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A Comparative Analysis of Multi-Parameter Regression and Fuzzy Logic Models for Short-Term Load Forecasting in the Libyan Power Grid

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تحليل مقارن لنماذج الانحدار متعدد المتغيرات والمنطق الضبابي للتنبؤ قصير المدى بالأحمال في شبكة الكهرباء الليبية

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Abstract:
Short-term load forecasting (STLF) is serious to power system reliability, assistant economic operation, generation arrangement, and maintenance planning through precise demand estimates. This paper compares Multi-Parameter Regression (MPR) and Fuzzy Logic (FL) for guessing load on the Libyan grid. Using temperature, humidity, and old peak loads as input variables, the MPR model applies statistical regression to create a linear relationship, while the FL model uses fuzzy rules to report nonlinearities and uncertainty. Both models are trained on local data, with the FL system simulated via MATLAB/Simulink. The predicting performance of both techniques was evaluated and compared using standard error indices. The results validate the efficiency of each method in short-term load forecast and offer insights into their relative accuracy, flexibility, and suitability for use in the Libyan electric network.

Keywords: short-Term Load Forecasting, Multi-Parameter Regression, Fuzzy Logic, Libyan Electric Grid

الملخص
يُعدّ التنبؤ قصير الأجل بالأحمال الكهربائية عنصرًا أساسيًا لضمان موثوقية أنظمة القدرة الكهربائية، إذ يدعم التشغيل الاقتصادي للشبكة، وجدولة التوليد، والتخطيط لأعمال الصيانة من خلال توفير تنبؤات دقيقة بالطلب على الطاقة الكهربائية. تهدف هذه الدراسة إلى إجراء مقارنة بين نموذج الانحدار متعدد المتغيرات ونموذج المنطق الضبابي، للتنبؤ بالأحمال الكهربائية في الشبكة الكهربائية الليبية. يعتمد نموذج الانحدار متعدد المتغيرات على استخدام درجة الحرارة، والرطوبة، وقيم الأحمال القصوى التاريخية كمتغيرات إدخال لتكوين علاقة خطية باستخدام أسلوب الانحدار الإحصائي، في حين يستخدم نموذج المنطق الضبابي قواعد ضبابية لمعالجة العلاقات غير الخطية وحالات عدم اليقين المرتبطة ببيانات الأحمال. وقد تم تدريب كلا النموذجين باستخدام بيانات محلية، كما جرت محاكاة نظام المنطق الضبابي باستخدام برنامج الماتلاب وتم تقييم أداء التنبؤ لكلا الطريقتين ومقارنتهما باستخدام مؤشرات الخطأ القياسية. وأظهرت النتائج فعالية كلٍ من النموذجين في التنبؤ قصير الأجل بالأحمال الكهربائية، مع تقديم رؤى واضحة حول الدقة النسبية، والمرونة، ومدى ملائمة كل منهما للتطبيق في الشبكة الكهربائية الليبية.

الكلمات المفتاحية: التنبؤ قصير المدى بالأحمال الكهربائية، الانحدار متعدد المتغيرات، المنطق الضبابي، الشبكة الكهربائية الليبية.

Introduction

Forecasting contains assessing coming events via analyzing past data and key effecting variables. In the Energy area, electric load predicting is essential to the cost-effective operation and reliable of electrical systems, making choices associated to generation planning, load controlling, maintenance arrangement, and long-term structure investment [1]. Based on the guess limit, load guessing is normally divided into three categories: short-term (STLF), medium-term (MTLF), and long-term (LTLF). STLF, which ranges from one hour to one week ahead, supports system security, economic dispatch, and unit commitment. MTLF, covering one month to one year, helps power purchase contracts, and operational scheduling, while LTLF, ranging beyond one year, informs strategy formulation, and capacity growth [2]. As power systems raise more complex and electricity markets become gradually deregulated, the want for true STLF has increased. High precision in guessing straight moderates operational prices, bolsters reliability, and expands general energy controlling. But, the task remains integrally hard due to the complex and often nonlinear impact of climate factors such as temperature and humidity [3, 4].

A large variety of statistical and intelligence techniques have been proposed for STLF. Statistical approaches normally involve linear and nonlinear regression analyses [5-10], while intelligent approaches are usually divided into two groups: Artificial Neural Networks (ANN) [11–15] and fuzzy logic systems [16–21]. Although these advancements, only a few efforts have focused on increasing load predicting accuracy for the Libyan power grid [8, 10, 16, 22, 23]. The unique characteristics of electricity consumption forms and weather circumstances in Libya require the advance of guessing approaches tailored to the local atmosphere. Consequently, this work compares two generally used predicting methods: Multi-Parameter Regression (MPR) and Fuzzy Logic (FL). Both models use key input variables touching electricity demand, with temperature, humidity, and old load data. The MPR model forms a statistical relationship between daily electric peak load demand and its influencing factors, while the FL model employs fuzzy inference rules to arrest nonlinear and uncertain system performance.

Key Influences on Load Demand

Several numbers of factors affect the load demand considerably. The impacts of all these factors which affect the load need to be studied in order to develop an accurate load forecasting model. Many economic factors such as the type of customers such as residential, agricultural, commercial and industrial, demographic conditions, population, per capita income, growth, national economic growth (GDP), and social activities etc. can cause a considerable change in the load pattern. These economic factors mainly affect the long and medium-term load forecasting. On the other hand, STLF is greatly affected by weather conditions such as temperature (dry bulb and wet bulb temperature), humidity, cloud coverage etc. The most important weather factor is the temperature. The changes considerably affect the load requirement for heating in winter and air conditioning in summer. STLF also affected by other factors such as humidity especially in hot and humid areas, precipitation, thunderstorms, wind speed and light intensity of the day. In addition, time and seasonal factors play an important role in forming load pattern. Moreover, load pattern might be varied by random disturbances that occur in the power system. The random disturbances include sudden shutdown or start of industries, wide spread strikes, marriages, special functions etc [2, 16].

Multi Parameter Regression

Multi parameter regression (MPR) method is one of the most widely used statistical techniques for short-term and medium-term load forecasting. It measures the impact of multi-independent variable over one dependent variable. In STLF, the MPR is generally used to model the relationship between load consumption and factors affecting load consumption such as weather that include temperature, humidity and wind speed [10]. The original MPR model, which includes the number of n independent variables, can be expressed by the following equation [8, 10].

$$y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \cdots + \beta_k X_{ki} + U_i \qquad (1)$$

$$y_i = \beta_0 + \sum_{j=1}^{k} \beta_j X_{ji} + U_i \qquad (2)$$

Where y_i is the dependent variable, $\beta_0, \beta_2, \dots, \beta_k$ are the regression coefficients, $X_{1i}, X_{2i}, X_{3i}, \dots, X_{ki}$ are the independent variables, and U_i is the random error that reflecting the difference between the observed and fitted linear relationship.
Equation (2) is the general form of the single following equations:

$$y_1 = \beta_0 + \beta_1 X_{11} + \beta_2 X_{21} + \cdots + \beta_k X_{k1} + U_1$$

$$y_2 = \beta_0 + \beta_1 X_{12} + \beta_2 X_{22} + \cdots + \beta_k X_{k2} + U_2 \qquad (3)$$

$$y_3 = \beta_0 + \beta_1 X_{13} + \beta_2 X_{23} + \cdots + \beta_k X_{k3} + U_3$$

$$y_N = \beta_0 + \beta_1 X_{1N} + \beta_2 X_{2N} + \cdots + \beta_k X_{kN} + U_N$$

Equations shown in (3) can be represented in matrix form as following:

$$\begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ . \\ . \\ . \\ y_N \end{bmatrix} = \begin{bmatrix} 1 & X_{11} & X_{21} & . & X_{K1} \\ 1 & X_{12} & X_{22} & . & X_{K2} \\ 1 & X_{13} & X_{23} & . & X_{K3} \\ . & . & . & . & . \\ . & . & . & . & . \\ . & . & . & . & . \\ 1 & X_{1N} & X_{2N} & . & X_{KN} \end{bmatrix} * \begin{bmatrix} \beta_0 \\ \beta_1 \\ \beta_2 \\ . \\ . \\ . \\ \beta_N \end{bmatrix} + \begin{bmatrix} U_1 \\ U_2 \\ U_3 \\ . \\ . \\ . \\ U_N \end{bmatrix} \qquad (4)$$

$$\bar{Y} = \bar{X}\beta + \bar{U} \qquad (5)$$

Where Y is a column vector of order $(N * 1)$, X is a matrix consists of the independent variables, β is a column vector of order $[1 * (1 + P)]$ consists of the unknown regression coefficients, and U is a column vector of order a $(N * 1)$ consists of the random variable values.
Considering the relationship of predictive variables are:

$$\mathrm{y}_\mathrm{i}' = b_0 + b_1 X_{1i} + b_2 X_{2i} + \cdots + b_p X_{pi} + e_i \qquad (6)$$

Where $\mathrm{y}_\mathrm{i}'$is the expected value for the dependent variables, $b_0, b_1, b_2, \dots, b_p$ are the value of $\beta_0, \beta_1, \beta_2, \dots, \beta_p$ respectively, and e_i is the difference between the real value and the expected value.
Least squares method can be used to estimate the MPR model coefficients as following [22]:

$$Y = Xb + e \quad (7)$$

$$e = Y - Xb \quad (8)$$

$$e^T e = (Y - Xb)^T \ (Y - Xb) \quad (9)$$

$$e^T e = Y^T Y - 2b^T X^T Y + b^T X^T X b \quad (10)$$

By partial differentiation of Equation (10) and equating by zero, gives:

$$\frac{\partial}{\partial b}(e^T e) = -2X^T Y + 2X^T X b = 0 \quad (11)$$

$$(X^T X)b = X^T Y \quad (12)$$

Multiplying equation (12) in $(X^T X)^{-1}$

$$(X^T X)^{-1}(X^T X)b = (X^T X)^{-1} X^T Y \quad (13)$$

$$b = (X^T X)^{-1} X^T Y \quad (14)$$

Where b is the regression coefficient to be found.

Application of STLF Model on the Libyan Electric Network

The MPR model will be applied to the peak load of the Libyan electric network using climate data. Prior to application, however, the model need to be confirmed via old data. For this target, daily peak load and matching climate records were gathered for the year 2022. The offered method includes developing a regression model using data from the first week of August 2022 to characterize the relationship between daily peak load (y_i) and two climate variables: temperature (T) and humidity (H). This resulting model is then applied to the second week of August 2022, using the forecasted temperature and humidity for that week to estimate daily peak loads. The old data for the first week of August 2022 including daily peak load and the related climate factors are existing in Table 1.

Table 1 Data for the first week of August 2022 [25].

Day	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Peak Load (MW)	8010	7426	7500	8000	7779	8338	8295
T (C^0)	32	32	32	32	33	33	33
H (%)	72	74	70	70	72	72	68

Based on Equation (1), the regression model incorporating two independent variables and one dependent variable can be expressed as follows:

$$y_i = \beta_0 + \beta_1 T + \beta_2 H \quad (15)$$

In matrix form, the equations are written as:

$$\begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ y_4 \\ y_5 \\ y_6 \\ y_7 \end{bmatrix} = \begin{bmatrix} 1 & T_1 & H_1 \\ 1 & T_2 & H_2 \\ 1 & T_3 & H_3 \\ 1 & T_4 & H_4 \\ 1 & T_5 & H_5 \\ 1 & T_6 & H_6 \\ 1 & T_7 & H_7 \end{bmatrix} * \begin{bmatrix} \beta_0 \\ \beta_1 \\ \beta_2 \end{bmatrix} \tag{16}$$

By substituting the observed values of y_{i}, temperature (T), and humidity (H) from Table 1 into Equation (16), the equation can be rewritten as follows:

$$\begin{bmatrix} 8010 \\ 7426 \\ 7500 \\ 8000 \\ 7779 \\ 8338 \\ 8295 \end{bmatrix} = \begin{bmatrix} 1 & 32 & 72 \\ 1 & 32 & 74 \\ 1 & 32 & 70 \\ 1 & 32 & 70 \\ 1 & 32 & 72 \\ 1 & 32 & 72 \\ 1 & 32 & 68 \end{bmatrix} * \begin{bmatrix} \beta_0 \\ \beta_1 \\ \beta_2 \end{bmatrix} \tag{17}$$

By using MATLAB, β_0 , β_1, β_2 are found as:
$\beta_0 = 765.7, \beta_1 = -60.49, \beta_2 = 352.9$
Based on the analysis, the regression model established for the first week of August 2022 is expressed as follows:

$$Y_F = 765.7 - 60.49\, H_F + 352.9 T_F \tag{18}$$

As the forecasted weather data can be obtained, the forecasted peak load for the second week of the same month can be estimated by substituting the forecasted weather data, which is given in table 2, in the regression model in (18).
Once the forecasted weather data are available, the peak load for the second week of August can be estimated by substituting the expected temperature and humidity values provided in Table 2 into the regression model given by Equation (18).

Table 2 Forecasted data for the second week of August 2022

Day	**1**	**2**	**3**	**4**	**5**	**6**	**7**
T (C^0)	33	32	32	32	32	32	33
H (%)	73	80	77	75	73	71	65

To validate the proposed approach, the Mean Absolute Percentage Error (MAPE) is computed as follows [10]:

$$MAPE = \frac{100}{n} \sum \left| \frac{Actual\ load - Expected\ \ load}{Actual\ load} \right| \tag{19}$$

Where n is the forecasted period.

The procedure applied to the second week of August 2022 can be repeated sequentially for the remaining weeks of the same month using the second week's model to forecast the third week, the third week's model for the fourth week, and so forth. The proposed method is validated using one representative month from each season.

Typical Fuzzy Logic System

A fuzzy logic (FL) is an intelligent control pattern, which accommodates estimated rather than precise reasoning. Established for managing data-driven systems, it permits values to be understood as partially true or false, rather than in binary terms. Its inherent ease has funded to its growing adoption in data-centric applications. The FLC operates through the design of fuzzy sets and rule-based inference. In contrast to classical set theory, where membership is absolute, fuzzy set theory permits for degrees of membership, thereby contribution greater flexibility and nuanced control capabilities [16].

A fuzzy set is characterized by gradual, rather than binary, membership. A conventional fuzzy logic (FL) is combine of four essential stages: fuzzification, a fuzzy rule base, a fuzzy inference engine, and defuzzification. In the fuzzification phase, numerical input and output variables are translated into linguistic labels such as low, medium, or high with their respective membership degrees determined with membership functions. The inference engine then processes these membership values in accordance via a predefined set of fuzzy rules. Lastly, defuzzification changes the linguistic inference results into crisp, numerical outputs by the rule base, rendering them actionable for real-world applications [16, 20]. The typical fuzzy logic system is depicted in Figure 1.

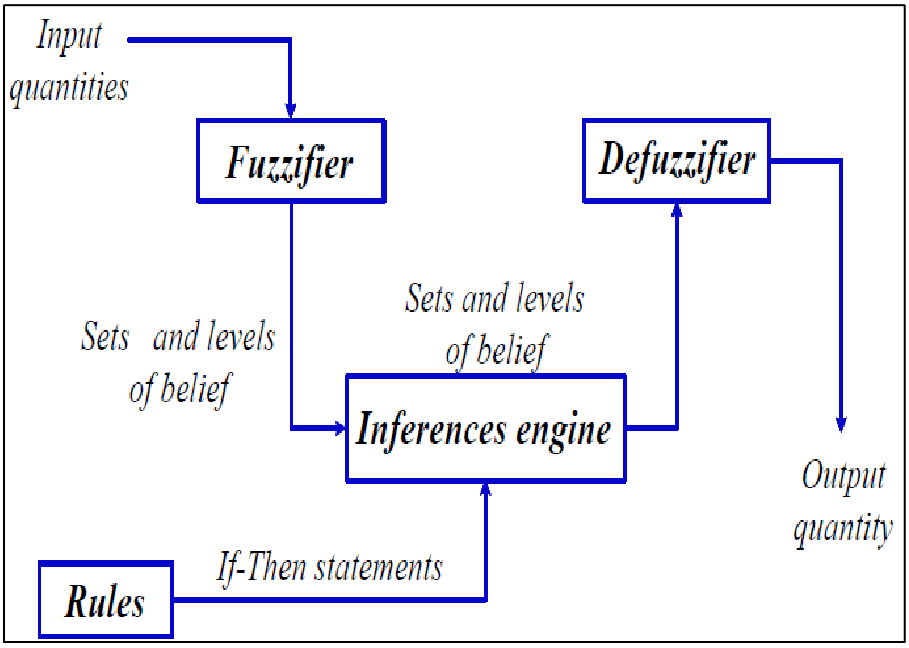


Figure 1. Block diagram for a typical fuzzy logic system

Fuzzy Logic System for Short-Term Load Forecasting

A. Fuzzification

Fuzzification is the method of changing crisp numerical values into degrees of membership within designated fuzzy sets. A membership function (MF) plots a precise input value to its matching degree of membership in the represented fuzzy set. In this work, Gaussian membership functions are used for both input and output variables, with humidity and temperature chosen as inputs for the STLF model. The fuzzy logic construction is designed according to the inference block diagram offered in Figure 1. As displayed in Figure 2, the model incorporates humidity, temperature, and historical peak load as inputs, and outputs the predicted peak load [16].

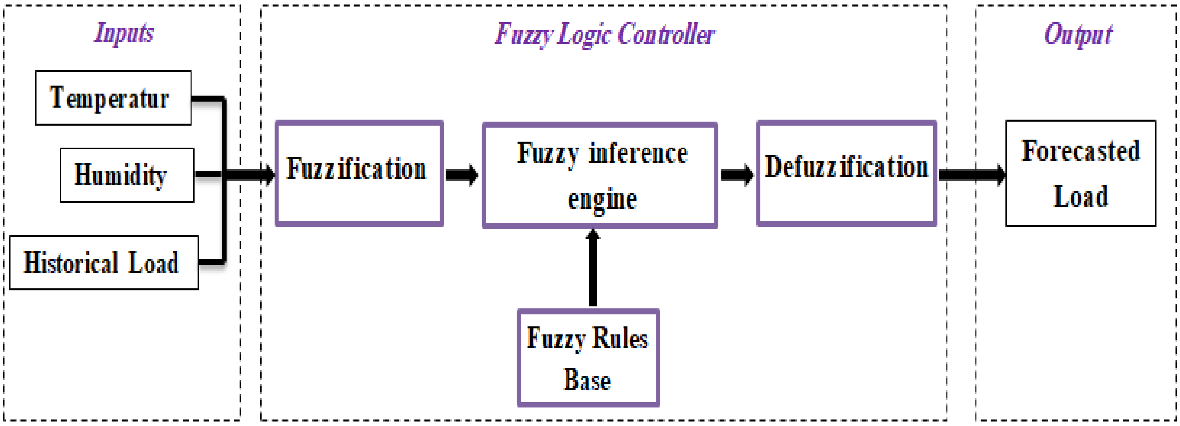


Figure 2. Block diagram of the proposed FL model

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

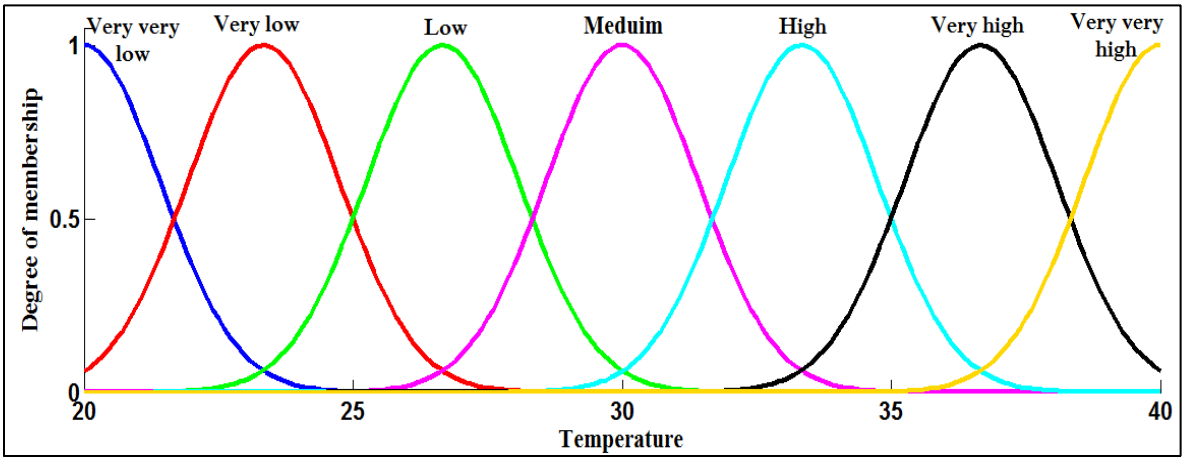


Figure 3. Membership function for temperature

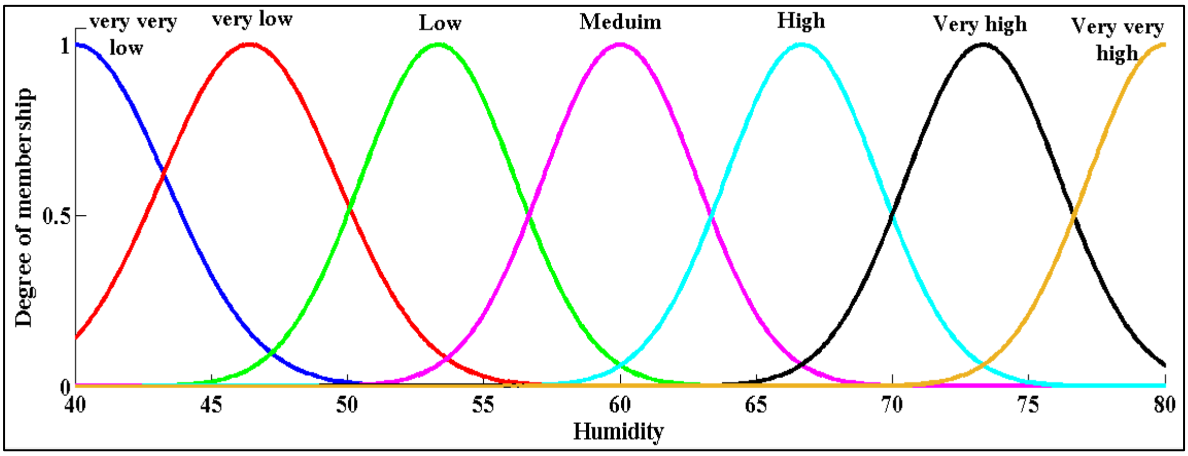


Figure 4. Membership function for humidity

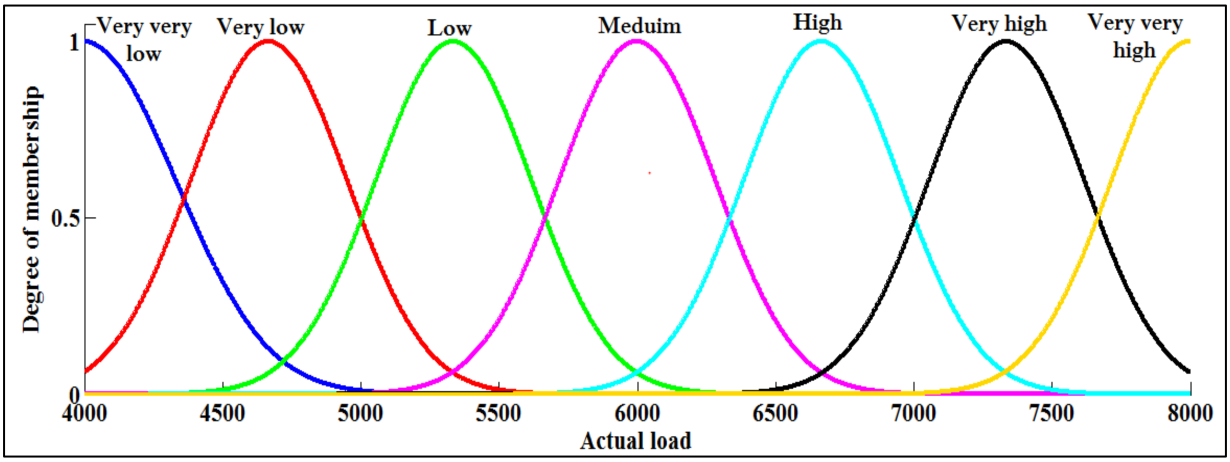


Figure 5. Membership function for peak load

B. Fuzzy Rule Base for Load Forecasting

This part creates the central of the fuzzy logic system, encapsulating the heuristic information of the guessing procedure through IF-AND-THEN rules. These rules are treated by the fuzzy inference engine, which calculates the input variables to produce the guessed load. In this work, a total of 343 rules were expressed, a selection of which is presented below. Illustrative examples include:

- 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).

Results and discussion

The comparative work of the MPR and FL procedures for short-term load guessing in the Libyan electric network was considered using four months of actual data from the year 2022. The dataset involved old daily peak loads and matching temperature and humidity, chosen to represent one month from each season. Guessing was made separately for each week of each month. The comparative study tells notable changes between the two models in terms of analytical accuracy, adaptability, and practical appropriateness. Likewise, the guessing performance of both procedures shown substantial seasonal difference, underscoring the impact of climatic circumstances on electricity consumption forms.

February 2022 Results

As can be seen of Figure 6 that during the February 2022 (winter months), the FL approach displayed consistently greater performance compared to the MPR approach thru all four weeks. The average relative errors for the FL approach ranged from 0.57% to 3.80%, while the MPR approach errors ranged from 2.31% to 17.82%. This significant difference recommends that the FL model's ability to handle nonlinear relationships and linguistic uncertainty offers a distinct advantage when guessing load during periods of high heating demand and variable climate conditions.

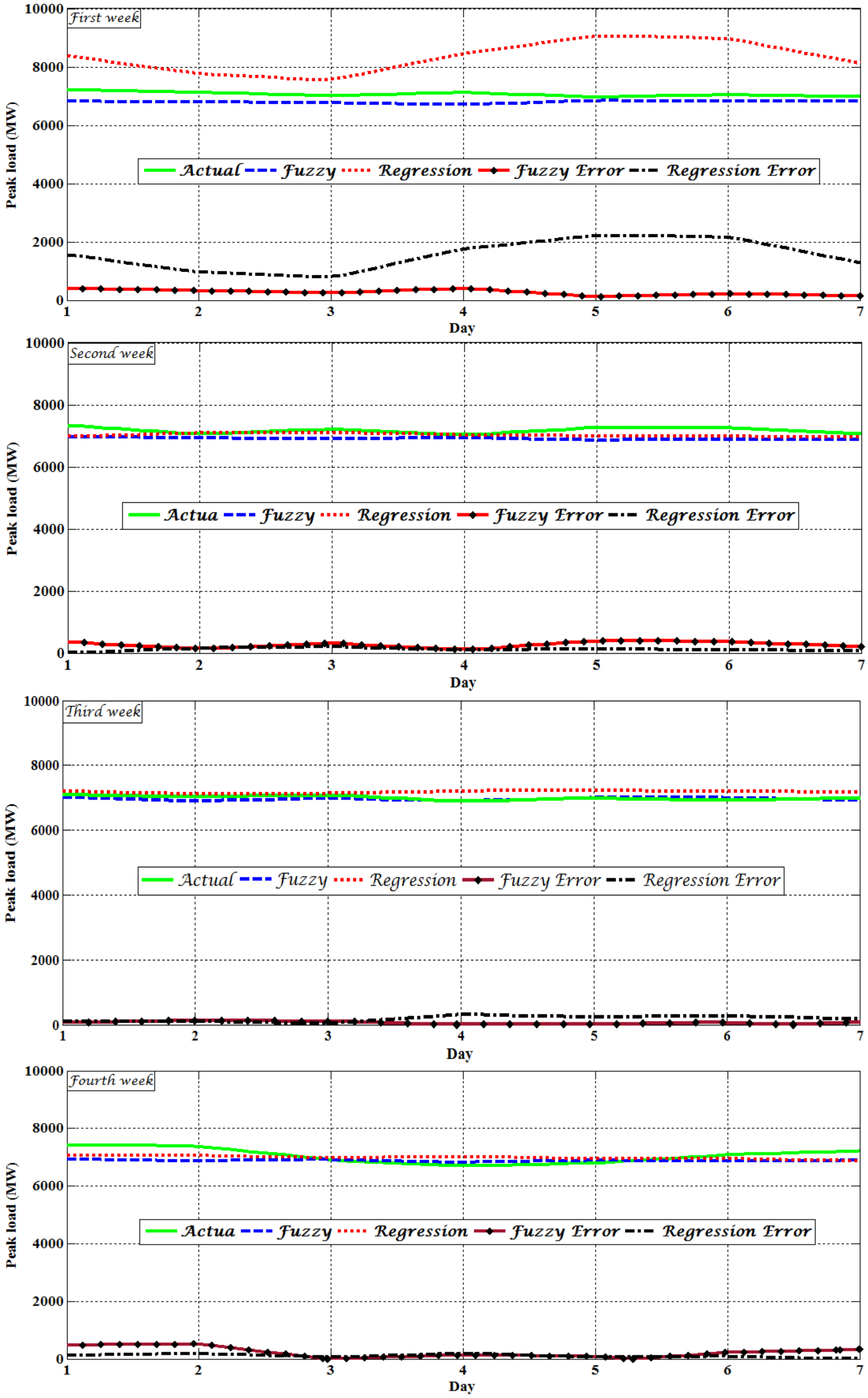
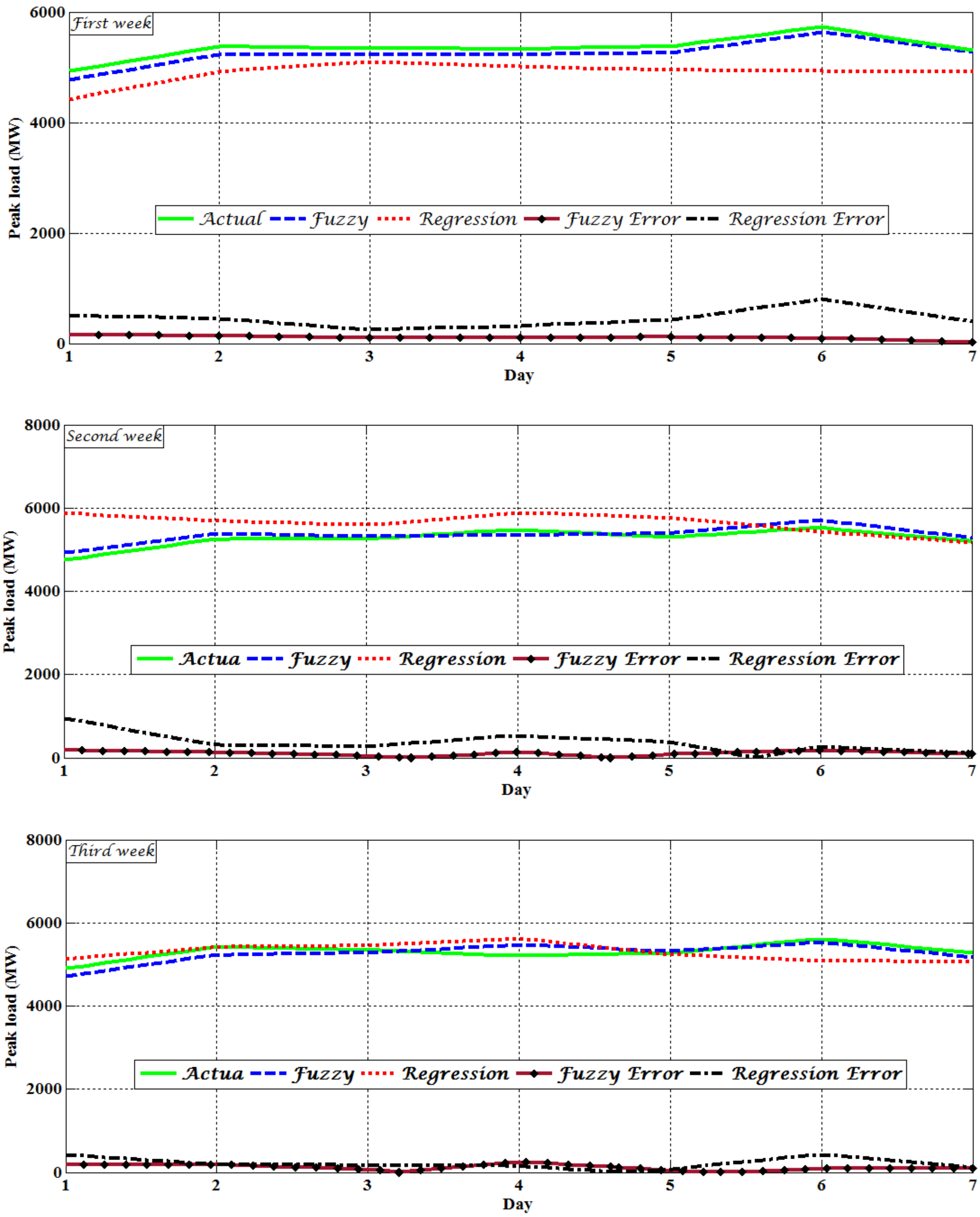


Figure 6. Actual and forecasted Peak Load for 4 Weeks of the Month of February 2022 by FL and MPR

April 2022 Results

As explained in Figure 7, both guessing techniques done higher accuracy during the April 22 (spring season), both techniques displayed enhanced accuracy relative to their winter performance, with the FL method keeping its advantage. The average relative errors for FL ranged from 0.58% to 2.00%, compared to 1.91% to 8.41% for the MPR technique. The narrower error margin between the two methods during spring may be attributed to more reasonable and stable climate conditions, which decrease the difficulty of the load climate relationship and thereby improve the performance of the simpler linear regression technique.



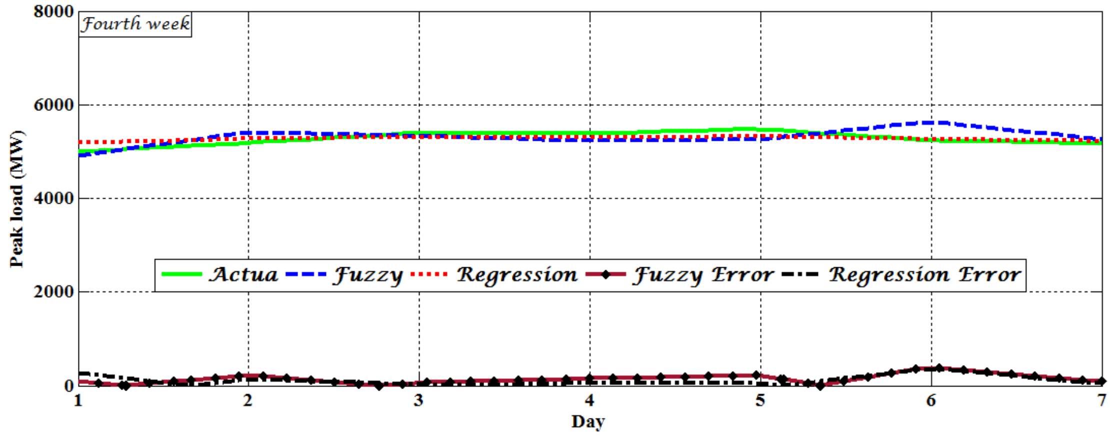
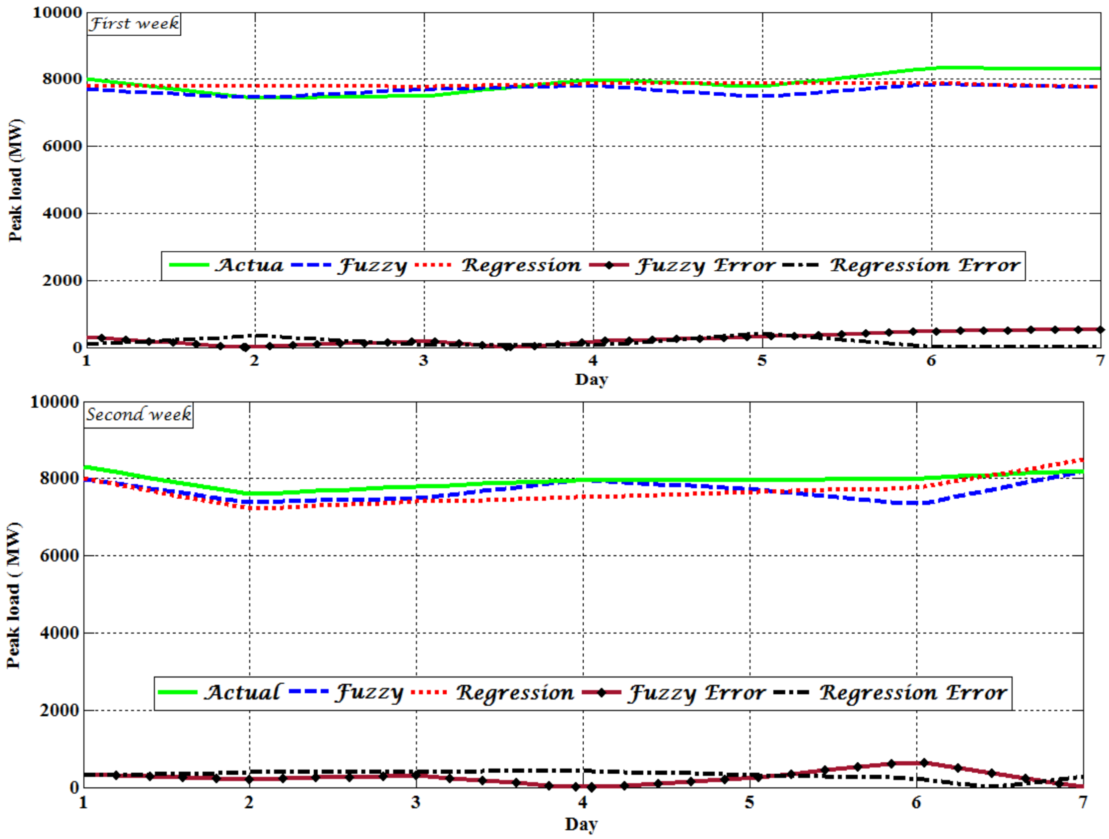


Figure 7. Actual and Forecasted Peak Load for 4 Weeks of the month of April 2022 by FL ad MPR

August 2022 Results

The August 2022 (summer season) considered the greatest demanding guessing period because of very high temperatures and high humidity levels, which lead to in substantial rises in air-conditioning demand. As can see in Figure 8, both guessing methods exhibited upper guess errors during this season, mainly in the first week when temperatures were at their highest. Despite these challenging conditions, the FL method consistently done better accuracy, with average relative errors ranging from 1.34% to 2.82%, compared with 3.46% to 4.17% for the MPR method. Although the FL method continued its superior performance, the difference in accuracy between the two methods was smaller than in the winter and spring seasons. This discovery recommends that the increased variability and uncertainty in electricity consumption under extreme summer weather conditions make accurate load guessing more challenging, thereby dropping the performance advantage of the FL method.



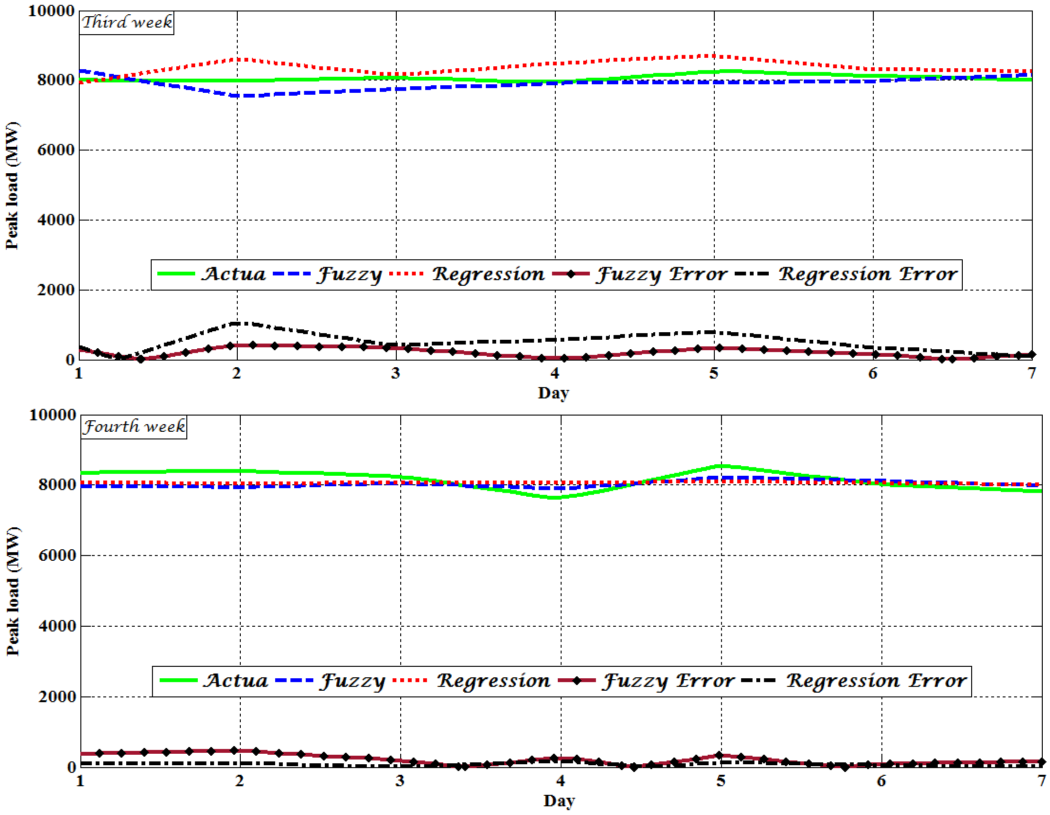
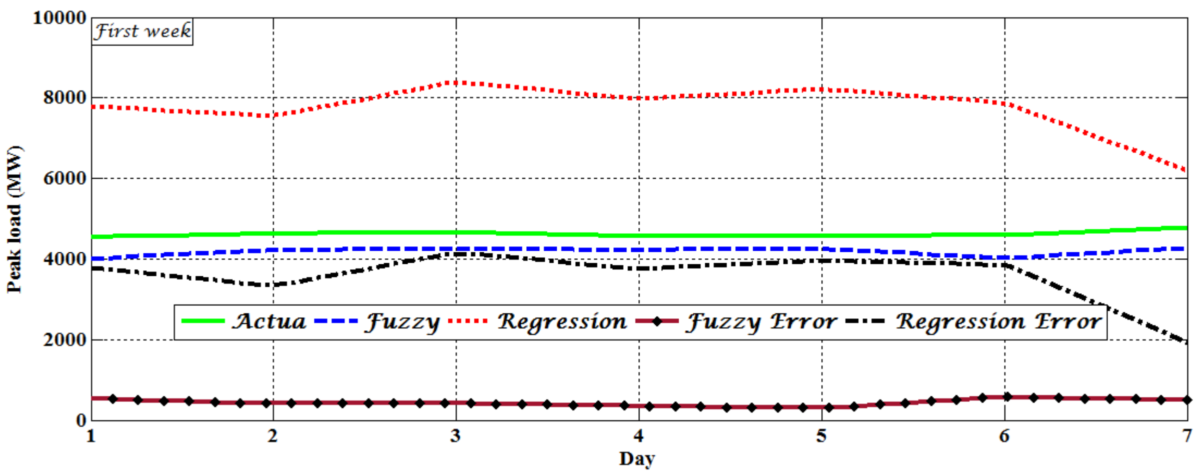


Figure 8. Actual and Forecasted Peak Load for 4 Weeks of the month of August 2022 by FL and MPR

November 2022 Results

The November 2022 (autumn season) revealed the most dramatic difference in model performance as presented in Figure 9. The MPR model exhibited exceptionally high errors during the first week, reaching 67.21% average relative error, with individual daily errors exceeding 70%. This anomalous performance coincided with a significant drop in load demand, indicating that the regression model failed to capture the transitional nature of load patterns during seasonal changeovers. The FL model, while also experiencing higher errors during this transitional period (averaging 9.52% in the first week), demonstrated substantially better adaptability, and with errors decreasing to 0.10% by the fourth week as load patterns stabilized.



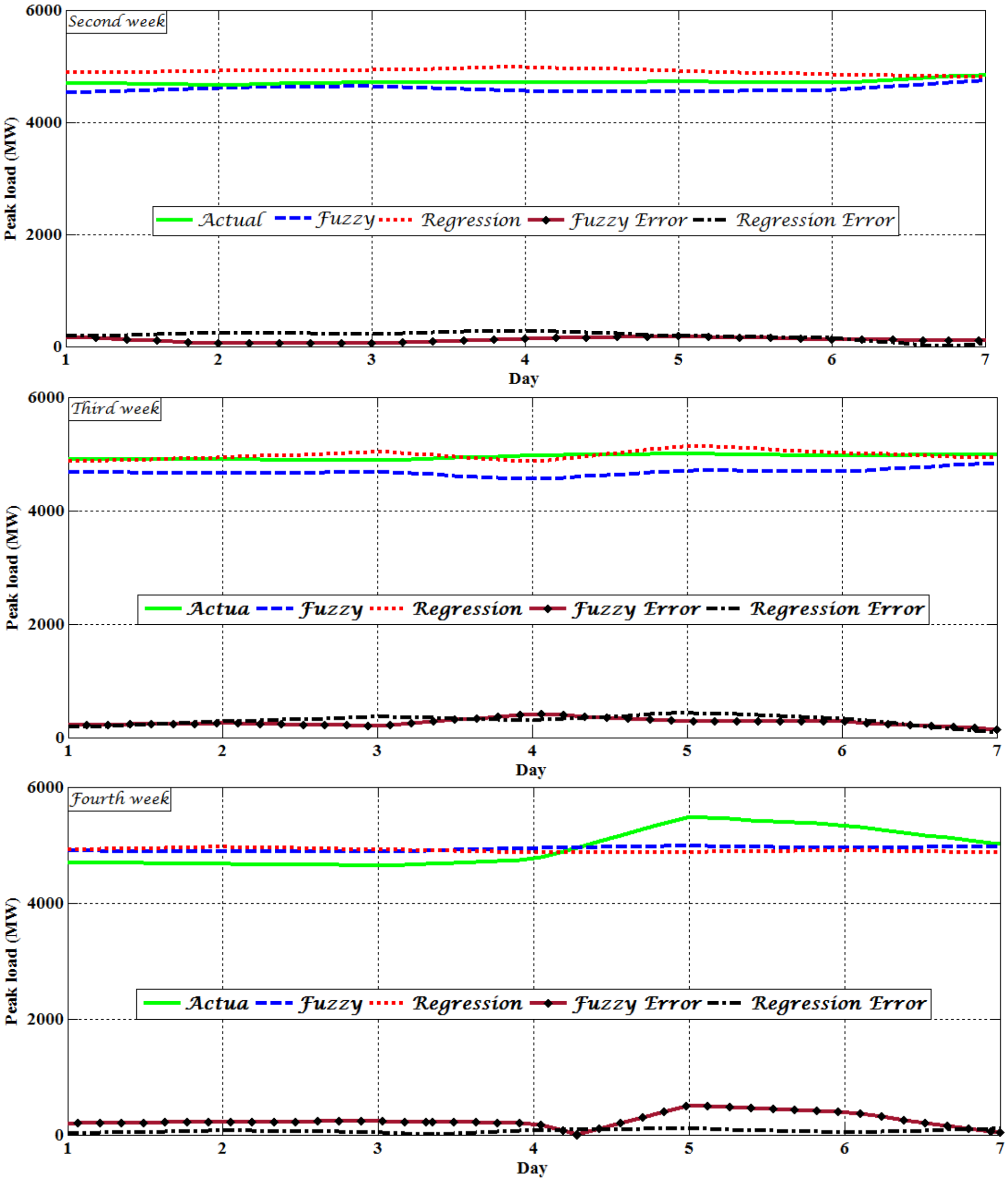


Figure 9. Actual and Forecasted Peak Load for 4 Weeks of the month of November 2022 by FL and MLR

Conclusion

In this work, a comparative study of multi-parameter regression (MPR) and fuzzy logic (FL) approaches for short-term load forecasting in the Libyan power grid is carried out, using 2022 data form all four season. The FL approach regularly overtook MPR, with errors of 0.10–9.52% versus 1.64–67.21%. The FL approach's edge was most notable in winter and transitional seasons, where nonlinear climate load relationships challenge linear regression. While simple and efficient, the MPR model fights with complex connections between temperature, humidity, and daily peak load, especially during extremes or rapid changes, limiting its operational reliability. Still, its transparency makes it useful for basic forecasts or as a benchmark. The FL model's rule-based approach and ability to handle uncertainty create it well matched for Libya's seasonal climate variability. Its steady performance supports its use as a primary guessing tool to advance scheduling, reliability, and cost efficiency, with MPR as a secondary validation option. Future research should use longer term data, include more weather variables, explore hybrid statistical intelligent methods, and develop adaptive FL systems that update automatically with new data.

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