Short-Term Load Forecasting in Deregulated Electricity Markets using Fuzzy Approach

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ABSTRACT

In this article, a fuzzy inference-based method for short-term load forecasting has been presented. Load data from European Energy Exchange has been selected for the case study. The “time,” “temperature,” and “historical load” are taken as inputs for the fuzzy logic controller and the “forecast load” is the output. Each of the input variables “time” and “temperature” has been divided into 7 triangular membership functions, whereas the input variable “historical load” has been divided into 10 triangular membership functions. The “forecast load” as output has been divided into 10 triangular membership functions. Then, 1 day ahead load forecast for each hourly interval has been performed using fuzzy logic method. Furthermore, performance of the fuzzy logic model is compared with a conventional model. It has been shown that the proposed method possesses better forecasting abilities than the other model.

Key words: Electricity markets, fuzzy logic, membership functions, short-term load forecasting

1. INTRODUCTION

The worldwide electric power industry has seen many changes over the last 20 years. During this period many regulated or state-owned monopoly markets have been deregulated. In an electricity market, electricity price is decided based on demand and supply bids from the market participants; therefore, the importance of Short-Term Load Forecasting (STLF) has been rising in these markets [1]. Load forecasting is an essential element of power system operation and planning involving prognosis of the future level of demand to serve as the basis for supply side and demand side planning. Load requirements are to be predicted in advance so that the power system operates effectively and efficiently. In the absence of accurate load demand information from some of the participants, forecast load information is used in many price-determining algorithms. Therefore, in deregulated markets, in addition to its conventional role of generation scheduling function and assessing power system security [2], STLF also plays a major role in price determination process.

Numerous forecasting methods, varying from statistical method [3-5] to neural network–based artificial intelligence techniques [6,7] have been developed in recent years for STLF problem. Recently, considerable interest has been focused on the application of Artificial Neural Networks (ANN) for load forecasting; but ANNs are not up-datable to changing conditions, for example, a sudden change in weather or a special event on the forecast day. Therefore, fuzzy set theory–based approach, in recent years has emerged as a complementary tool to mathematical approach for solving power system problems [8]. Fuzzy logic approach can model the non-linearities in the power system effectively. Fuzzy logic models (FLMs) have been proposed as an appropriate forecasting method when the historical data are not real numbers, but linguistics values [9,10]. Application of FLM on European Energy Exchange (EEX) data has yet to be explored and has been carried out in this study.

In this work, historical load, temperature, and time of day information have been converted into “fuzzy” information. A fuzzy rule base has been developed to produce “fuzzy” forecasts and defuzzification has been performed to generate a crisp estimate for system load. The prediction results of FLM have been compared with a conventional method.

2. EUROPEAN ENERGY EXCHANGE

2.1 Market Operation

The Leipzig-based EEX is the most important energy exchange in continental Europe today with delivery
in Germany, Austria, and Switzerland [11]. In intraday trading on EEX, hourly power contracts with delivery on the same or on the following day are traded. On the real time intraday market of EEX, the trading participants can trade the individual hours of the current day (D-day) up to 75 min prior to the beginning of the delivery. On the day-ahead intraday market, power is traded for the next day. Trading of hour and block contracts takes place on each exchange trading for those contracts that lead to the delivery of electricity on the following day. For each trading day D, participants need to submit their bids on the D-1, during 7:30 am to 8:00 am.

EEX offers day-ahead trading for 2 market areas: for Germany/Austria and for Switzerland. The German/Austrian market area comprises all German balance areas as well as the balance area of Austria. On every exchange trading day, one auction each takes place at 12:00 am for the 24 h of the next day. In addition to this, base and peak load blocks can be traded continuously in the morning. The Swiss market area comprises the balance area of Swiss grid. On every exchange trading day, one auction each takes place for every one of the 24 h of the following day at 10:30 am. The Swissix (“Swiss Electricity Index”) is the average of the prices of the 24 h traded for the Swiss market area. The Swissix is available both as a base load and as a peak load index. The trading process for all spot contracts on EEX is divided into the trading phases of pretrading, main trading, posttrading and batch processing.

2.2 Characteristics of Load Series in EEX

The system load is the sum of all the individual demands at all the nodes of the power system. In principle, one could determine the system load pattern if each individual consumption pattern were known. However, the demand or usage pattern of an individual load or customer is quite random and is highly unpredictable. Also, there is a very broad diversity of individual usage pattern in a typical utility. The system load is influenced by a number of factors, such as like economic, time, weather, and random effects. Because price is strongly affected by load demand in deregulated markets, predicting load with reasonable accuracy becomes all the more important. All these characteristics can be clearly observed from Figure 1 in which the average load variations in EEX during the year 2005 have been shown. It can be clearly observed that the average load during the winter season (October to December) is high and it is low during the spring season (April to June). The average load in December is the maximum and it is minimum in March. The average daily demand usually varies from 8000 to 13,500 MW.

To forecast the load the following variables have been considered in this study: - (i) historical load, (ii) historical temperature, and (iii) time of day. Load forecast has been performed for 1 week in each of the 4 seasons in year 2005.

3. FORECASTING METHODOLOGY

3.1 Conventional Method

For load forecasting, the conventional method (CM) is used based on the characteristics of the load curve, which follows a daily and weekly pattern; therefore, the load of the previous week is extrapolated as the load of the next week [2]. It does not take into consideration the following: economic, time, weather, and random factors of the following weeks. Load during a particular hour of a trading day ($DEM_{D,t}$) may assume to be equal to the previous week’s load during the same hour of the corresponding weekday ($DEM_{D-7,t}$).

$$DEM_{D,t} = DEM_{D-7,t}$$  \hspace{1cm} (1)

3.2 Fuzzy Logic Model

The present work makes use of simplified fuzzy inference in which the consequence of the fuzzy rule is expressed in crisp number. Fuzzy inference is the process of formulating the mapping from a given input to an output using the fuzzy logic. The mapping then provides a basis from which decision can be made. The process of fuzzy inference involves all of the components, such as membership functions, logic operators, and if–then rules. The basic structure of a fuzzy inference system consists of 3 conceptual components: a rule-base, which contains a selection of fuzzy rules; a database, which defines the membership functions used in fuzzy rules; and a reasoning mechanism, which performs...
the inference procedure on the rules and given facts to derive a reasonable output or conclusion. The values for the inputs and outputs need not be numerical and may be expressed in natural language.

One of the attractive features in fuzzy logic is that the fuzzy rule is capable of easily adding the new membership function to existing ones. Fuzzy approach proposed can be used as an aid to forecast the load with different lead times [12]. A more accurate fuzzy expert system is obtained by dividing the region into intervals [13]. The intervals for the time (Input 1) have been divided into 7 membership functions, which are as follows:

- Mid Night (Mid Nig)
- Dawn (Dawn)
- Morning (Mor)
- Fore Noon (F Noon)
- After Noon (A Noon)
- Evening (Even)
- Night (Night).

The triangular membership functions of time are shown in Figure 2.

The intervals for temperature (Input 2) have also been divided into 7 triangular membership functions, which are as follows:

- Low (LOW)
- Below normal (B.NOR)
- Normal (NORM)
- Above normal (AB.NORM)
- Moderately high (M.High)
- High (HIGH)
- Very high (V.HIGH)

The triangular membership functions of temperature are shown in Figure 3.

The load data corresponding to previous days, that is, (D-2), (D-3), and (D-7) where “D” denotes the day of load forecast, has been divided into 10 triangular membership functions, which are as follows:

- very very low (V.V.LOW)
- very low (V.LOW)
- low (LOW)
- moderately normal (MNORM)
- normal (NORM)
- above normal (ABNORM)
- high (HIGH)
- very high (V.HIGH)
- very very high (V.V.HIGH)
- extremely high (E.HIGH)

The triangular membership functions of historical load data are shown in Figure 4.
The forecast load (output) has been divided into 10 triangular membership functions, which are as follows:

- very very low (V.V.LOW)
- very low (V.LOW)
- low (LOW)
- moderately normal (MNORM)
- normal (NORM)
- above normal (ABNORM)
- high (HIGH)
- very high (V.HIGH)
- very very high (V.V.HIGH)
- extremely high (E.HIGH)

The triangular membership functions of output load are shown in Figure 5.

Fuzzy system acquires knowledge from domain experts, which is encoded within the algorithm in terms of set of IF–THEN rules. The membership functions and fuzzy rules in the fuzzy logic formulation provide an intuitive and straightforward manner to include heuristics into the load forecasting problem formulation. Utilizing the knowledge of fuzzy logic-based approach the rule-base for the load forecast has been developed. This is shown in Figures 6 and 7.
4. TEST RESULTS AND DISCUSSIONS

In this article, hourly short-term load forecasting has been done for EEX using fuzzy logic approach. The rule-base has been developed based on historic load and weather data for 4 years (2002–2005). Among the weather variables, only temperature has been considered. The mean absolute percentage error (MAPE) has been considered as the accuracy criterion to assess the forecasting performance of the models.

\[
\text{MAPE} = \frac{1}{N} \sum_{i=1}^{N} \left| \frac{P_A - P_F}{P_A} \right| \times 100
\]

Where, \(P_A\) is the actual load, \(P_F\) is the forecast load, \(N\) is the number of samples.

**Table 1: Actual and forecasted hourly load using CM and FLM for 7th March, 2005**

<table>
<thead>
<tr>
<th>Hour</th>
<th>Actual Load</th>
<th>CM</th>
<th>FLM</th>
<th>APE using CM</th>
<th>APE using FLM</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>9787.1</td>
<td>8836.0</td>
<td>8980</td>
<td>9.71</td>
<td>8.24</td>
</tr>
<tr>
<td>2</td>
<td>9152.0</td>
<td>8745.8</td>
<td>8860</td>
<td>4.43</td>
<td>3.19</td>
</tr>
<tr>
<td>3</td>
<td>9301.5</td>
<td>8757.3</td>
<td>8860</td>
<td>5.84</td>
<td>4.74</td>
</tr>
<tr>
<td>4</td>
<td>9225.7</td>
<td>8606.9</td>
<td>8860</td>
<td>6.71</td>
<td>3.95</td>
</tr>
<tr>
<td>5</td>
<td>8737.8</td>
<td>8849.7</td>
<td>8860</td>
<td>1.28</td>
<td>1.40</td>
</tr>
<tr>
<td>6</td>
<td>8701.4</td>
<td>8863.7</td>
<td>8800</td>
<td>1.86</td>
<td>1.13</td>
</tr>
<tr>
<td>7</td>
<td>8662.6</td>
<td>9725.3</td>
<td>8800</td>
<td>12.27</td>
<td>1.50</td>
</tr>
<tr>
<td>8</td>
<td>8747.6</td>
<td>9953.4</td>
<td>8800</td>
<td>13.78</td>
<td>0.60</td>
</tr>
<tr>
<td>9</td>
<td>8627.2</td>
<td>10001.5</td>
<td>8400</td>
<td>15.93</td>
<td>2.63</td>
</tr>
<tr>
<td>10</td>
<td>8576.9</td>
<td>10133.0</td>
<td>8900</td>
<td>18.15</td>
<td>3.77</td>
</tr>
<tr>
<td>11</td>
<td>8802.4</td>
<td>10101.2</td>
<td>8670</td>
<td>14.76</td>
<td>1.49</td>
</tr>
<tr>
<td>12</td>
<td>8136.4</td>
<td>9727.0</td>
<td>8290</td>
<td>19.55</td>
<td>1.89</td>
</tr>
<tr>
<td>13</td>
<td>8255.1</td>
<td>9437.4</td>
<td>8670</td>
<td>12.97</td>
<td>7.32</td>
</tr>
<tr>
<td>14</td>
<td>8555.6</td>
<td>9437.4</td>
<td>8670</td>
<td>10.30</td>
<td>1.33</td>
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<tr>
<td>15</td>
<td>8643.5</td>
<td>9745.9</td>
<td>8670</td>
<td>12.76</td>
<td>0.31</td>
</tr>
<tr>
<td>16</td>
<td>9079.8</td>
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<td>8670</td>
<td>8.16</td>
<td>4.51</td>
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<tr>
<td>17</td>
<td>9208.4</td>
<td>9491.7</td>
<td>8950</td>
<td>3.08</td>
<td>2.80</td>
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<tr>
<td>18</td>
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<td>10.31</td>
<td>1.98</td>
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<tr>
<td>19</td>
<td>9166.4</td>
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<td>8950</td>
<td>6.89</td>
<td>2.35</td>
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<td>20</td>
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<td>8770</td>
<td>9.91</td>
<td>3.97</td>
</tr>
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<td>21</td>
<td>9188.6</td>
<td>8397.1</td>
<td>8810</td>
<td>8.61</td>
<td>4.12</td>
</tr>
<tr>
<td>Average APE</td>
<td>9.38</td>
<td>3.12</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Table 2: Weekly MAPE comparison of both the models**

<table>
<thead>
<tr>
<th>Week</th>
<th>Duration</th>
<th>MAPE using CM</th>
<th>MAPE using FLM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spring week</td>
<td>07-03-05 to 13-03-05</td>
<td>8.43</td>
<td>3.46</td>
</tr>
<tr>
<td>Summer week</td>
<td>13-06-05 to 19-06-05</td>
<td>6.15</td>
<td>4.08</td>
</tr>
<tr>
<td>Fall week</td>
<td>19-09-05 to 25-09-05</td>
<td>8.44</td>
<td>3.61</td>
</tr>
<tr>
<td>Winter week</td>
<td>19-12-05 to 25-12-05</td>
<td>6.13</td>
<td>3.30</td>
</tr>
<tr>
<td>Average MAPE</td>
<td></td>
<td>7.28</td>
<td>3.61</td>
</tr>
</tbody>
</table>
the number of data points. Four weeks test period from year 2005, selecting 1 week from each season, has been considered for assessing the forecasting performance of the models. The actual and forecast load values for 1 test day (March 7, 2005) are shown in Table 1. It can be observed that forecasting errors using FLM are quite small as compared with CM.

The weekly MAPE comparison for the test period is shown in Table 2. From this table it has been observed that FLM model outperforms CM during each of the 4 weeks. Overall performance of FLM is better than CM by 50.41%.

Furthermore, the actual and forecast load using FLM have been shown graphically in Figures 7–10 for each of the test weeks. It can be observed that the predicted load curve follows the actual load curve quite closely.

5. CONCLUSION

In this work, short-term load forecasting in EEX has been addressed and 2 models have been tested on the data. The performance of the FLM has been found to be better than the conventional method. In summary, the flexibility of fuzzy-based load forecasting approach, which offers logical sets of rules, readily adaptable and understandable by an operator, may be a very effective solution for load forecasting.

REFERENCES


Author queries

AQ1: Please check highlighted text

AQ2: Please check the placement of the following “Characteristics of Load Series in EEX. The system load is the sum of all the individual demands at all the nodes of the power system”?

AQ3: Provide high quality of images for figures 2-7
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