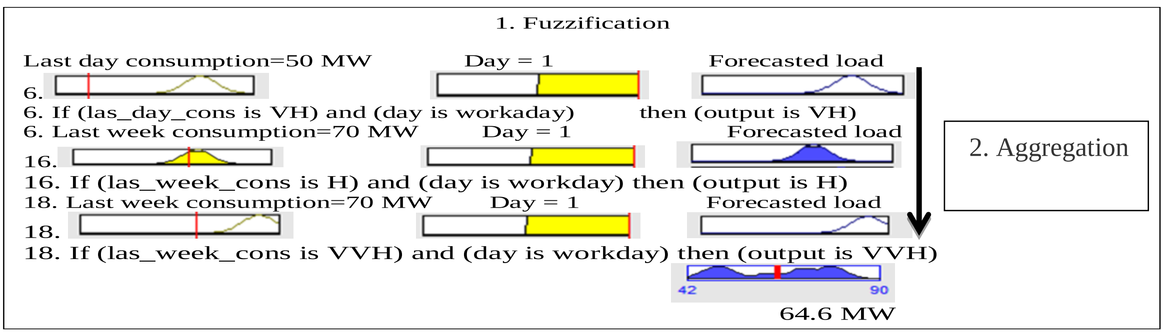

Fig.11. Forecasting process using Fuzzy Logic

percentage error (MAPE) is used to measure the error for the proposed method.

Table. 1. Comparison between actual and fuzzy forecasted load in 28/2/2011

Time	Fuzzy forecasted load(MW)	Actual load(MW)	Fuzzy error (%)
1	51.8	51.8	0.00
2	48.4	47.9	0.01
3	47.3	46.3	0.02
4	45.9	44.3	0.04
5	45.6	43.8	0.04
6	46.6	44.1	0.06
7	47.9	45.8	0.04
8	59.7	53.3	0.07
9	62	60.4	0.02
10	63.6	59.2	0.07
11	63.7	61.4	0.04
12	66.2	65.7	0.007
13	63.3	62.7	0.009
14	62.5	61.2	0.02
15	60.5	60.2	0.005
16	62.4	60	0.04
17	64.5	61.2	0.05
18	68.5	68.5	0.00
19	79.2	80.4	-0.01
20	77.5	78.6	-0.01
21	75	74.6	0.005
22	74.5	73.5	0.01
23	68.9	68	0.01
24	65.1	62	0.05
Average Error		0.024(2.4%)	

Table. 2. Comparison between actual and fuzzy forecasted load in 11/3/2011

Time	fuzzy Load(MW)	actual Load(MW)	Fuzzy error(%)
1	53.2	53.1	0.002
2	49.3	49	0.006
3	47.9	46.9	0.021
4	47.7	45.6	0.046
5	47.5	45.1	0.053
6	48.1	45.8	0.050
7	48.5	47.5	0.021
8	52.9	52.7	0.003
9	62.3	62.2	0.001
10	65.6	65.1	0.007
11	68.3	66.5	0.027
12	65.1	65	0.001
13	64.7	64.4	0.004
14	62.8	61	0.029
15	61.4	59.7	0.011
16	62.6	60.1	0.041
17	63	62.7	0.005
18	65.8	66.8	-0.014
19	77	80.3	-0.041
20	77.3	80.2	-0.036
21	76.4	78.9	-0.031
22	73.1	71.7	0.019
23	69.7	66.8	0.043
24	64	61.1	0.050
Average Error		0.006(0.6%)	

$$MAPE = \frac{(Forecastedload) - (Actualload)}{Actualload}$$

Fig. 14 to 15 shows small deviation (<3%) between the actual load and the fuzzy set evaluation that is due to the limitation of the dispatchers data collected by NEPCO and due to the sudden variations occur in the load consumption rate under the effect of different climatically conditions.

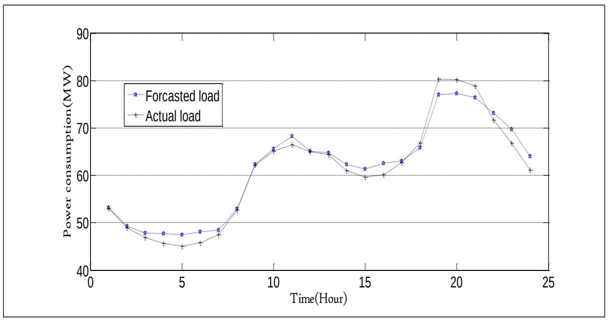

Fig. 14 .Comparison between actual and fuzzy load in 28/2/2011

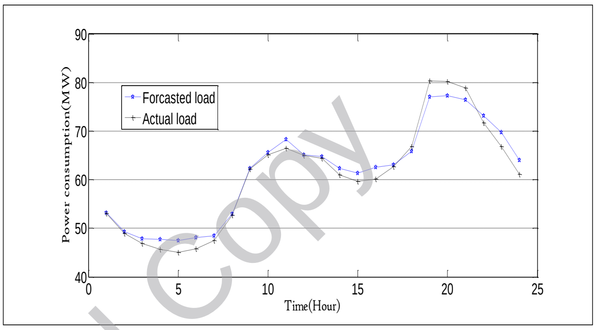

Fig. 15 .Comparison between actual and fuzzy load in 11/3/2011

5. Conclusions

In the present paper, a fuzzy logic framework is proposed for the sake of short-term load forecasting (STLF) issue. The proposed STLF method is examined on a real distribution power networks it is shown that the load forecasting using fuzzy implementation is faster and more accurate than the conventional forecasting methods that deals with rigid data and have a long processing time. Also, the present fuzzy STLF model helps the utility economically, stage, by reducing the error in load predictions.

6. References

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