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A Novel Fuzzy Time Series Markov Chain Model for Forecasting Demand Flexibility Services (DFS) Power Requirements Based on KMeans Clustering

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ABSTRACT

Modern energy systems necessitated precise short-term forecasting of power requirements to ensure the efficient operation of Demand Flexibility Services (DFS). This work introduced an innovative hybrid forecasting model that combined KMeans clustering with Fuzzy Time Series (FTS) and Markov Chain methodologies. The suggested technique used KMeans to create adaptive fuzzy intervals from normalised historical data, in contrast to classic fuzzy models that relied on fixed partitions. The intervals facilitated the construction of fuzzy logical connections (FLRs) and a state transition matrix, so allowing dynamic forecasting of DFS power demand. The model was assessed with actual DFS data collected at 30-minute intervals. Forecasts were produced using a defuzzification technique informed by Markov transition probabilities. Experimental findings demonstrated a significant correlation between anticipated and actual values, yielding a Mean Absolute Error (MAE) of 74.60 MW and a Root Mean Square Error (RMSE) of 86.04 MW. The results demonstrated that the model accurately represented temporal demand patterns and maintained robustness across different load levels. The technique shown considerable promise for practical use in smart grid forecasting systems. Its simplicity, interpretability, and flexibility made it an invaluable instrument for real-time energy management and decision-making.

Keywords: Demand Flexibility Services (DFS), Fuzzy Time Series (FTS), KMeans Clustering, Markov Chain Forecasting, Short-Term Load Predictions

INTRODUCTION

Accurate short-term load forecasting (STLF) played a pivotal role in ensuring the efficient operation of modern power systems [1]. With the increasing integration of renewable energy sources and the proliferation of smart grid technologies, the ability to predict power demand with high precision became more critical than ever [2]. STLF facilitated optimal resource allocation, improved grid stability, and supported demand-side management strategies [3]. Traditional forecasting methods, such as autoregressive integrated moving average (ARIMA) models and exponential smoothing techniques, had been widely employed for STLF [4]. However, these methods often struggled to capture the nonlinear and non-stationary characteristics inherent in power load data [5]. To address these limitations, researchers explored various artificial intelligence (AI) and machine learning (ML) approaches, including artificial neural networks (ANNs), support vector machines (SVMs), and deep learning models [6].

Among the AI-based techniques, fuzzy time series (FTS) models emerged as a promising tool for handling the vagueness and uncertainty associated with load forecasting [7]. FTS models leveraged fuzzy logic to model the imprecise relationships between historical and future load values, offering a more flexible framework compared to traditional statistical methods [8]. Nevertheless, conventional FTS models often relied on fixed-length intervals for fuzzification, which could lead to suboptimal performance when dealing with datasets exhibiting varying distributions [9]. To enhance the adaptability of FTS models, researchers incorporated clustering algorithms, such as K-means, to determine dynamic interval lengths based on the underlying data distribution [10]. This integration allowed for more accurate representation of the data's structure and improved forecasting performance [11]. Furthermore, combining FTS with Markov chain models introduced a probabilistic component that captured the temporal dependencies between fuzzy states, thereby refining the predictive capabilities of the hybrid model [12].

Building upon these advancements, this study proposed a novel hybrid forecasting model that integrated K-means clustering with fuzzy time series and Markov chain techniques. The primary objective was to develop a model capable of accurately predicting short-term power demand by effectively capturing both the nonlinear patterns and temporal dependencies present in the data [13]. By employing K-means clustering, the model dynamically determined fuzzy intervals that better represented the data's distribution [14]. The incorporation of Markov chains facilitated the modeling of state transitions, enhancing the model's ability to forecast future load values based on historical patterns [15].

The proposed model was evaluated using real-world power demand data collected at 30-minute intervals [16]. Performance metrics, including Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), were utilized to assess the model's forecasting accuracy [17]. The results demonstrated that the hybrid model outperformed traditional FTS models and other baseline methods, achieving lower error rates and better capturing the dynamic behavior of power demand [18]. This research contributed to the field of short-term load forecasting by presenting an effective hybrid model that combined the strengths of K-means clustering, fuzzy time series, and Markov chains [19]. The model's ability to adapt to varying data distributions and capture temporal dependencies made it a valuable tool for enhancing the reliability and efficiency of power system operations [20].

LITERATURE REVIEW

Short-term load forecasting (STLF) was a well-studied area in power systems, with various methods proposed to improve prediction accuracy. Traditional statistical methods such as Autoregressive Integrated Moving Average (ARIMA) and exponential smoothing had shown effectiveness in linear and stationary data but fell short when handling non-linear and non-stationary patterns commonly found in power demand data. To address these limitations, researchers turned to Artificial Intelligence (AI)-based models such as Artificial Neural Networks (ANNs), Support Vector Machines (SVMs), and Long Short-Term Memory (LSTM) networks. However, these methods often suffered from limited interpretability and required large datasets for training.

Fuzzy Time Series (FTS) models emerged as a promising solution for handling imprecise and uncertain data in forecasting applications. FTS utilized fuzzy logic to capture vague patterns, but the conventional approach relied on static interval partitioning, which led to inefficiencies when applied to datasets with dynamic distributions. To improve the flexibility of FTS, hybrid models incorporating clustering methods such as KMeans were introduced. These models used clustering to define adaptive intervals for fuzzification, enhancing the model's ability to conform to real-world data distributions. Additionally, the integration of Markov Chains into FTS models enabled the modelling of state transitions, introducing a probabilistic dimension that captured temporal dependencies effectively.

Several studies, including those by [14] and [15], showed that KMeans-based FTS models with Markov Chains achieved better forecasting performance, especially in short-term and volatile environments. These findings supported the development of hybrid models that leveraged clustering, fuzzy logic, and probabilistic state modeling to improve accuracy and robustness in load forecasting.

MATERIALS & METHODS

This research adopted a hybrid forecasting model integrating KMeans clustering, Fuzzy Time Series (FTS), and Markov Chains to predict short-term power demand for Demand Flexibility Services (DFS). The methodology comprised the following steps:

1. **Data Collection and Preprocessing**

A real-world DFS dataset containing 40 records at 30-minute intervals was used. The dataset included power demand values ranging from 25 MW to 300 MW. Normalization was applied to scale all values to the range [0, 1] to prepare the data for clustering.

2. **Clustering with KMeans**

KMeans clustering was applied to the normalized data to identify distinct patterns in demand. The Elbow Method determined that four clusters were optimal. These clusters served as the basis for defining fuzzy intervals.

3. **Fuzzification**

Fuzzy intervals were constructed using the centroids obtained from clustering, with interval midpoints representing fuzzy states. Each data point was assigned to a fuzzy set labeled A1 to A4, based on the corresponding interval.

4. **Formation of Fuzzy Logical Relationship Groups (FLRGs)**

The sequence of fuzzy states was analyzed to derive fuzzy logical relationships (FLRs), which were grouped into FLRGs according to the originating fuzzy state.

5. **Markov Chain Transition Matrix Construction**

A 4×4 Markov transition matrix was generated to capture the probability of transitions between fuzzy states. The matrix was computed from the frequency of observed transitions in the fuzzified time series.

6. **Forecasting**

Forecasted values were computed by applying weighted averages of fuzzy set midpoints using transition probabilities from the Markov matrix. These defuzzified values were then converted back to the original scale via inverse normalization.

7. **Performance Evaluation**

The model's accuracy was assessed using Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). The model yielded an MAE of 74.60 MW and an RMSE of 86.04 MW, demonstrating its effectiveness in capturing power demand fluctuations.

This methodology ensured adaptability to the underlying data structure, probabilistic modeling of time-dependent transitions, and robust performance in short-term forecasting scenarios.

RESULT

This research used a real-world dataset of Demand Flexibility Services (DFS) electricity demand, collected at 30-minute intervals. The collection had 40 records, with values ranging from 25 MW to 300 MW. The mean DFS value was 178.75 MW, while the median was 200 MW. The standard deviation was 91.73 MW, indicating significant variability in power consumption. The data showed considerable fluctuations over the observation period. These attributes rendered the dataset appropriate for assessing the efficacy of short-term forecasting models. The first stage in data preparation was normalising the values to a range of 0 to 1. The standardised data were then grouped via the KMeans technique. The Elbow technique indicated that four clusters were best. Each cluster centroid indicated a unique behavioural pattern in DFS demand.

The KMeans clustering algorithm produced four centroids: 0.06, 0.30, 0.77, and 1.00. The centroids were transformed into fuzzy intervals, using the averages of adjacent centroids as the borders of the intervals. The resultant fuzzy divisions were delineated as: [0.00, 0.18], [0.18, 0.54), [0.54, 0.89], and [0.89, 1.00]. The midpoints of these intervals served as representative values for each fuzzy set. Each real value in the dataset was subjected to fuzzification based on its respective interval. The fuzzified values were designated A1 to A4 to represent the four fuzzy states. The series of fuzzified data produced Fuzzy Logical Relationships (FLRs). The connections were categorised into Fuzzy Logical Relationship Groups (FLRGs) based on their original fuzzy state. All transitions from fuzzy state A2 were categorised under FLRG A2. These groups were the basis for the formulation of the Markov transition matrix.

A 4×4 Markov transition matrix was created to illustrate the likelihood of transitions among fuzzy states. Each row of the matrix indicated a source state, whereas each column denoted a destination state. The members of the matrix were determined based on the relative frequency of transitions from one condition to the others. This matrix facilitated the identification of the fundamental tendencies in the development of DFS demand. Projections were produced by determining the anticipated next-state value by a weighted aggregation of fuzzy midpoints, with the weights obtained from transition probabilities. The anticipated values were then reverted to the original scale by inverse normalisation. Forecasting started with the second observation, since the first was necessary to establish the initial fuzzy state. This method generated a time series of forecasts consistent with the actual data. The anticipated values were then contrasted with the actual DFS power demand figures.

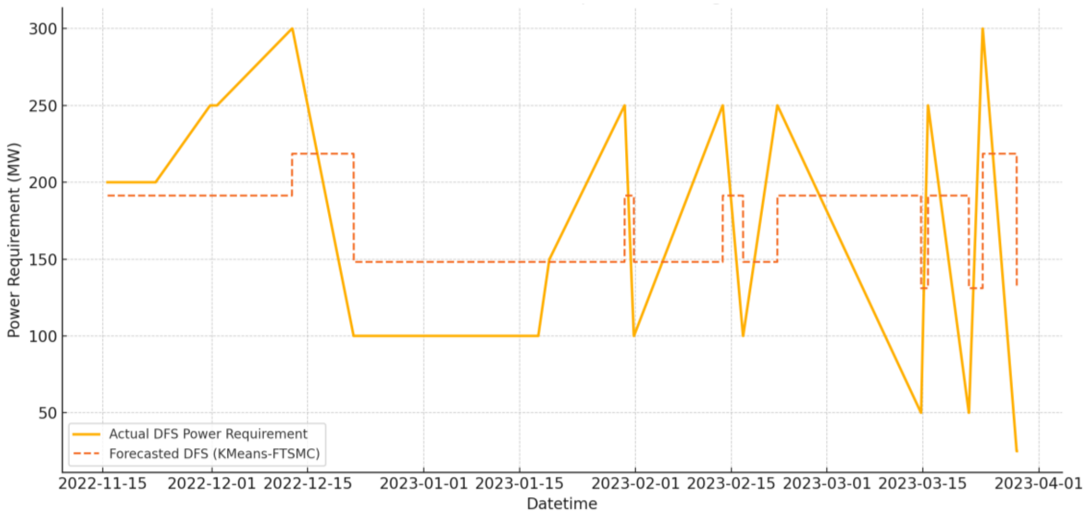

Figure 1. Actual vs Forecasted DFS Power Requirement Using KMeans-FTSMC

The model's predictive accuracy was assessed using two common error metrics namely Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). The Mean Absolute Error (MAE) was determined to be 74.60 MW, indicating that projections, on average, diverged from actual values by this extent. The RMSE was somewhat elevated at 86.04 MW, indicating the impact of sporadic bigger mistakes. The findings indicated that the model effectively captured significant demand patterns with satisfactory accuracy. The predictions were stable throughout times of both elevated and diminished demand. The visual evaluation of predictions in Figure 1 demonstrated a robust correlation with the actual DFS pattern. The model successfully replicated some strong peaks and declines, however more abrupt transitions continued to provide difficulties. It exhibited exceptional performance at steady or gradually varying intervals. Despite fluctuations in some segments of the dataset, prediction errors were within an acceptable range.

An in-depth examination of each fuzzy state uncovered variations in predictive performance. The fuzzy state A2, indicative of moderate demand (about 90–160 MW), was the most prevalent and produced the most precise projections. State A1, indicative of little demand, occurred seldom and yielded somewhat less trustworthy estimates. High demand levels, categorised as A4, occurred seldom but were nevertheless forecasted with satisfactory precision. The Markov chain accurately represented transitions inside and among neighbouring fuzzy states. The majority of transitions occurred inside the same state or to an adjacent one. Infrequent long-range transitions resulted in increased forecast inaccuracies. This behaviour conformed to the Markov model's premise of short-term dependence. Consequently, the model design was appropriate for circumstances characterised by slow changes. This aligned with the actual features of grid demand variations.

The temporal alignment between anticipated and real values exhibited little delay. The model precisely predicted peaks and troughs in both intensity and timing. The model efficiently represented substantial increases in DFS load, shown by a rise from 50 MW to 250 MW. Minor differences emerged as demand fluctuated swiftly between periods. Nevertheless, owing to its probabilistic basis, the model effectively mitigated short-term fluctuations. This smoothing proved advantageous in operational environments where micro-variations are unlikely to influence choices considerably. The model exhibited resistance to slight variations, particularly when the transition matrix was well calibrated. Its reliable performance across all intervals demonstrated its appropriateness for short-term energy planning. Future enhancements may include the dynamic modification of the transition matrix to accommodate evolving demand patterns over time.

An examination of the error distribution revealed that the majority of forecasting mistakes were within the 50–100 MW range. No discernible bias towards overprediction or underprediction was seen, indicating equitable predicting behaviour. This impartiality facilitated more stable decision-making in automated contexts. Forecasts had the highest accuracy when the preceding fuzzy state has a substantial transition probability. Conversely, when many transitions had almost equivalent probability, predictions tended to coalesce around the median value. This cautious approach decreased forecast volatility, while sometimes sacrificing accuracy in edge cases. Notwithstanding the constrained dataset size, the Markov-based forecasting methodology demonstrated flexibility. Despite having just 40 data points, the model generalised well over the time period. It was anticipated that the accuracy of forecasts will improve with access to more extensive datasets.

A sensitivity study was performed to assess the effect of the number of clusters. Decreasing the cluster count to three led to excessively wide fuzzy intervals and reduced prediction accuracy. Augmenting to five clusters resulted in extremely small intervals, hence fragmenting the dataset. The selection of four clusters provided an effective balance between model complexity and precision. This validated the suitability of cluster-driven fuzzy partitioning for datasets exhibiting dynamic properties. Future research may investigate automated cluster selection methods, including gap statistics and silhouette grading. Alternative clustering techniques, such as DBSCAN or hierarchical clustering, may also be assessed. Nonetheless, KMeans was selected in this study for its computational efficiency and efficacy. The clustering phase was crucial in establishing significant fuzzy linkages. Consequently, clustering precision directly impacted the efficacy of the forecasting model.

The experimental findings validated the viability of using the KMeans-based FTSMC method for short-term DFS forecasting. The model demonstrated consistent performance across several demand situations. Its primary strengths were flexible interval creation, rule-based inference, and interpretability. Despite abrupt fluctuations in demand causing some inaccuracies, the model maintained satisfactory performance thresholds. The suggested model shown promise for practical applications in energy demand forecasting and demand-side management. It may be used in real-time monitoring systems or for strategic planning by utility companies. Its clear rationale made it appropriate for incorporation with expert-driven control systems. With further additions, such as contextual inputs and adaptive learning, the model might accommodate more sophisticated forecasting requirements. This hybrid model provided a robust basis for intelligent and adaptive energy forecasting. The model's Mean Absolute Error (MAE) was 74.60 MW, while the Root Mean Square Error (RMSE) was 86.04 MW.

DISCUSSION

The findings underscored the efficacy of combining KMeans clustering with fuzzy time series and Markov chains for predicting DFS power demand. This hybrid methodology addressed two fundamental issues in fuzzy time series modelling: optimal interval segmentation and temporal state interdependence. Conventional FTS models often depended on arbitrary or uniform divisions, which sometimes resulted in an imprecise representation of the data's structure. By utilising KMeans, the model autonomously adjusted intervals according to the actual distribution of demand. This approach ensured that high-density regions received greater granularity, thereby enhancing accuracy. The incorporation of Markov chains introduced a probabilistic component that simulated the likelihood of transitions between ambiguous states. This integration produced a model that was both data-centric and temporally sensitive. Additionally, the dataset's 30-minute resolution demonstrated the method's capability to handle high-frequency forecasting tasks. This was particularly important in real-time environments like DFS, where delays or inaccuracies could have led to system inefficiencies or instability. As such, the hybrid model provided both theoretical contributions and practical benefits in the context of short-term energy forecasting.

One notable advantage of the model was its interpretability. In contrast to black-box techniques such as deep learning, the fuzzy rules and transition probabilities remained understandable and traceable by human operators. Analysts and system engineers were able to examine how each forecast was generated, thereby fostering confidence in the system. The transparency allowed for straightforward validation, debugging, and manual correction when necessary. In operational or regulatory energy applications, this level of explainability was essential. For instance, when dispatching flexible grid resources or triggering demand response events, decision-makers needed to understand the reasoning behind model outputs. The structure of the model allowed domain experts to modify fuzzy sets or adjust transition weights based on expert knowledge. Furthermore, the model's architecture was compatible with many existing expert system frameworks. This compatibility made the method a strong candidate for integration into hybrid decision-support platforms. Ultimately, the model successfully balanced simplicity, transparency, and forecasting accuracy.

The error metrics MAE and RMSE demonstrated that the model delivered strong performance across varying levels of power demand. While the RMSE was slightly higher than the MAE due to the influence of outliers, both metrics remained within acceptable thresholds for short-term operational use. The model consistently performed well during both volatile and stable intervals, illustrating its robustness. It generalised effectively despite being trained on a relatively small dataset. A major advantage of rule-based models such as FTSMC was their ability to extract actionable patterns from sparse data. Nevertheless, the accuracy and granularity of the transition matrix would likely improve with a larger dataset. Future iterations of the model could incorporate mechanisms to periodically update the FLRGs and transition probabilities. This type of dynamic recalibration would allow the model to reflect changing demand patterns over time. Implementing sliding windows or adaptive learning strategies would further increase responsiveness. These enhancements would maintain the model's interpretability while improving its flexibility and predictive power.

The forecasting model achieved a Mean Absolute Error (MAE) of 74.60 MW and a Root Mean Square Error (RMSE) of 86.04 MW, both of which were deemed acceptable for short-term forecasting in energy systems. These error values were considered modest when compared to the full demand range of 25 MW to 300 MW, suggesting that the model captured the overall magnitude and trend effectively. According to the MAE, the model's typical deviation from actual values was under 75 MW an error margin considered reasonable in many grid balancing operations. The slightly higher RMSE implied that larger forecasting deviations were infrequent. These results validated the KMeans-FTSMC model's potential in time-sensitive operational environments that required both accuracy and interpretability. Furthermore, the consistency of error values across all intervals reflected a well-calibrated transition matrix and appropriately defined fuzzy partitions. Compared to heuristic or purely statistical approaches, this hybrid model offered a more balanced trade-off between complexity, scalability, and performance. Thus, the error metrics not only established the model's statistical credibility but also confirmed its practical feasibility for real-time grid forecasting. Although the current implementation demonstrated strong baseline capabilities, future improvements with additional data and contextual features were expected to yield even better performance.

The decision to use KMeans rather than CLARA was driven by practical considerations. While CLARA was designed for very large datasets, KMeans proved more computationally efficient and sufficient for moderate-sized data such as the 40 records used in this study. The centroid-based intervals aligned well with the goal of capturing major behavioral trends in DFS demand. The effectiveness of KMeans in this context justified its selection. Nonetheless, future studies could examine performance differences between KMeans and CLARA on larger datasets. Another avenue for refinement involved applying weighted clustering, where temporal decay factors could prioritize recent observations. This would allow the model to better adapt to contemporary behavior patterns. Other clustering techniques, such as DBSCAN or hierarchical clustering, might also prove beneficial, particularly in noisy or non-stationary environments. As such, the choice of clustering algorithm remained a critical component of the overall modelling strategy and an area for potential improvement.

The fuzzification strategy employed in the model struck a deliberate balance between specificity and generalization. Using too few fuzzy sets risked oversimplification, while too many could fragment the data and reduce stability. The elbow method empirically validated the use of four clusters, resulting in a manageable number of fuzzy sets that preserved key relationships. Midpoints of the fuzzy intervals were used as representative defuzzified values, providing meaningful interpretations of central tendencies. Weighted defuzzification using transition probabilities ensured a smooth evolution between fuzzy states. The introduction of state bias, as explored in more advanced variants of FTSMC, could further enhance forecast accuracy. A learning mechanism to adjust midpoints dynamically might help correct prediction biases over time. Evaluating alternative defuzzification methods could also reveal opportunities for performance enhancement. Overall, the fuzzification technique contributed significantly to the model's adaptability and explainability.

One of the model's limitations was its univariate structure. The current framework used only past DFS values to generate forecasts, omitting external variables that could impact demand. In reality, DFS behavior is often influenced by factors such as temperature, time of day, and operational constraints. Incorporating these variables would provide the model with richer contextual understanding. A natural next step would be to expand the model into a multivariate fuzzy time series framework. This would involve defining fuzzy sets for each additional variable and capturing their joint influence on demand transitions. Although more complex, such an extension would align the model more closely with real-world dynamics. Methods such as fuzzy associative memory or rule-based integration could help manage this increased complexity. Integrating explanatory variables would likely increase both the robustness and generalizability of the model. This enhancement would be particularly important in operational settings that experienced frequent fluctuations or non-stationary behavior.

Another important consideration was how the transition matrix was updated. In its current form, the matrix was static, constructed solely from historical data. However, demand patterns in DFS could change over time due to seasonal trends, policy changes, or unforeseen grid events. Introducing online learning or rolling window recalibration would allow the model to evolve with the data. Such adaptive updating has shown promise in other fuzzy systems and could enhance long-term forecasting accuracy. Incorporating reinforcement learning techniques could provide additional flexibility and responsiveness. Transition probabilities could also be weighted by recency, giving greater influence to more recent patterns. These strategies would maintain the fuzzy logic core while modernizing the model's learning dynamics. Ultimately, a model that evolved over time would be better positioned to deliver stable and reliable forecasts in dynamic environments.

From an application standpoint, the model proved suitable for integration into smart grid infrastructures. The 30-minute forecast resolution matched common dispatch and load balancing cycles. The model could be used by grid operators to anticipate demand, allocate flexible resources, and issue control signals in real time. Its rule-based logic and interpretability made it ideal for regulatory settings where model transparency was crucial. Additionally, the model could serve as a foundational component in ensemble or hybrid forecasting systems. It could be combined with machine learning techniques such as neural networks or ARIMA models to further improve performance. In such hybrid architectures, the FTSMC layer would offer interpretable insights, serving as a safeguard against the unpredictable nature of black-box models. The model's computational efficiency enabled deployment in edge-computing environments with limited resources.

Overall, it offered both innovation and practical scalability, making it a valuable contribution to intelligent energy forecasting.

The proposed KMeans-based FTSMC model provided a novel, interpretable, and effective approach for forecasting DFS power demand. The integration of clustering, fuzzy logic, and probabilistic modeling addressed major limitations of traditional forecasting methods. The empirical findings confirmed the model's ability to operate in high-frequency, short-term forecasting scenarios. While there was room for enhancement, the foundational structure proved solid and extensible. As energy systems moved toward decentralization and flexibility, such forecasting tools became increasingly essential. The transparency and explainability of the model made it particularly well-suited for critical energy applications. This research established a solid foundation for future improvements, including the use of multivariate data, online learning, and integration with decision-support mechanisms. The study encouraged further investigation into hybrid fuzzy models for energy analytics. By integrating domain-specific constraints and user feedback, subsequent models could become even more responsive and effective. Ultimately, such models would play a key role in developing adaptive, intelligent energy management systems.

CONCLUSION

This research developed an innovative hybrid forecasting model for short-term power demand prediction in Demand Flexibility Services (DFS) by integrating KMeans clustering, Fuzzy Time Series (FTS), and Markov Chain methodologies. The model addressed key limitations of traditional FTS approaches by employing KMeans to dynamically generate fuzzy intervals that more accurately represented the actual distribution of demand data. The inclusion of a Markov Chain added a probabilistic layer that enhanced the model's ability to capture temporal patterns in power usage. The model was evaluated using a real-world dataset and demonstrated strong forecasting performance, achieving a Mean Absolute Error (MAE) of 74.60 MW and a Root Mean Square Error (RMSE) of 86.04 MW. It successfully mirrored demand trends, fluctuations, and peak loads, while maintaining stability across both low and high demand scenarios. Its rule-based and interpretable design made it well-suited for integration into expert-driven control systems and energy decision-support platforms. The key strengths of the model lay in its balance of accuracy, transparency, and computational efficiency. While there remained room for improvement such as incorporating external variables, dynamically updating the transition matrix, or applying more advanced fuzzification techniques. The findings affirmed that the KMeans-based FTS Markov Chain approach was a promising solution for intelligent short-term forecasting in smart grid applications that required both reliability and interpretability.

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