



## OPEN Fuzzy time series for short-term residential load forecasting in smart grids

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Load forecasting is used primarily to predict future loads for a particular system over a given time period. Short-term loads are typically treated as variable elements influenced by factors such as historical load information and weather datasets, including precipitation, wind speed, and temperature. A precise forecasting with an individual model is almost impossible. The primary challenge for utility companies worldwide is accurately forecasting energy consumption. Accurate short-term load forecasting (STLF) is a cornerstone of smart grid operation, enabling demand-side management (DSM), demand response programs, and efficient integration of distributed energy resources. This study proposes a fuzzy time series (FTS)-based methodology for residential electricity consumption forecasting at hourly, daily, and weekly scales. By addressing overfitting during data partitioning and refining the fuzzification process, our approach improves prediction accuracy compared to traditional FTS models. Simulation results using real consumption data demonstrate up to 40% improvement in hourly forecasting and up to 58% and 84% improvements in daily and weekly forecasts, respectively. These results highlight the potential of FTS-based models to enhance residential demand forecasting, reduce peak-demand uncertainty, and support grid operators in achieving more resilient, flexible, and sustainable smart grid systems.

**Keywords** Smart grid, Short-term load forecasting, Fuzzy time series, Demand-side management, Residential energy consumption, Demand response, Renewable integration

The transition from conventional power networks to smart grids has introduced new challenges and opportunities in energy management. Smart grids integrate advanced communication, control, and forecasting systems to enhance reliability, efficiency, and sustainability. Within this framework, residential energy consumption accounts for a significant portion of overall demand and plays a crucial role in demand-side management (DSM) and demand response programs. Accurate short-term load forecasting (STLF) at the residential level enables utilities to balance supply and demand, reduce peak loads, optimize distributed generation, and design dynamic pricing strategies. However, forecasting residential loads remains challenging due to diverse user behaviors, seasonal variations, and nonlinear consumption patterns. To address these challenges, this study explores fuzzy time series (FTS)-based forecasting models, which are robust to uncertainty and yield higher accuracy than conventional approaches.

The residential economy industry is the world's third-largest energy consumer, encompassing all energy systems used in economic sectors, including manufacturing, transportation, domestic, and industrial sectors. Almost 21% of the entire power consumption in the U.S.A. is accounted for by the residential market<sup>1,2</sup>. Due to the rapid increase in global population, electricity demand is also projected to rise by 24% by 2035<sup>3</sup>.

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Consequently, energy sources must be properly managed to optimize their use, reduce production costs, and minimize ecological risks.

DSM is an essential means of ensuring the consistency and sustainability of energy systems while addressing environmental concerns. Dynamic DSM has not been taken into account due to diverse usage patterns, unpredictable user behavior, and limited computational skills. Various DSMs have been used, employing different techniques<sup>4</sup>. These systems used for controlling energy architecture are classified into three groups: domestic, industrial, and commercial power systems. We aim to emphasize the management of the residential energy system. Moreover, from the customer's perspective, various practices such as Load Forecasting, appliance scheduling, and a dynamic pricing system are employed to manage power flow. These techniques help optimize energy consumption, reduce peak-to-average load ratios, and lower total costs.

Load forecasting (LF) is a technique for predicting a system's future energy demand based on past weather conditions, historical data, and the availability of renewable energy sources. It is considered the initial milestone for planning utility measures. This maintains stability in the energy supply and demand. LF is primarily used to predict future loads for a given system over a specified time period. These predictions can operate for a fraction of an hour and for planning purposes for 20–50 years<sup>4</sup>. The classification of load forecasting can be categorized into the following major areas such as:

1. Short-term-based load forecasting is used to predict load profiles on a daily, weekly, and hourly basis.
2. Medium-term LF typically forecasts load for successful strategic management on a weekly, monthly, and annual basis.
3. Long-term load forecast is used to forecast load for the range of 1–50 years to support planning for development<sup>5</sup>.

A large number of research papers on accurate STLF have been published in recent years, given their impact on reliable power system operation and economic efficiency<sup>6–19</sup>. Some characteristics of fuzzy time series make them more desirable than traditional predictive methods. Firstly, both crisp and fuzzy values can be processed. However, as with mathematical prediction models, it does not require large datasets<sup>20</sup>. Traditional forecasting methods can handle only numerical data and do not address problems involving linguistic values. Conventional methods require linearity in time series, but fuzzy time series can capture nonlinear relationships between inputs and outputs.

In the literature review, many time series and neural network-based forecasting methods are introduced for accurate predictions. An algorithm for a deep neural network based on a convolutional neural network (CNN) used for short-term energy load forecasting<sup>7</sup>. The main processes in this deep Energy system consist of feature extraction and forecasting. The comparison shows that the proposed deep Energy produces the best results among all neural network algorithms, with the lowest MAPE and CV-RMSE. Moreover, it exhibits higher accuracy due to its robustness. K. Muralitharan et al.<sup>10</sup> presented an optimization approach for neural networks to predict the load consumption at the consumer end. First, a convolutional neural network (CNN) is applied to predict energy demand, and then optimization approaches, including the genetic algorithm (GA) and particle swarm optimization (PSO), are employed. In this way, we can enhance accuracy and convergence time; however, computational cost can be high, and overfitting remains a concern. Sébastien Bissey et al.<sup>11</sup> proposed a fuzzy logic algorithm for predicting short-term load consumption (STLC). The main objective of their work was to minimize electricity costs by managing peak demand. The contribution of this methodology lies in its ability to predict day-to-day residential energy consumption using fuzzy logic algorithms.

Power systems are evolving toward greater flexibility, intelligence, and interactivity through the integration of renewable energy sources. Therefore, load forecasting, especially for individual consumers, plays an important part in the management and operation of the grid. Moreover, forecasting a single user's load will be challenging due to the high uncertainty and volatility inherent in the process. Weicong Kong et al.<sup>12</sup> present a long short-term memory (LSTM) residential load model based on a recurrent neural network (RNN) to address the aforementioned problem. Jian Zheng et al.<sup>15</sup> proposed a system that presents a short-term load forecasting approach, playing a significant role in forecasting load on both hourly and weekly bases. To address this problem, the approach proposed above employs an LSTM-based RNN.

Big data analysis in load forecasting is a rapidly growing area of research. As data volumes in the power industry increase, big data analysis for load forecasting may achieve greater accuracy. Xishuang Dong et al.<sup>13</sup> proposed a model that presents a machine learning technique based on a model combining the architecture of CNN with the algorithm of K-means clustering approach to improve scalability for short-term load forecast. Hossein Javedani Sadaei et al.<sup>14</sup> proposed a methodology that combines the method of conventional neural networks with fuzzy time series for an accurate short-term load forecasting. The main contribution of their approach is to address the overfitting problem that arises in deep learning models, particularly CNNs.

In recent years, numerous fuzzy time series forecasting models have been proposed and applied to aid in economic predictions<sup>21–29</sup>. Woo-Joo Lee et al.<sup>16</sup> proposed a hybrid approach that incorporates dynamic (i.e., reliance on air temperature for energy consumption) and fuzzy time series methods to be employed in separate areas, including home, public, utility, and industrial settings. The proposed hybrid model yields better predictions compared to the Koyck and ARIMA models. Riswan Efendi et al.<sup>17</sup> proposed a new method for evaluating linguistic out-of-sample prediction using linguistic methodology with index numbers. The proposed approach is used to forecast day-to-day TNB electricity load data (240 observations). For time complexity, the computational time can be considerably reduced, achieving  $T(n) = 3n$  in  $O(n)$ . Vladimir Popov et al.<sup>18</sup> examine the use of fuzzy

time series for forecasting monthly electricity consumption. It applies in particular to Ukraine, where, currently and in the coming years, not all users are fully equipped with automatic power measurement systems.

Motivated by the growing need for accurate and computationally efficient short-term residential load forecasting in smart grid environments, this study seeks to address key limitations of existing fuzzy time series-based approaches, particularly their susceptibility to overfitting and limited adaptability across forecasting horizons. By refining the training-stage inputs of FTS models and systematically evaluating their performance at multiple temporal resolutions, the proposed methodology aims to improve forecasting reliability while maintaining low computational complexity. Within this context, the main contributions of this paper are summarized as follows:

- It introduces an overfitting-aware fuzzy time series (FTS) framework for short-term residential load forecasting by optimizing the universe of discourse, employing equal-length interval partitioning, and constructing fuzzy logic relationship groups (FLRGs) to improve model generalization.
- It develops a unified multi-horizon forecasting methodology that systematically evaluates residential electricity demand at hourly, daily, and weekly time scales, directly supporting smart grid operations such as demand response, day-ahead scheduling, and medium-term planning.
- Using real residential load data from the Polish power system, the proposed approach demonstrates substantial accuracy improvements over conventional FTS models, achieving up to 40%, 58%, and 84% error reductions for hourly, daily, and weekly forecasts, respectively.
- It provides a rigorous comparative evaluation of multiple FTS variants, showing that transformation FTS is most effective for hourly forecasting, while high-order FTS consistently outperforms others for daily and weekly horizons, offering clear guidance for model selection in smart grid applications.

### Fuzzy time series

A time series is typically a sequence of numbers collected periodically over time. The analysis of time series requires techniques for extracting meaningful statistics and other features from data<sup>30</sup>. Time series predictions accurately forecast future values based on previously observed data.

Fuzzy set theory is widely used across disciplines, including decision-making, strategy, hypothesis testing, systems, artificial intelligence, economics, and control, among others<sup>19</sup>. The Fuzzy Time Series (FTS) integrates the principles of fuzzy sets into time-series analysis. The benefits of adopting a systematic, efficient, and quantitative approach to address the vagueness inherent in human knowledge support the use of fuzzy sets rather than crisp ones.

This section describes the proposed algorithm of fuzzy time series, which comprises of following steps as shown below:

Step 1: Defining the universe of discourse, i.e.,  $U$  for the whole dataset of three years from the Polish power system, using the (1):

$$U = [D(\min) - D_1; D(\max) + D_2] \quad (1)$$

Here,  $D_{\min}$  and  $D_{\max}$  represent the minimum and maximum values across our entire time-series dataset. At the same time,  $D_1$  and  $D_2$  are positive numbers used to smooth the upper and lower boundaries of the consumption profile.

Step 2: Data partition for the entire universe into equal-sized length of intervals as shown in (2):

$$U = [u_1, u_2, u_3, \dots] \quad (2)$$

Here

$$u_1 = [d_1; d_2] ; \quad u_2 = [d_2; d_3] \dots \dots .u_m = [d_m; d_{m+1}]$$

Where

$$\begin{aligned} d_1 &= D_{\min} - D_1 \\ d_{m+1} &= D_{\max} + D_2 \end{aligned}$$

Step 3: Defining fuzzy sets on each interval of our universe based on (3):

$$A_i = \sum_{j=1}^n \frac{k_j}{u_j} \quad (3)$$

If  $j=i-1$ , then  $k_j=0.5$ ; If  $j=i$ , then  $k_j=1$ .

If  $j=i+1$ , then  $k_j=0.5$ ; else  $k_j=0$ .

Step 4: Fuzzification of the historical data. Fuzzify the whole consumption profile by introducing the equation of delta on which we give membership values to our data from 0 to 1, as given in (4)

$$\Delta_u = U(2,1) - U(1,1) \quad (4)$$

$$\Delta = \left| D(m) - \frac{\Delta_u}{2} \right|$$

Step 5: Making of the fuzzy logic relationship (FLR) between the previous state and current state of each fuzzy set based on the fuzzification matrix. FLR is represented as  $A_i \rightarrow A_j$ .

Step 6: Creating the fuzzy logic relationship groups (FLRGs) based on the principle that if the states are of a higher model, the same left-hand sides (LHS) of FLR are grouped to reduce the recurrence of former states in FLR. For example,

$$A_i \rightarrow A_k, A_i \rightarrow A_j, A_i \rightarrow A_n$$

These states can be grouped as:

$$A_j, A_k, A_n \rightarrow A_i$$

Step 7: Forecast load values based on fuzzified FLR data, using the characteristics of each forecasting model.

## Forecasting models of Fts

In this section, different FTS models are discussed and implemented in MATLAB R2018a.

### Chen's model FTS

The proposed model's algorithm employs simple arithmetic operations to forecast hourly load values<sup>21</sup>. The basic equation to find the forecasted time series is measured by finding the midpoints of intervals corresponding to each fuzzy set, i.e.,

$$F(t) = [M_1, M_2, \dots, M_i] \quad (5)$$

### Yu's weighted model FTS

The proposed algorithm builds on the previous model presented by Chen. This model emphasizes fuzzy sets, which recur in their respective consumption profiles. So, weights are assigned to each fuzzy set depending upon their occurrence in the FLR matrix<sup>22,23</sup>.

Finding the weights according to (6)

$$W_t = \left[ \frac{w_1}{\sum_{h=1}^k w_h}, \frac{w_2}{\sum_{h=1}^k w_h}, \dots, \dots, \frac{w_k}{\sum_{h=1}^k w_h} \right] \quad (6)$$

The forecasted time-series values are calculated using (7).

$$F(t) = [M_1, M_2, \dots, M_i] * [W_1, W_2, \dots, W_i]T \quad (7)$$

### Exponential model FTS.

The proposed Exponential model improves on the concept of assigning weights to the recurrent FLRs compared with the previous weighted model<sup>24,25</sup>. This model suggested that each FLR weight increases exponentially rather than assuming a linear relationship. The improved weighted equation for this model is shown in (8).

$$W_t = \left[ \frac{1}{\sum_{h=1}^k w_h}, \frac{c}{\sum_{h=1}^k w_h}, \frac{c^2}{\sum_{h=1}^k w_h}, \dots, \frac{c^{k-1}}{\sum_{h=1}^k w_h} \right] \quad (8)$$

The proposed model uses the default average value of  $c$  is 1.2, satisfying the condition  $c \geq 1$ .

### Transformation model FTS

The transformation model employs the Box-Cox transformation to normalize the data distribution<sup>26</sup>. In this transformation,  $\lambda$  is our parameter of interest because it provides the best approximation of our desired variable for the normal distribution. All values of  $\lambda$  in the range  $-5$  to  $5$  are considered for transformation to choose the optimal value for our whole time series. In this way, the proposed transformation reduces noisy effects in time series, thereby improving forecasting performance.

The algorithm for implementing Transformation FTS is described in the following steps:

Step 1: Apply the Box-Cox Transformation to the entire time series to estimate  $\lambda$  and the  $z$  vector. The formula for the Box-Cox transformation is shown in (9):

$$z_t^\lambda = \begin{cases} \frac{z_t^\lambda - 1}{\ln^\lambda(z_t)} & \lambda \neq 0 \\ \lambda = 0 \end{cases} \quad (9)$$

Where  $\lambda$  is our constraint of significance for the time series  $Z_1, Z_2, \dots, Z_N$ . The choice of optimal value of  $\lambda$  is a solution to maximize the given expression, i.e.

$$l(\lambda) = -\frac{n}{2} \ln \left[ \frac{1}{n} \sum_{t=1}^n \left( z_t^{(\lambda)} - \bar{z}^{(\lambda)} \right)^2 \right] + (\lambda + 1) \sum_{t=1}^n \ln(z_t) \quad (10)$$

Step 2: The modelling of time series using transfer function ds is defined in (11):

$$d_s = \left[ \frac{z_s^\lambda - z_{s-1}^\lambda}{z_s^\lambda} \right]_{s=2, 3, \dots, t} \quad (11)$$

Step 3: For data portioning, finding the optimal length of interval using Freedman and Diaconi's (12).

$$l = \frac{2 \text{IQR}(d_s)}{n^{1/3}} \quad (12)$$

Where IQR is the interquartile range with respect to the values in  $d_s$ , i.e.,  $\text{IQR} = Q3 - Q1$ .

Step 4: Apply Yu's Weighted FTS model to get our initial forecasted value using the vector  $\hat{d}_s$ , i.e.,

$$\hat{d}_s = [M_1, M_2, \dots, M_i]x[W_1, W_2, \dots, W_i]^T$$

Step 5: To revert our transformed data to the original scale, calculate the vector  $\hat{y}_s$  using (13)

$$\hat{d}_s = \frac{1}{1 - \hat{d}_s} \quad (13)$$

Step 6: Calculate  $\hat{z}_t^\lambda$  vector to get our originally scaled values using (14).

$$\hat{z}_t^\lambda = \hat{y}_s \times z_t^\lambda \quad (14)$$

Step 7: The Final Forecasted time series of this model is based on (15).

$$F(t) = (\lambda \hat{z}_t^\lambda + 1)^{1/\lambda} \quad (15)$$

### High order FTS model

The proposed high-order model is based on the concept of using multiple former states and their fuzzy-logic relationships (FLRs) to generate forecasts<sup>27</sup>. It is used to measure a single forecasted data value based on sequences of multiple previous fuzzy sets, rather than a single former state. This model yields high-accuracy results, making it particularly useful when analyzing seasonal and multi-seasonal time series. The forecast equation used at the high order is shown in (16).

$$F(i) = \frac{\sum_{j=1}^k M_j}{k} \quad (16)$$

### Interval FTS model

The interval FTS model focuses on allocating values within their respective intervals while accounting for forecasting uncertainty. This method extended point-based forecasting by incorporating fuzzy uncertainty to integrate fuzzy bounds into predictions<sup>28</sup>. In the forecasting procedure of interval FTS, select all FLR groups whose  $\mu_j > 0$ , then these chosen FLR groups create an interval with minimum and maximum bounds with respect to their corresponding fuzzy sets in FLR groups, as shown in (17)-(19).

$$I_u = \{I_{min}^f, I_{max}^f\} \quad (17)$$

$$I_{min}^f = \min\{A_1, A_2, \dots, A_K\} \quad (18)$$

$$I_{max}^f = \max\{A_1, A_2, \dots, A_K\} \quad (19)$$

To find the final forecasted value,  $I^f$  calculate the summation of all FLRG intervals multiplied by the associated membership value of each FLRG according to (20).

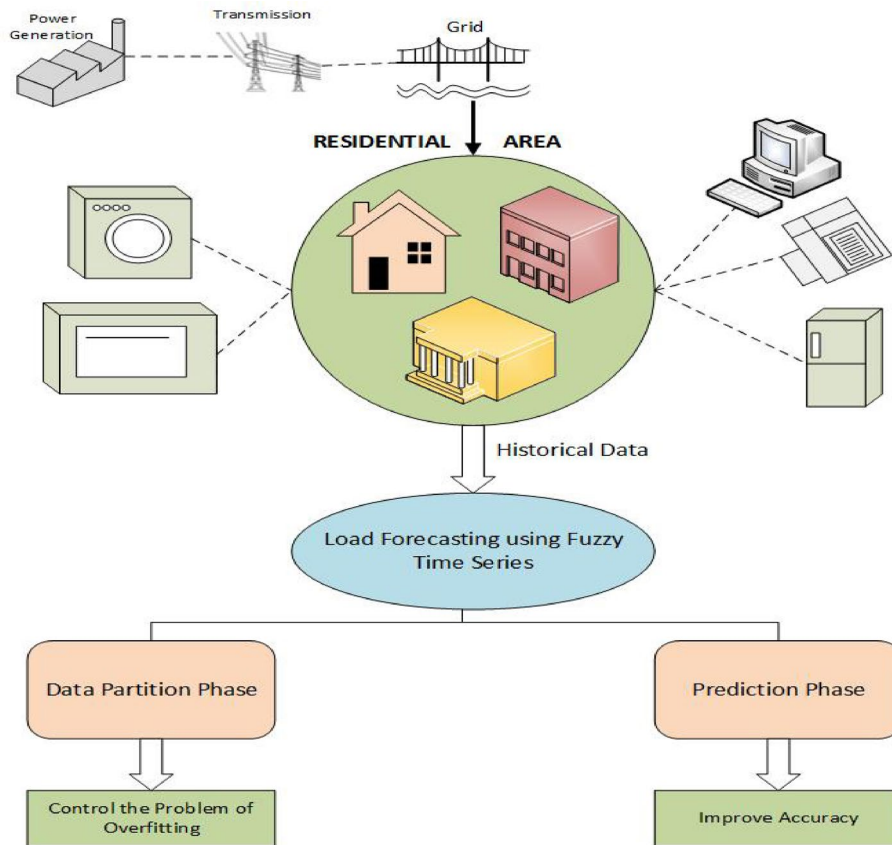
$$I_{(min, max)}^f = \frac{\sum_{j \in A} \mu_j I_j^f}{\sum_{j \in A} \mu_j} \quad (20)$$

A single point forecasted value can be generated by using an arithmetic function.

### Proposed methodology

The proposed approach involves deploying fuzzy time series for short-term load forecasting in a residential area. In this regard, this manuscript focuses on hourly, daily, and weekly forecasting of electricity consumption using historical data from the Polish Electric Power System<sup>31</sup>. Our system operates primarily in two phases: the data partition phase and the prediction phase, as shown in Fig. 1. In the data partition phase, we address overfitting by defining the universe of discourse, partitioning it into intervals, and assigning fuzzy sets to these intervals. In the next prediction phase, our proposed approach improves accuracy by identifying fuzzy-logic relationships and applying defuzzification to yield crisp outputs. In this method, we implemented a fuzzy relationship matrix to calculate fuzzy-logic relationship groups between the previous and current states of fuzzy sets.

In fuzzy time series, there are two options for improving the system methodology and enhancing its results. Firstly, model modifications include improving the basic equations, introducing higher-order sequencing,



**Fig. 1.** The overall proposed FTS-based methodology for residential smart grid load forecasting, addressing overfitting and improving prediction accuracy.

employing hybrid models, and increasing the importance of weights to address recurrence issues in fuzzy logic relationships. Secondly, the rule of thumb is that to improve model accuracy, one must improve the inputs to these models, i.e., the inputs used during training. Now there are four important training inputs are used to enhance the performance of these models that are defining universe of discourse, data partition of universe into intervals, fuzzification of past dataset and establishing the fuzzy logic relationship FLRs and fuzzy logic relationship groups FLRGs as shown in Fig. 2. In data partition phase, there are two possibilities to divide the data into number of intervals i.e., equal sized intervals and unequal size intervals. Here, we partition the data into equal-sized intervals because unequal-sized intervals can lead to overfitting due to limitations in clustering techniques, such as fuzzy c-means and k-means. Additionally, the fuzzification of time series plays a crucial role in improving forecasting performance by selecting the optimal curve and identifying the maximum membership function values.

$$d_1 = D_{min} - D_1$$

$$d_{m+1} = D_{max} + D_2$$

**Mathematical explanation**

*Optimal partitioning*

The universe of discourse is defined as.

$$U = [u_1, u_2, u_3, \dots, u_n]$$

Here

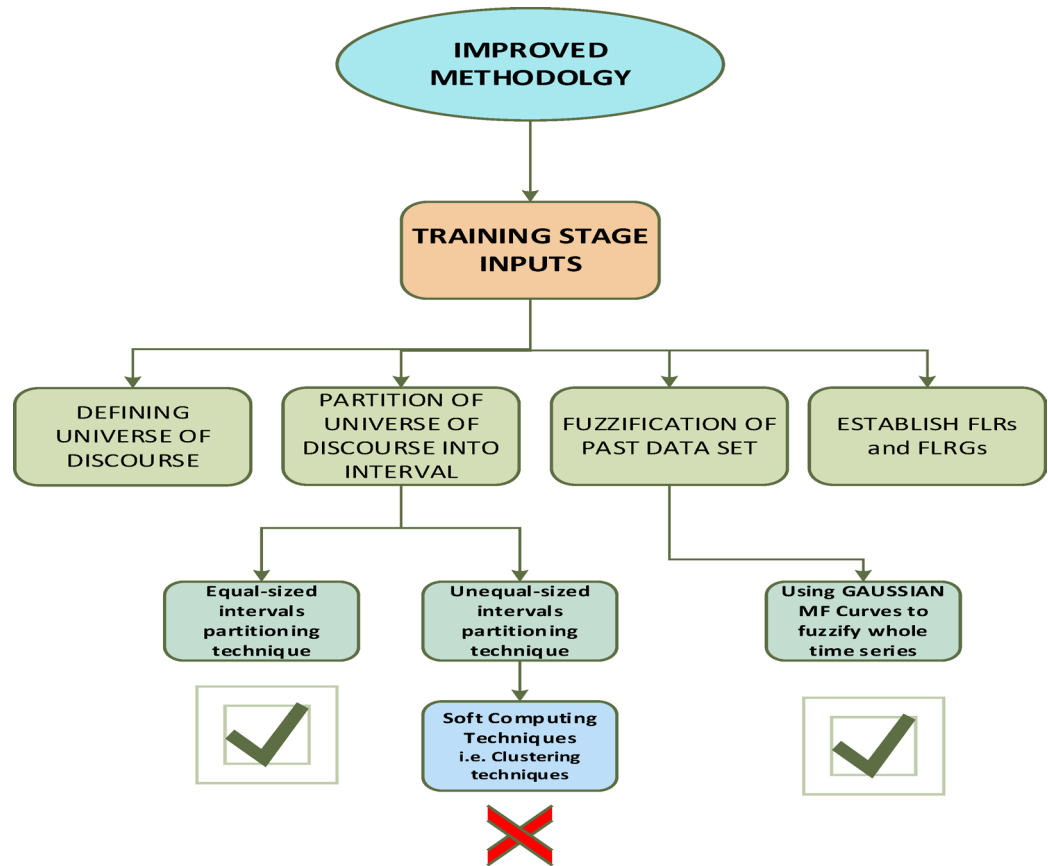
$$u_1 = [d_1; d_2] ; u_2 = [d_2; d_3] \dots \dots u_m = [d_m; d_{m+1}]$$

where  $D_{min}$  and  $D_{max}$  are the minimum and maximum of the training data, and  $D_1$  and  $D_2$  are small positive numbers used for boundary extension. The optimal number of intervals for this study was determined to be 28, creating a balanced granularity that avoids overfitting.

*Fuzzy logic relationship groups (FLRGs)*

We explicitly model the state transitions using a fuzzy relationship matrix based on the principal  $A_i \rightarrow A_j$ . The core innovation is the grouping of all future states for a given previous state into a single FLRG.

$$A_i \rightarrow A_k, A_i \rightarrow A_j, A_i \rightarrow A_n$$



**Fig. 2.** Proposed Methodology for training stage inputs based on four important training inputs to enhance the results of FTS models.

$$A_j, A_k, A_n \rightarrow A_i$$

This grouping is vital as it reduces recurrence and overfitting by preventing the model from memorizing single, specific state transitions and instead forcing it to learn a probabilistic distribution of possible next states.

### Simulation and results discussion

This paper focuses on energy demand prediction using historical data from the Polish Electric Grid, disaggregated by hour, day, and week. Performance based on comparisons among different fuzzy time series models is tested on short-term load forecasting problems from 2002 to 2004<sup>31</sup>. This comprises three consecutive years of hourly energy-consumption measurements, yielding 24 records per day. Based on domain knowledge, weekend data (Saturdays and Sundays) and holidays were excluded from the training and testing sets. This is a standard practice in energy load forecasting, as weekend consumption patterns are fundamentally different and non-stationary from weekdays, and their inclusion has been found to introduce significant noise and degrade model performance. Moreover, a preliminary analysis confirmed that the number of missing values in the weekday data was negligible (less than 0.1% of data points) and appeared random. Given their small volume and non-systematic nature, they were not considered to distort the overall time-series pattern; therefore, no sophisticated imputation was performed. The series' continuity was maintained by using the preceding valid value in these rare instances. Specifically, the first two years of data (2002–2003) were used solely for model training, and the third year (2004) was reserved for final testing and evaluation. All experiments were conducted using MATLAB R2018a. The computations were performed on a standard workstation equipped with an Intel Core i5 CPU at 3.70 GHz and 8 GB of RAM. No GPU acceleration was used for these experiments. The execution times reported in Tables 1, 2 and 3 are measured in seconds. In the testing phase, hourly electric load data are used to verify forecasting accuracy. In this work, three cases should be considered based on hourly load for the time period 2002–2004, such as:

1. Assessment of forecasting data on an hourly basis by using the entire time series.
2. Assessment of forecasting data on a daily basis, hourly prediction by using the entire time series except holidays.
3. Assessment of forecasting data on a weekly basis, hourly prediction, and measuring the average of the day by using the entire time series, except holidays.

Models	MaPe	IQR	Smape	Maape	Order of complexity	Execution time
Chen's Model FTS	1.7692	1.8325	1.7693	1.7686	$O(n^2)$	2619.271 s
YU'S Weighted FTS	2.0742	2.0797	2.0743	2.0729	$O(n)$	5495.556 s
Exponential FTS	1.8976	1.9402	1.8976	1.8966	$O(n)$	2743.614 s
Transformation FTS	1.0139	0.8564	1.0140	1.0139	$O(n^2)$	2734.472 s
High Order FTS	2.9154	3.1018	2.9155	2.9128	$O(n(n+1))$	3588.610 s
Interval FTS	1.6107	1.1298	1.6107	1.6104	$O(n^2)$	3027.422 s

**Table 1.** Hourly load forecasting results using the proposed FTS methodology for residential smart grid applications.

Models	MAPE	IQR	SMAPE	MAAPE	Order of complexity	Execution time
Chen's Model FTS	4.9906	3.1980	4.9950	4.9620	$O(n^2)$	156.297 s
YU'S Weighted FTS	5.9951	4.3695	6.0006	5.9588	$O(n)$	308.595 s
Exponential FTS	6.2430	4.6881	6.2488	6.2058	$O(n)$	163.008 s
Transformation FTS	6.4477	5.0972	6.4533	6.3855	$O(n^2)$	142.830 s
High Order FTS	1.9418	1.9545	1.9464	1.9387	$O(n(n+1))$	199.268 s
Interval FTS	5.0107	2.7417	5.0135	4.9861	$O(n^2)$	173.301 s

**Table 2.** Daily load forecasting results using the proposed FTS methodology to support day-ahead smart grid scheduling.

Models	MAPE	IQR	SMAPE	MAAPE	Order of complexity	Execution time
Chen's Model FTS	2.2088	2.1707	2.2217	2.2065	$O(n^2)$	25.248 s
YU'S Weighted FTS	2.4308	2.3658	2.4454	2.4279	$O(n)$	47.586 s
Exponential FTS	2.2935	2.2292	2.3069	2.2910	$O(n)$	24.631 s
Transformation FTS	2.1295	1.9094	2.1480	2.1204	$O(n^2)$	22.175 s
High Order FTS	0.6514	0.4746	0.6564	0.6512	$O(n(n+1))$	32.152 s
Interval FTS	2.8302	1.7994	2.8387	2.7871	$O(n^2)$	44.191 s

**Table 3.** Weekly load forecasting results using the proposed FTS methodology for medium-term smart grid planning.

### Data analysis and behavior of load curves over the entire time series

Figure 3, in the broader context, illustrates a combination of cyclic and seasonal variations over three years, presented hourly. At the beginning of the year, load consumption peaks due to increased use of heating appliances during the winter season. Midyear, the load consumption profile shows a downward trend as heating appliance use decreases during the summer. In the second half of the year, the load consumption profile shows an upward trend as spring arrives. Over the last couple of months, the load consumption profile has returned to its peak and completed the annual pattern.

The resulting behavior of the load curve tends to repeat and follow the previous pattern synchronously over the next couple of years. Thus, the overall consumption profile indicates that energy is primarily consumed during the winter season, primarily due to cold weather conditions and the use of heating appliances.

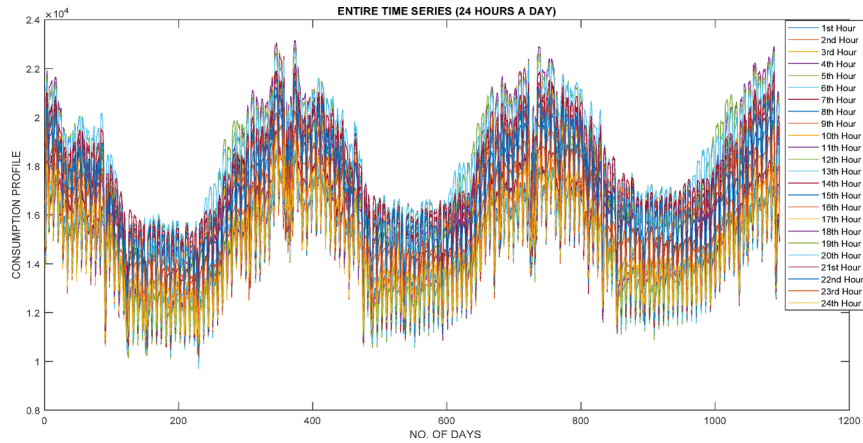
### Comparison criteria

The performance of all FTS models is compared and evaluated using the well-known four forecasting errors, as given in (21)-(24).

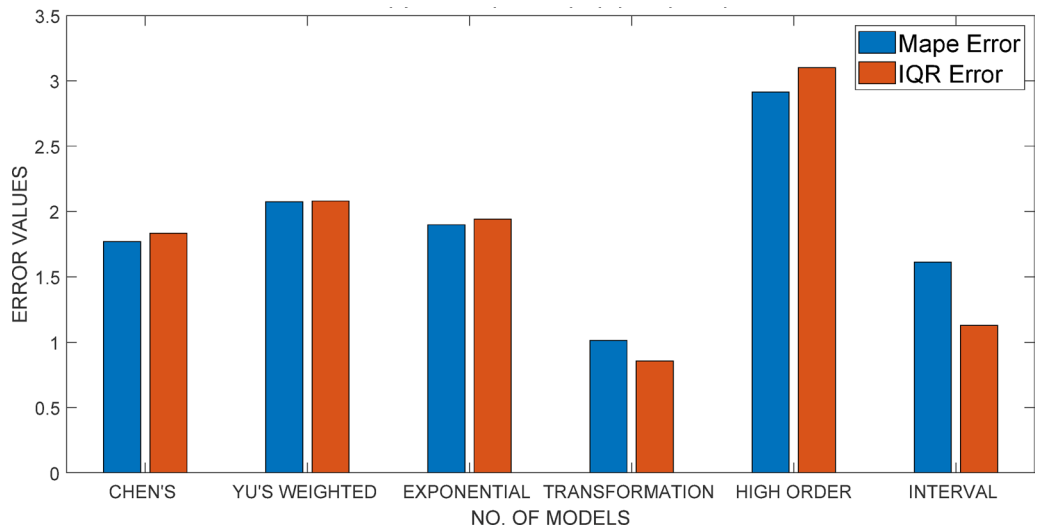
$$MAPE = \frac{1}{n} \sum_{i=1}^n \frac{|Actual(i) - Forecasted(i)|}{|Actual(i)|} \times 100 \quad (21)$$

$$SMAPE = MAPE + \frac{1}{n} \sum_{i=1}^n \frac{|Actual(i) - Forecasted(i)|}{(|Actual(i)| + |Forecasted(i)|) / 2} \times 100 \quad (22)$$

$$MAAPE = \arctan \frac{|Actual(i) - Forecasted(i)|}{|Actual(i)|} \quad (23)$$



**Fig. 3.** Load consumption of three years obtained from Electric System data, Poland, for the entire grid from 2002–2004, with maximum peaks occurring in January (24 h).



**Fig. 4.** Comparison of MAPE and IQR errors for FTS Models in hourly based forecasted time series, with respect to each model, reveals that the transformation FTS is a leading model in terms of accuracy.

$$IQR = Q3 - - - Q1 \tag{24}$$

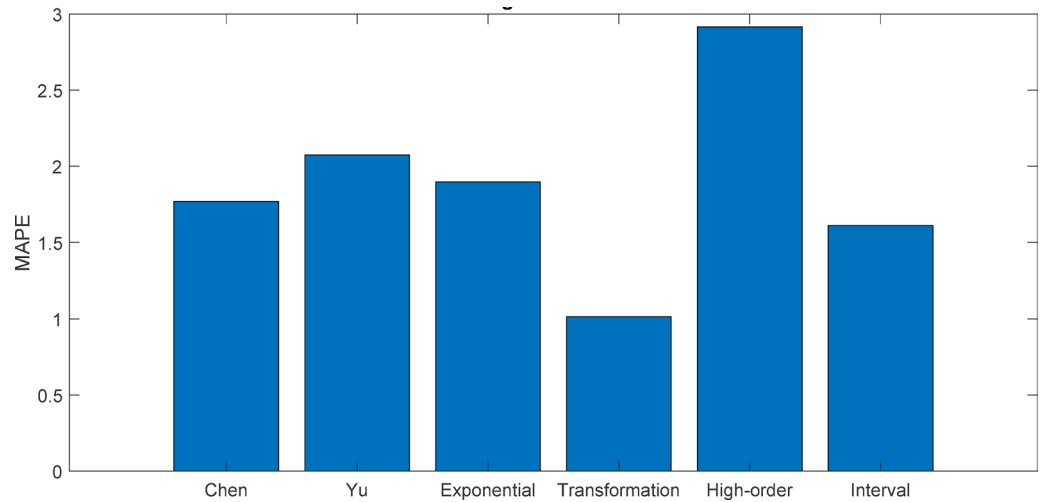
Where *Actual* (*i*) and *Forecasted* (*i*) are the actual load values and predicted load values at time *i*, respectively, and Q3 is the Third Quartile, i.e., the median of the upper half of the dataset, and Q1 is the First Quartile, i.e., the median of the lower half of the dataset.

**Cases**

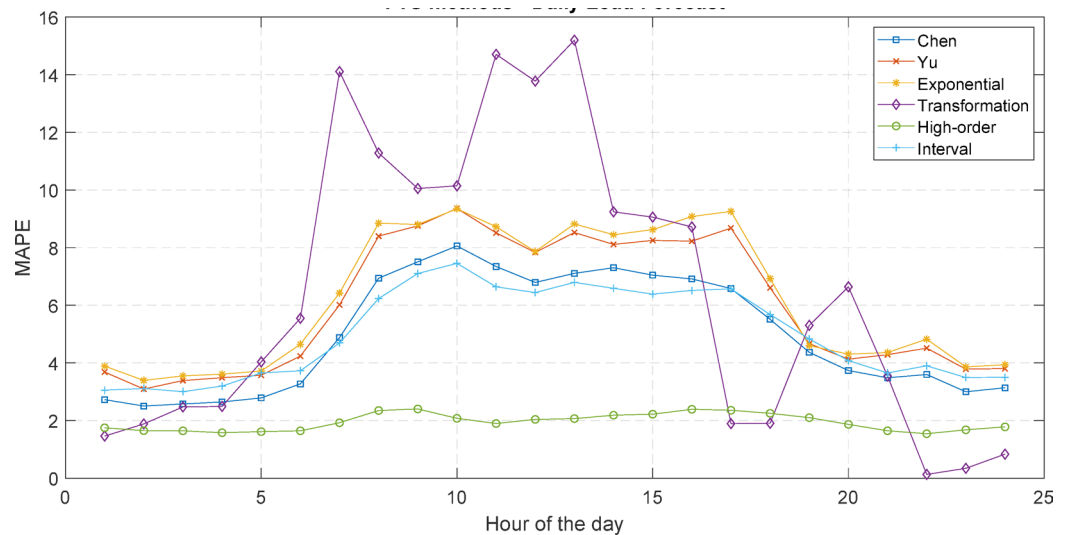
All FTS models discussed in Sect. 3 are now implemented across three evaluation cases, enabling analysis of their results and rankings in each case.

*Hourly based forecast*

Accurate hourly forecasting is crucial in smart grids to enable real-time demand response, balance supply with demand fluctuations, and facilitate dynamic pricing strategies. The forecasting errors mentioned above are used to examine the performance of all FTS models in this scenario. Moreover, the order of complexity and execution time for each model is included to aid understanding of each case, as shown in Table 1. The forecasting errors (i.e., MAPE and IQR) for hourly-based forecast time series for each model are shown in Fig. 4. In this case, all FTS models showed improved results, with errors less than 3%. Here, transformation FTS is the best performer, presenting approximately 1% MAPE error, while high-order FTS has the least performance, as shown in Fig. 5.



**Fig. 5.** Ranking of FTS models in the Hourly Case with respect to their MAPE errors, showing transformation FTS is the best performer, presenting approximately 1% MAPE error.



**Fig. 6.** Analysis of forecasting performance, based on MAPE, for the daily load forecast of FTS models for each Hour of the day demonstrates that higher-order FTS show stable results throughout the day.

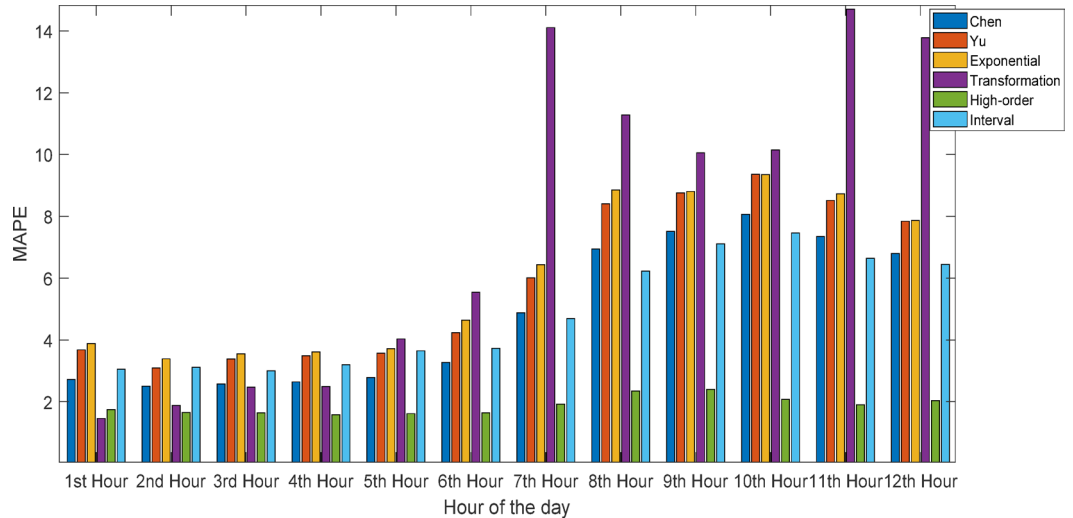
#### Daily based forecast

Daily load forecasting enables grid operators to optimize day-ahead scheduling, manage distributed energy resources, and mitigate operational uncertainties in residential demand. To analyze the performance of FTS models on a daily basis, average hourly forecasting errors are used. The execution time of models in this case is far better than in the hourly-based forecast case due to the loops or cut-offs used for daily-based forecasting, as shown in Table 2. As stated, High-order FTS is a leading performer, presenting less than 2% error; however, Transformation FTS shows worse results and is the least effective in this case. All FTS models have exhibited errors below 7%.

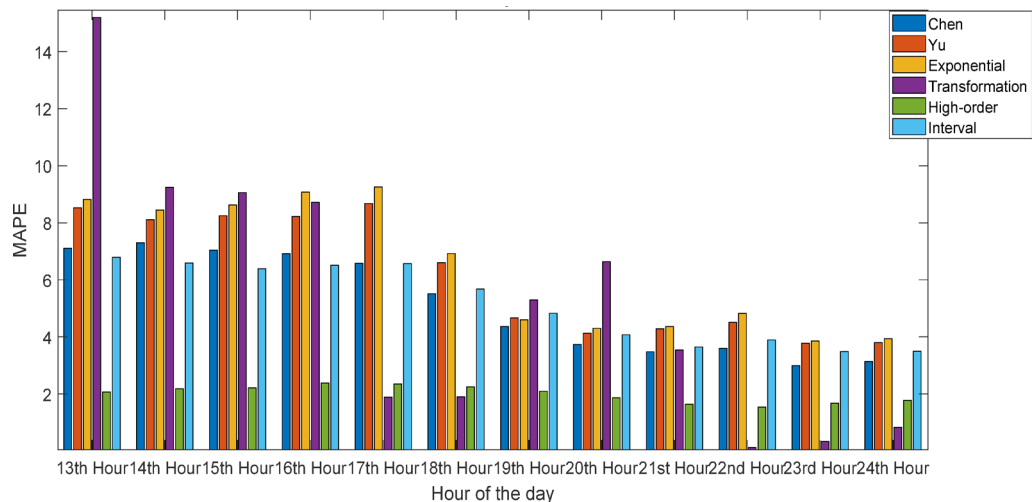
The forecasting error (i.e., MAPE) varies over the 24-hour day for all FTS models due to users' consumption profiles, as shown in Fig. 6. Because our entire time series is univariate, forecasting performance depends entirely on users' consumption behavior. Moreover, the performance of all FTS models depends on the time period or range used for forecasting, as shown in Figs. 7 and 8. The models perform better during nighttime than during other hours of the day. The analysis of the results shown in Figs. 7 and 8 also demonstrates an upward trend in the 1st half of the day and a downward trend in the 2nd half of the day.

#### Weekly based forecast

Weekly forecasting supports medium-term planning in smart grids, enabling utilities to anticipate consumption trends, improve the integration of renewables, and enhance grid resilience. Average forecast errors are used



**Fig. 7.** MAPE of the daily load forecast of FTS models during the 1st Half of the day demonstrates an upward growing trend and assesses better results for night hours.



**Fig. 8.** MAPE of the Daily Load Forecast of FTS models during the 2nd Half of the day demonstrates the downward trend and assesses better results for night hours.

to evaluate the performance of FTS models on a weekly basis, as shown in Table 3. Each weekday is analyzed separately on an hourly basis throughout the entire time series to perceive the behavior of these models in this scenario, as shown in Fig. 9. In this case, all FTS models give promising and fast results because execution time for each model is very small compared to the Hourly and Daily load forecast cases.

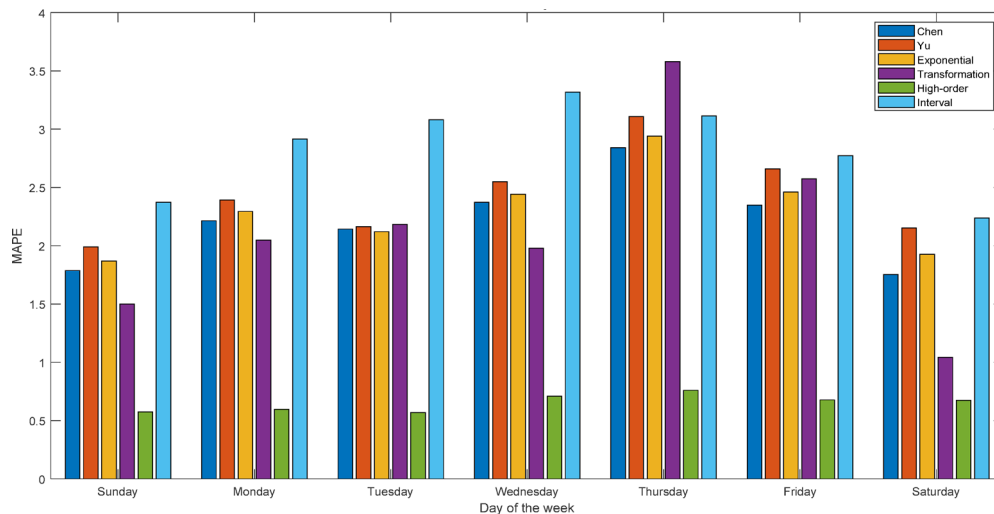
The MAPE forecast shows variation across the seven days of the week, as shown in Table 4. All FTS algorithms perform better for weekends as compared to weekdays due to their dependency on user consumption behavior, as seen in Fig. 9. High-order FTS again perform better and present less than 1% error. Other FTS models also perform better in this case, with an error below 3%.

### Comparison of results between proposed methodology and base system

To investigate the performance of our proposed methodology, comparison with previous work is essential<sup>30</sup>. The comparison is based on two forecasting errors, i.e., MAPE and IQR, because the previous approach<sup>30</sup> considers only these two errors, as shown in Table 5. Moreover, Chen's model is an additional algorithm in the proposed methodology and yields results consistent with those of the models used in the previous method. The comparison is also divided into three categories subject on their STLF cases.

#### Hourly based forecast

The performance of FTS models in the proposed methodology yields improved results compared with the previous approach, which used a higher number of intervals (which overfits) and a model without FLRGs, as



**Fig. 9.** Analysis of forecasting performance based on MAPE of Weekly Load Forecast of FTS models according to their Weekday, and evaluating accuracy better for weekends as compared to weekdays.

Models	1	2	3	4	5	6	7
Chen's Model FTS	1.7876	2.2147	2.1429	2.3736	2.8408	2.3492	1.7529
YU'S Weighted FTS	1.9905	2.3919	2.1643	2.5497	3.1086	2.6587	2.1520
Exponential FTS	1.8695	2.2946	2.1208	2.4408	2.9405	2.4617	1.9264
Transformation FTS	1.4993	2.0488	2.1829	1.9785	3.5802	2.5736	1.0434
High Order FTS	0.5738	0.5968	0.5683	0.7102	0.7605	0.6773	0.6726
Interval FTS	2.3726	2.9151	3.0811	3.3185	3.1133	2.7730	2.2381

**Table 4.** MAPE error of models according to their weekdays.

Models	Proposed methodology		Base system models (without optimal intervals & FLRGs) <sup>6</sup>	
	Mape	IQR	Mape	IQR
Chen's Model FTS	1.7692	1.8325		
YU'S Weighted FTS	2.0742	2.0797	3.4546	3.2890
Exponential FTS	1.8976	1.9402	3.0827	3.1297
Transformation FTS	1.0139	0.8564	1.0135	0.8564
High Order FTS	2.9154	3.1018	3.0951	3.3393
Interval FTS	1.6107	1.1298	2.1301	1.1494
Mean	<b>1.88</b>	—	<b>2.56</b>	
Std. Deviation	<b>0.62</b>	—	<b>0.99</b>	—

**Table 5.** Hourly based forecast error comparison of models b/w the proposed methodology and previous work.

shown in Table 5. Here, Transformation FTS yields the same results across both methodologies because it relies solely on time-series data rather than training-stage inputs and shares the same structure as the algorithms. There is a substantial improvement in models such as Yu's Weighted and Exponential FTS. Additionally, Chen's FTS model within the proposed methodology yields better results than previous FTS models, except for Transformation FTS.

*Daily based forecast*

The performance of FTS models in the proposed methodology yields improved results compared with the previous approach, which used a higher number of intervals (which overfits) and a model without FLRGs, as

Models	Proposed methodology		Base system models (without optimal intervals & FLRGs) <sup>6</sup>	
	MAPE	IQR	MAPE	IQR
Chen's Model FTS	4.9906	3.1980	—	—
YU'S Weighted FTS	5.9951	4.3695	7.0030	6.1449
Exponential FTS	6.2430	4.6881	6.5257	5.3246
Transformation FTS	6.4477	5.0972	6.3924	5.0735
High Order FTS	1.9418	1.9545	4.6974	4.8980
Interval FTS	5.0107	2.7417	5.3653	4.5187
Mean	<b>5.10</b>	—	<b>6.00</b>	—
Std. Deviation	<b>1.67</b>	—	<b>0.94</b>	—

**Table 6.** Daily based forecast error comparison of models b/w the proposed methodology and previous work.

Models	Proposed methodology		Base system models (without optimal intervals & FLRGs) <sup>6</sup>	
	Mape	IQR	Mape	IQR
Chen's Model FTS	2.2088	2.1707	—	—
YU'S Weighted FTS	2.4308	2.3658	5.3694	5.4577
Exponential FTS	2.2935	2.2292	4.6480	4.6977
Transformation FTS	2.1295	1.9094	2.1187	1.8886
High Order FTS	0.6514	0.4746	4.2228	4.3423
Interval FTS	2.8302	1.7994	9.1721	9.5512
Mean	<b>2.09</b>	—	<b>5.11</b>	—
Std. Deviation	<b>0.75</b>	—	<b>2.57</b>	—

**Table 7.** Weekly based forecast error comparison of models b/w the proposed methodology and previous work.

shown in Table 6. The higher-order FTS model of the proposed approach shows better results than the earlier approach. Still, other FTS models in the proposed methodology show only minor improvements in accuracy. The additional Chen's model also yields better results than the previous method.

#### *Weekly based forecast*

The performance of FTS models in the proposed methodology outperforms that of the previous approach, which used a larger number of intervals (which overfits) and lacked FLRGs, as shown in Table 7. Here, the higher-order FTS again yields excellent results and a significant improvement over the previous FTS model. The analysis of Interval FTS in this case demonstrates that the proposed methodology yields satisfactory results. Chen's FTS model of the proposed methodology shows better results than previous FTS models, except for the High-order FTS.

### **Conclusion and future work**

In this work, the importance of short-term load forecasting is discussed and analyzed to maintain stability between generation, transmission, and the consumer end. Consumers exhibit unpredictable consumption profiles, which are the most significant barrier to effective LF-based DSM. In DSM, our primary objective is to minimize peak demand and enhance system efficiency and stability, which can only be achieved by understanding consumers' consumption patterns. This work demonstrates the potential of fuzzy time series (FTS) models for accurate short-term residential load forecasting, thereby directly contributing to the operational efficiency of smart grids. By overcoming challenges related to overfitting and enhancing forecasting precision, our methodology supports demand-side management, peak load reduction, and improved scheduling of distributed energy resources. The superior performance of the high-order FTS model in daily and weekly forecasting, as well as the transformation FTS in hourly forecasting, underscores its applicability in diverse smart grid contexts.

## Limitations

**Handling High-Dimensional Data:** Traditional FTS models can face scalability challenges when integrating a large number of external features (e.g., multiple weather variables and economic indicators), as the fuzzy rule base can grow exponentially, thereby impacting computational efficiency.

**Dynamic Adaptation:** The current model uses a static universe of discourse and interval partitioning. This may not handle time series with non-stationary volatility or long-term structural shifts in the data optimally.

**Feature Integration:** Our current work focuses on the historical load data. Excluding explicit external variables, such as real-time temperature, humidity, or holiday indicators, is a limitation, as these factors are known to influence power consumption significantly.

## Future work

Looking ahead, integrating these models with hybrid approaches, clustering techniques, and adaptive features could further improve robustness and scalability. Coupling FTS forecasting with renewable generation profiles, electric vehicle charging, and home energy management systems will enable more intelligent, flexible, and resilient smart grids. A primary direction for future research is to develop a hybrid FTS framework that can effectively and efficiently incorporate key external features, such as weather data and calendar effects, to improve forecast accuracy during anomalous events.

## Data availability

This study didn't generate any new data. It utilized publicly available data, which can be accessed at [31].

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### Author contributions

All authors (Uzair Kazim, Mohsin Ullah, Jawad Usman Arshed, Mehtab Afzal, Fazeel Abid, Shtwai Alsubai, Onur Osman, and Jawad Rasheed) contributed equally to each section (from conceptualization to Writing - original draft, review, and editing).

### Declarations

### Competing interests

The authors declare no competing interests.

### Additional information

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