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A Fuzzy Logic Model for Short-Term Load Forecasting in the Libyan Power Network

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ABSTRACT

Short-term load forecasting is an essential system for predicting electricity demand, with a lead time ranging from one hour to one month. This is crucial for effectively scheduling and operating the power system. Achieving high forecasting accuracy is of utmost importance, requiring a thorough analysis of load characteristics and the identification of key factors influencing demand. In electricity markets, factors such as season, day type, weather, and electricity prices have intricate relationships with system load. This study focuses on conducting short-term load forecasting for the Libyan electric grid using a fuzzy logic technique. Input variables for the fuzzy logic include temperature, humidity, and the previous day's peak load. The design and simulation of the fuzzy logic system are implemented using MATLAB SIMULINK software. The results demonstrate that weather factors significantly impact the electric system's load. The model's error margin ranges between +3.67% and -3.75%. Additionally, the study concludes that the fuzzy logic method is easy for forecasters to understand due to its use of simple "IF-THEN" statements.

Keywords: Short-term load, load forecasting, Fuzzy logic, Libyan power network

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التنبؤ بالأحمال في المدى القصير لنظام القدرة الليبية باستخدام تقنية المنطق الضبابي

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ملخـــــص البحـــــث

التنبؤ بالأحمال على المدى القصير هو في الأساس نظام للتنبؤ بالأحمال بفترة زمنية تتراوح من ساعة واحدة إلى شهر واحد، وهو أمر ضروري لجدولة وتشغيل نظام الطاقة بشكل مناسب. تعد دقة التنبؤ العالية من أهم الاحتياجات الحيوية للتنبؤ بالأحمال على المدى القصير ومن الأهمية ايضا تحليل خصائص الحمل وتحديد العوامل الرئيسية التي تؤثر على الحمل. في أسواق الكهرباء، الحمل التقليدي يتأثر بعدة عوامل مثل الموسم ونوع اليوم والطقس، وسعر الكهرباء له علاقة معقدة مع حمل النظام. في هذا البحث، سيتم إجراء التنبؤ بالأحمال قصيرة المدى للشبكة الكهربائية الليبية باستخدام تقنية

المنطق الضبابي. سوف يتم استخدام درجة الحرارة والرطوبة واقصى حمل سابق كمتغيرات المدخلات للمنطق الضبابي. سوف يستخدم الماتلاب لتصميم ومحاكاة نظام المنطق الضابي. تُظهر النتائج أن العوامل الجوية تؤثر بشكل كبير على حمل نظام الكهرباء. يتراوح هامش الخطأ في النموذج بين +3.67% و -3.75%. بالإضافة إلى ذلك، تُشير الدراسة إلى أن طريقة المنطق الضبابي سهلة الفهم بالنسبة للمحللين نظرًا لاعتمادها على عبارات بسيطة من نوع "إذا- فإن."

الكلمات الدالة: أحمال المدى القصير، التنبؤ بالأحمال، المنطق الضبابي؛ شبكة الكهرباء الليبية.

1. Introduction

Accurate electric power load forecasting models are crucial for the effective operation and planning of utility companies. Load forecasting enables utilities to make critical decisions, such as those related to power purchasing, generation, load switching, and infrastructure development. It is particularly important for energy suppliers, financial institutions, and other stakeholders involved in the generation, transmission, distribution, and markets of electric energy [1]. There are three main types of load forecasting: short-term load forecasting (STLF), medium-term load forecasting (MTLF), and long-term load forecasting (LTLF). STLF focuses on predicting system load with a lead time of one hour to one month, while MTLF covers a period from one week to a year, and LTLF forecasts beyond one year. The primary goal of STLF is to optimize economic load dispatch, load scheduling, and assess system reliability and security. High accuracy and fast response are critical for analysing load characteristics in STLF, as it deals with energy transactions, security, fuel consumption, maintenance, and unit scheduling. MTLF, on the other hand, is used to guide power system infrastructure development and purchase agreements. LTLF helps plan for future expansions, improved distribution facilities, economic planning, and technological advancements, taking into account factors such as population growth. Several factors influence STLF, including weather variables like temperature, humidity, and wind speed, as well as load consumption variables such as hourly, weekly, and peak loads [1, 2].

Various statistical and intelligence techniques have been developed for short-term load forecasting (STLF). Statistical methods include linear and nonlinear regression analysis [3-7]. Intelligence techniques can be categorized into two main groups: Artificial Neural Networks (ANN) [8-13], and fuzzy logic systems [14-19]. However, when it comes to the Libyan power grid, there have been limited efforts in the literature to improve the accuracy of load forecasting models [20-25]. To date, no studies have been found that specifically address STLF for the Libyan electric grid using fuzzy logic techniques.

The importance of this paper lies in utilizing fuzzy logic techniques to develop a model for accurately forecasting the daily peak load for the Libyan electric grid one week in advance. The model incorporates weather factors, such as temperature and humidity, along with daily peak load as input parameters. The fuzzy logic toolbox in MATLAB software is employed for this purpose.

2. Factors Influencing Electrical Load Patterns

Numerous factors significantly impact load demand. To develop an accurate load forecasting model, it is essential to analyse and understand the effects of these factors carefully.

2.1 Economic Factors

Various economic factors, including customer types (residential, agricultural, commercial, and industrial), demographic trends, population size, GDP growth, national economic development, and social activities, can significantly influence load patterns. These factors primarily impact long-term load forecasting.

2.2 Weather Factor

Weather conditions, such as temperature, humidity, and cloud cover, play a crucial role in load forecasting. Among these, temperature is the most significant factor, as variations greatly influence heating demand in winter and air conditioning usage in summer. Other factors, including humidity, particularly in hot and humid regions, wind speed, and daylight intensity, also impact load forecasting.

2.3 Time and Seasonal Factors

Time-related factors are critical for accurate load forecasting as they can significantly alter load patterns. Key considerations include:

- Seasonal Variation: Changes in seasons (summer, winter, rainy, autumn), daylight hours, and average temperature can all affect load demand.
- Daily Variation: Consumption patterns differ between daytime and nighttime.
- Weekly Cycle: Weekday and weekend consumption patterns vary noticeably.
- Holidays and Special Days: Load patterns on holidays differ from regular weekdays and weekends, while special occasions like festive days can also impact load demand.

2.4 Random Disturbances

Random disturbances in the power system can significantly disrupt load patterns. These disturbances include unexpected events such as the sudden shutdown or startup of industries, widespread strikes, weddings, special functions, and other similar occurrences.

2.5 Other Factors

In addition to the factors mentioned above, load patterns can also be influenced by geographical conditions (urban or rural areas), the type of consumers (urban or rural), home appliance sales data, and television programs (such as sports or serials) [26, 27].

3. Typical Fuzzy Logic System

A fuzzy logic controller is considered an intelligent controller, based on fuzzy set theory, which handles approximate rather than precise reasoning. It was developed to regulate data-based systems and allows values to be understood as true or false to varying degrees. Its simplicity makes it increasingly popular for data-driven system applications. The fuzzy logic controller operates through the use of fuzzy sets and rules. Unlike traditional set theory, where an object either belongs to a set or does not, fuzzy set theory allows for partial membership, enabling more flexible and nuanced control.

A fuzzy set is defined as a class with varying degrees of membership. A typical fuzzy logic controller consists of four main components: fuzzification, a fuzzy rule base, a fuzzy inference engine, and defuzzification. During the fuzzification step, numerical input and output variables are converted into linguistic terms (e.g., low, medium, high), and their corresponding degrees of membership are determined through membership functions. The fuzzy inference process then combines these membership values according to established fuzzy rules. In the final step, defuzzification, the linguistic results from the fuzzy inference are converted into precise values using the provided rule base. This step translates the fuzzy outputs into crisp, actionable values [27, 28]. Figure 1 illustrates the overall fuzzy logic process.

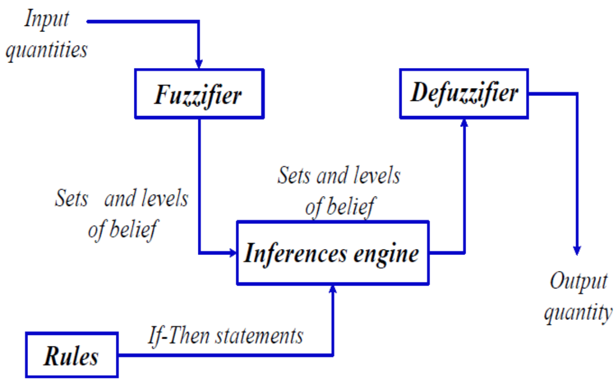

Figure 1. Block diagram for a typical fuzzy logic system

4. Fuzzy Logic system for Short Term Load Forecasting

4.1 Fuzzification

Fuzzification is the process of transforming crisp numerical values into degrees of membership corresponding to specific fuzzy sets. A membership function (MF) takes a crisp value as input and returns the degree to which that value belongs to the fuzzy set it represents [28]. In this work, triangular membership functions are used for both the input and output variables. Humidity and temperature are considered inputs for short-term load forecasting (STLF). The fuzzy logic model is structured based on the fuzzy inference block diagram shown in Figure 1. As illustrated in Figure 2, the model takes humidity, temperature, and historical peak load as inputs, while the fuzzy logic output provides the forecasted peak load.

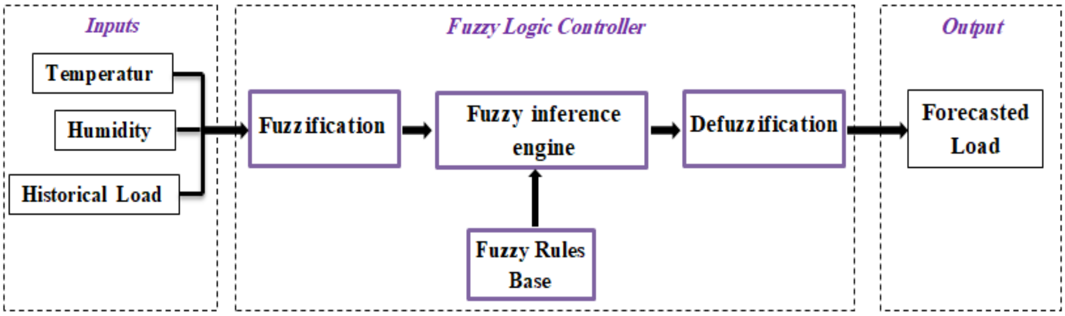

Figure 2. Block diagram of the proposed work

As illustrated in Figures 3, 4, and 5, the three input variables—humidity (H), temperature (T), and peak load—are fuzzified into seven sets using triangular membership functions.

4.2 Fuzzy Rule Base Load Forecast

This section forms the core of the fuzzy logic system, where the forecast's heuristic knowledge is represented through IF-AND-THEN rules. These rules are processed by the fuzzy inference system, which analyzes the input data to generate the forecasted load output. In this work, 343 rules were created as shown in Figure 6, (some of them are as follows), including examples such as:

If (Temperature is VVL) and (Humidity is VVL) and (Input load is VVL),

then (forecasted load is VVL).

If (Temperature is VVL) and (Humidity is VVL) and (Input load is VL), then (forecasted load is VL).

If (Temperature is VVL) and (Humidity is VVL) and (Input load is L),

then (forecasted load is L).

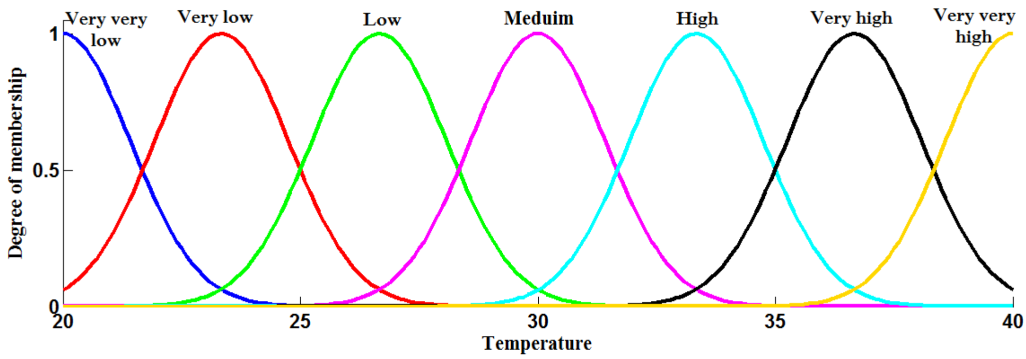

Figure 3. Membership function for temperature

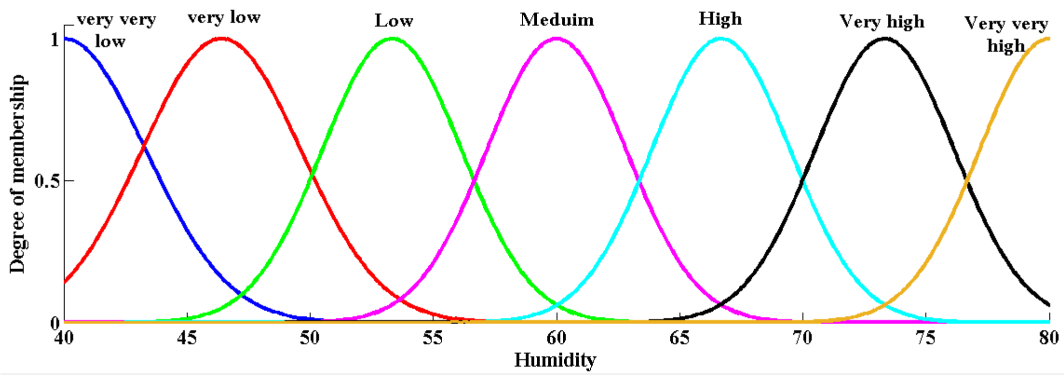

Figure 4. Membership function for humidity

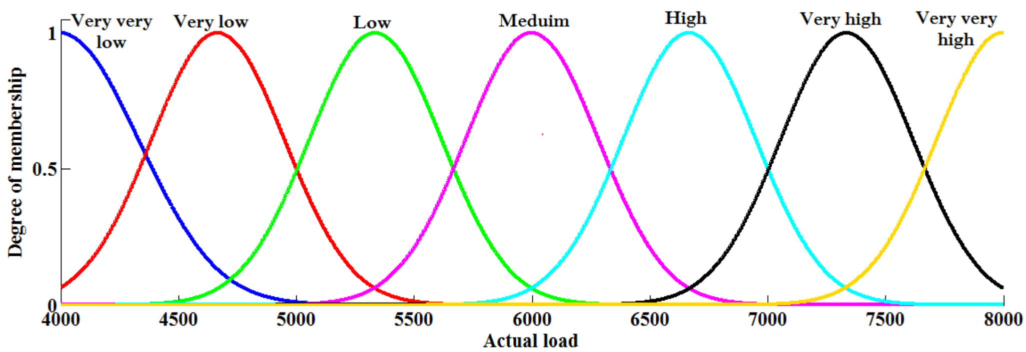

Figure 5. Membership function for peak load

5. System Simulation

The fuzzy logic simulation model used in this study is depicted in Figure 7. MATLAB software was utilized for the simulation. The actual load data and input variables are sourced from the workspace file and incorporated into the simulation diagram, as illustrated in Figure 7.

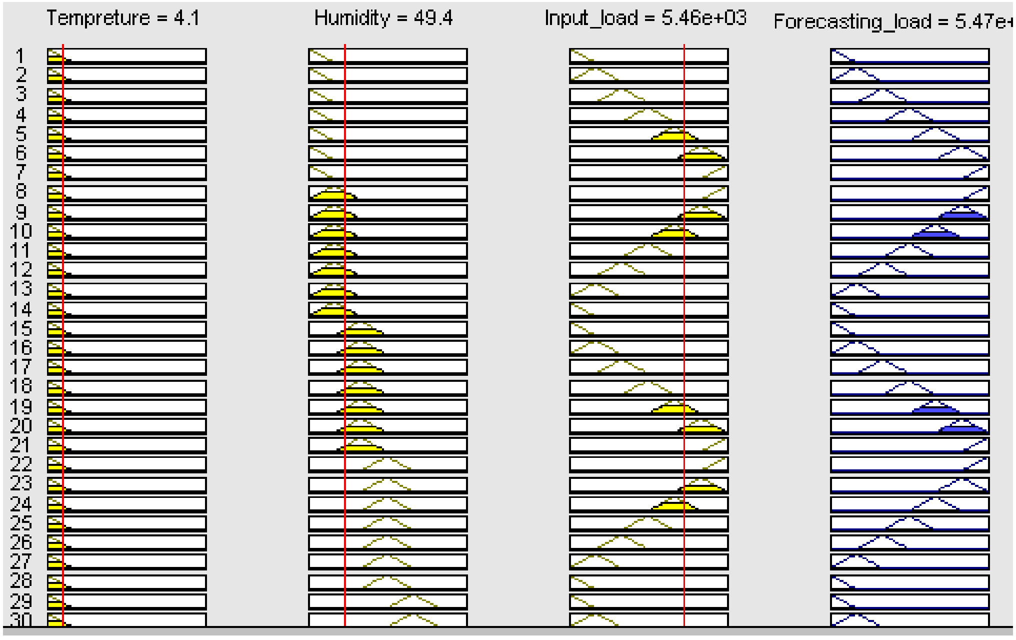

Figure 6: Some of the created load forecasting rules

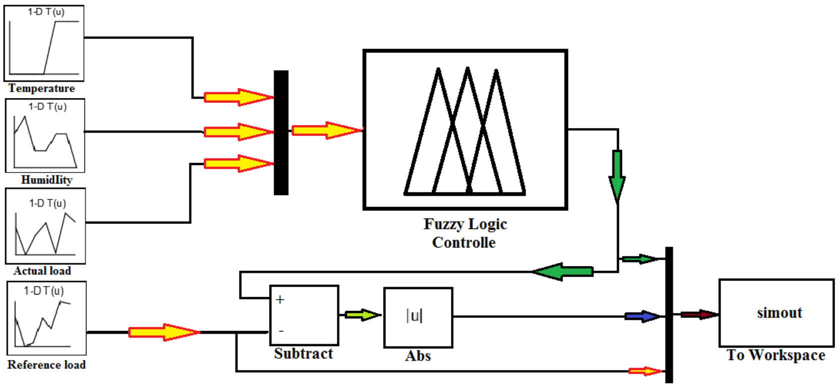

Figure 7. Simulation model of proposed work

6. Results and Discussion

The proposed fuzzy logic technique was tested using four months of real data from 2022, including daily peak load and weather data (temperature and humidity). Table 1 presents the data for the first week of February 2022, used to explain the fuzzy logic procedure. The test data was selected to represent one month from each season, capturing weather characteristics that influence load demand. Forecasting was performed every week for each month. Figure 8 compares the actual and forecasted peak load for the four weeks of February 2022. The results in Figure 8 show that the deviation between the actual and forecasted load is minimal, with the Mean Absolute Percentage Error (MAPE) for the four weeks being 2.94%, 2.44%, 1.92%, and 2.26%, respectively. This small deviation indicates that the proposed technique is effective for short-term load forecasting (STLF). Additionally, the minor error confirms the

Table 1: data for the first week of February 2022

Day	1	2	3	4	5	6	7
Temperature (C^0)	17	16	16	18	20	19	19
Humidity (%)	64	68	70	65	63	62	70
Peak load (MW)	6921	6867	6870	6720	6960	6865	6960

significant impact of weather factors on peak load demand. The same procedure was applied to April, August, and November, with the results shown in Figures 9, 10, and 11, respectively.

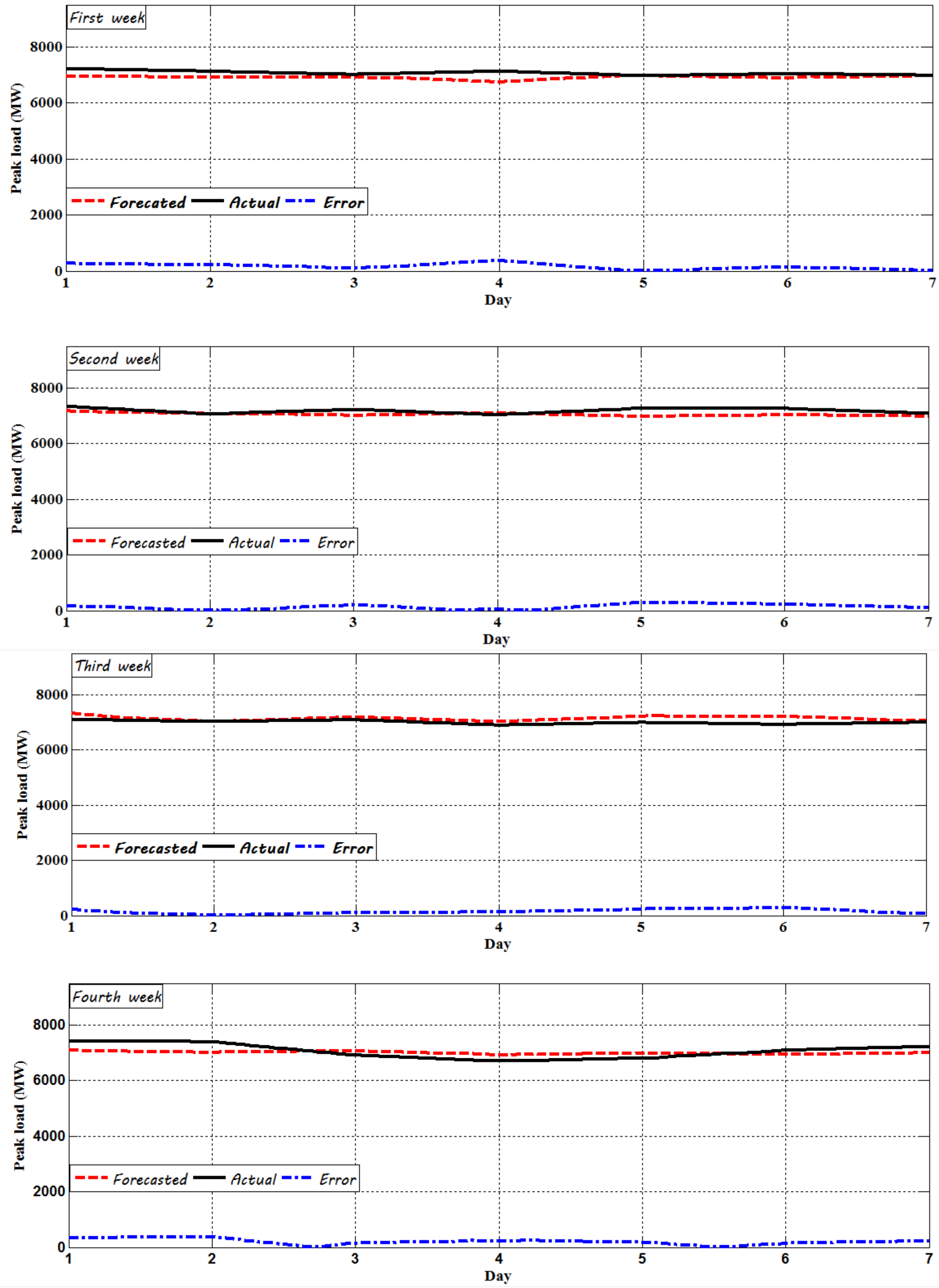

Figure 8. Actual and Expected Peak Load for 4 Weeks of February 2022

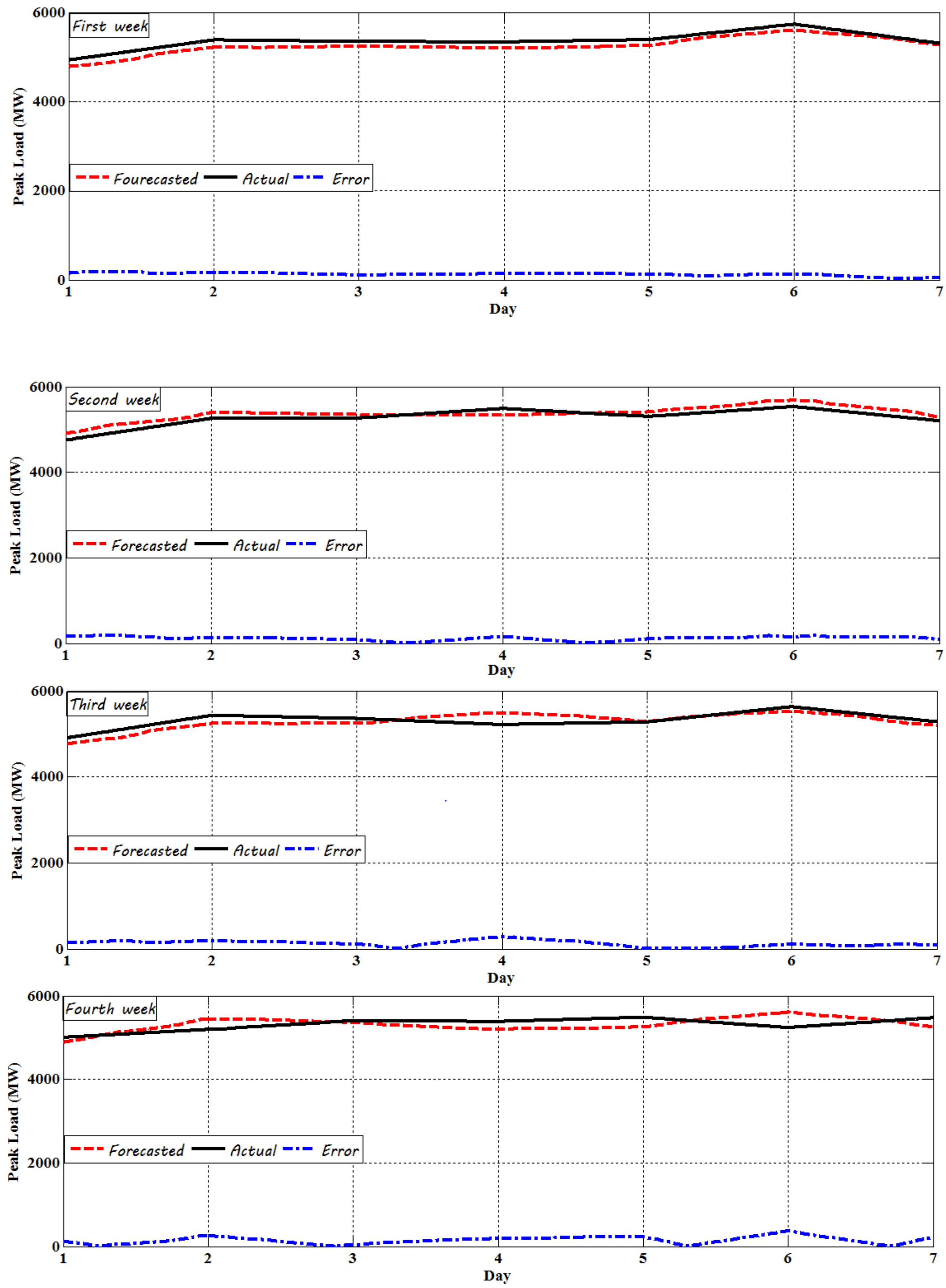

Figure 9. Actual and Expected Peak Load for 4 Weeks of April 2022

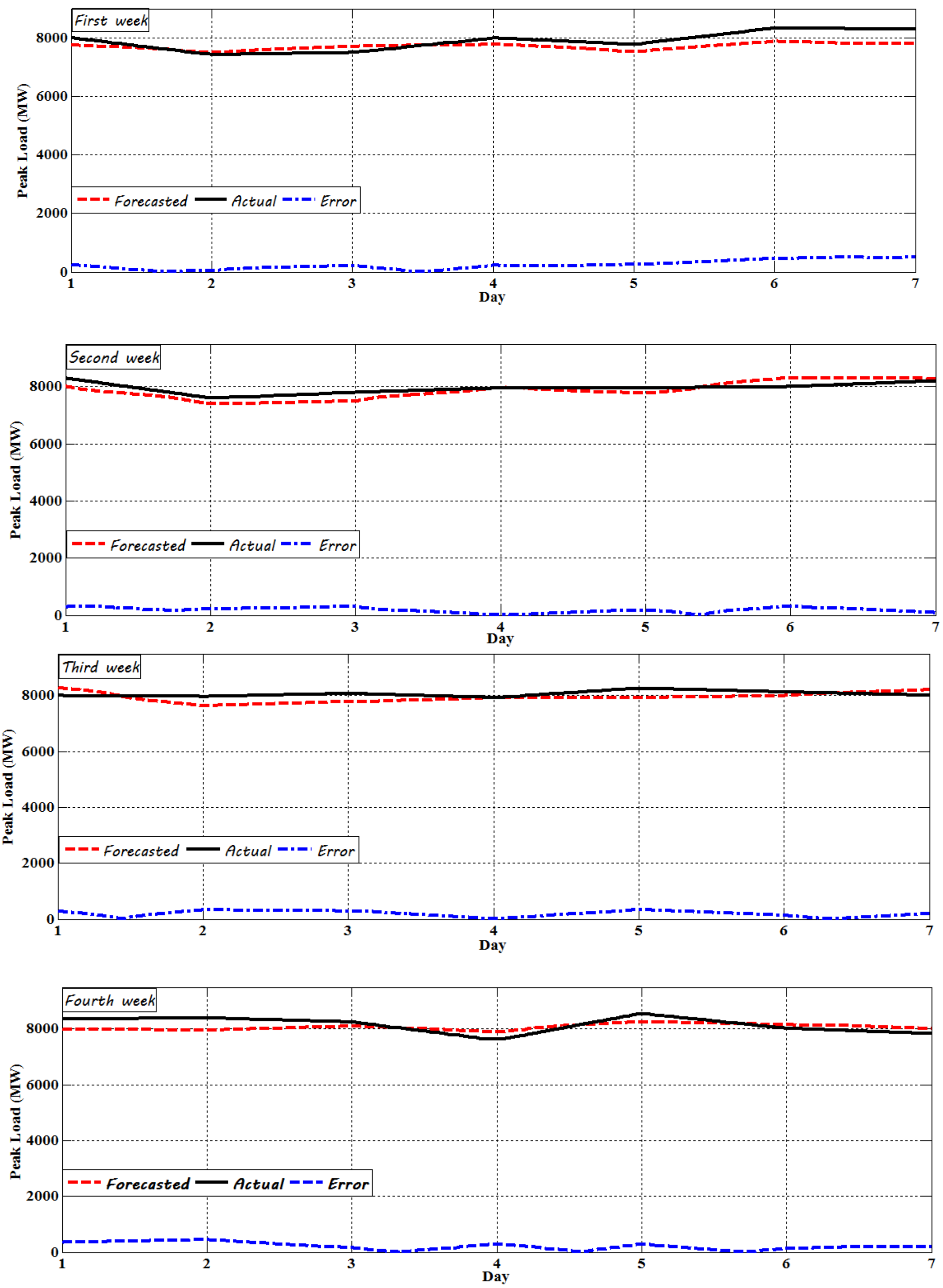

Figure 10. Actual and Expected Peak Load for 4 Weeks of August 2022

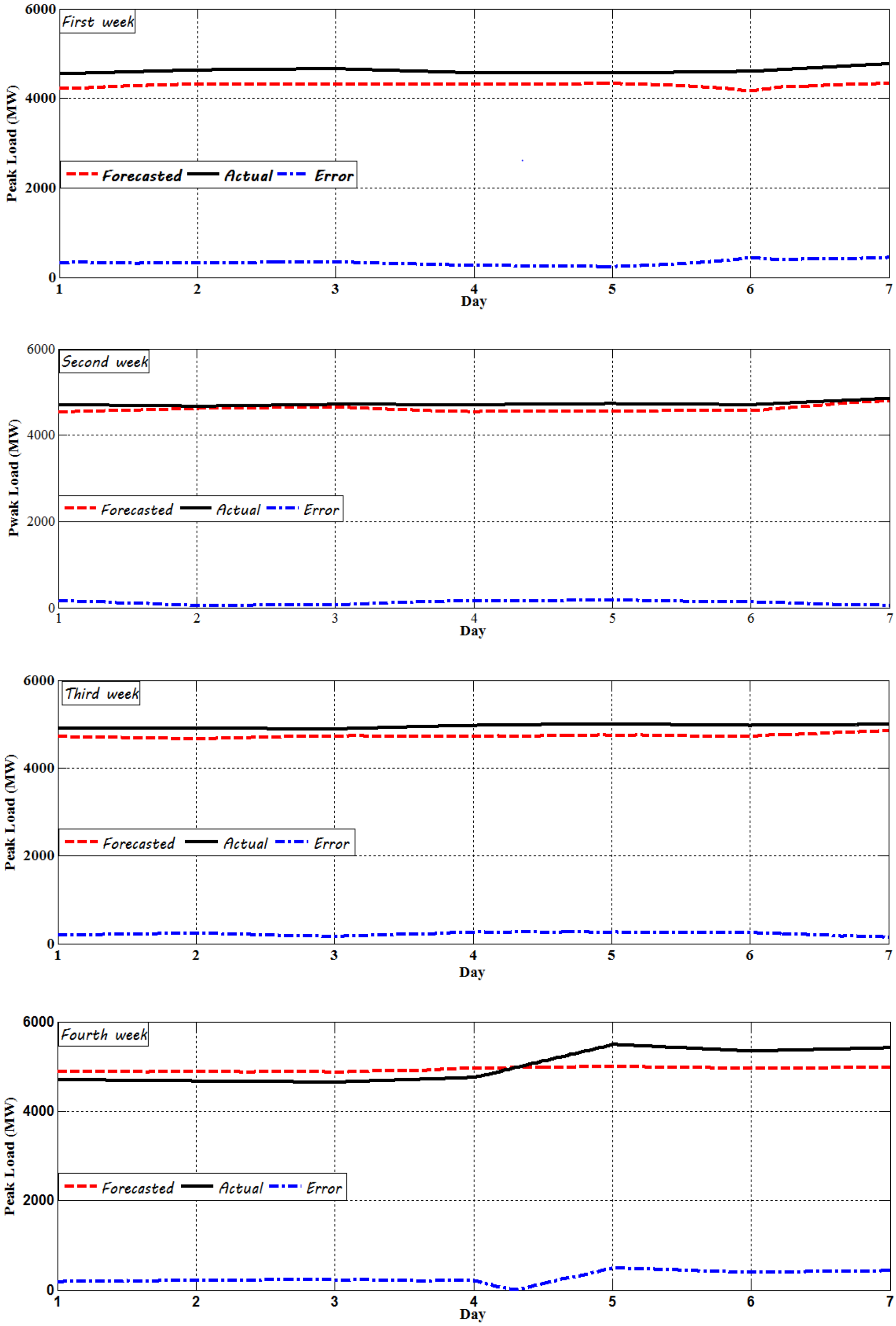

Figure 11. Actual and Expected Peak Load for 4 Weeks of November 2022

7. Conclusion

This paper presents a fuzzy logic-based approach for forecasting the daily peak electricity demand one week in advance. The input variables used for the fuzzy logic model include temperature, humidity, and the previous day's peak load. MATLAB SIMULINK was employed for designing and simulating the fuzzy logic system. The results demonstrate that weather factors significantly impact the electric system's load. The model's error margin ranges between +3.67% and -3.75%. Additionally, the study concludes that the fuzzy logic method is easy for forecasters to understand due to its use of simple "IF-THEN" statements. On the other hand, it is essential to recognize the limitations of fuzzy logic, such as the absence of formal mathematical foundations, and the inherent subjectivity in defining membership functions.

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