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Fuzzy Histograms on Load Forecasting

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ABSTRACT Short-term load forecasting (STLF) is crucial for the efficient and reliable operation of modern power grids. However, forecasting accuracy can be challenged by the inherent nonlinearity, seasonality, and uncertainty present in load data and influencing factors like weather. This report investigates the application of fuzzy logic concepts, specifically fuzzy feature engineering and Fuzzy C-Means (FCM) clustering, integrated with a deep learning model (Bidirectional LSTM) built using TensorFlow/Keras, to enhance STLF performance. While the initial theme involves "Fuzzy Histograms," the practical implementation focuses on leveraging fuzzy membership functions for descriptive feature creation and FCM for deriving cluster-based features using the Scikit-fuzzy library. A baseline 3-layer Bidirectional LSTM model trained on standard time-series and weather features is compared against a hybrid Fuzzy-LSTM model incorporating these additional fuzzy and cluster-based features. Both models are trained and evaluated on the Tetouan City power consumption dataset, focusing on hourly predictions for specific days within selected months, using data manipulation via Pandas/NumPy and scaling/metrics via Scikit-learn. Evaluation metrics including Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), R-squared (R^2), and a custom tolerance-based accuracy metric demonstrate that the hybrid Fuzzy-LSTM model achieves significantly superior forecasting accuracy compared to the baseline LSTM model (overall RMSE reduced by 22.2% to 1644.95, MAE reduced by 20.4% to 1292.79, and 15% tolerance accuracy increased from 85.71% to 94.35%), highlighting the potential of integrating fuzzy concepts with deep learning for enhanced STLF.

INDEX TERMS Load forecasting, short-term load forecasting (STLF), fuzzy logic, fuzzy sets, membership functions, fuzzy features, Fuzzy C-Means (FCM), clustering, Long Short-Term Memory (LSTM), deep learning, TensorFlow, Keras, Scikit-fuzzy, Adam optimizer, time series analysis, hybrid models.

I. INTRODUCTION

Accurate forecasting of future electricity demand is indispensable for the stable, secure, and economic operation of power systems [15], [25]. Utility companies rely on load forecasts for critical decision-making processes across various time scales, including generation scheduling, unit commitment, energy trading, grid stability management, and long-term infrastructure planning [1]. Short-Term Load Forecasting (STLF), which predicts load from an hour up to a week ahead, is particularly vital for optimizing daily operations and minimizing operational costs [1], [30]. An error reduction of even 1% in STLF can lead to significant cost savings [13].

However, achieving high accuracy in STLF is inherently challenging. Electricity consumption is a complex process influenced by a multitude of factors, exhibiting strong temporal dependencies and nonlinear characteristics [45], [50]. Key influencing factors include:

1. **Seasonality:** Load patterns vary significantly on hourly, daily, weekly, and annual cycles.
2. **Weather Dependence:** Variables like temperature and humidity have a strong, often nonlinear, impact on heating and cooling loads [12], [50].
3. **Calendar Effects:** Weekdays, weekends, and public holidays exhibit distinct consumption profiles [11], [21].
4. **Uncertainty and Vagueness:** Customer behavior, economic activity, and unforeseen events introduce randomness and imprecision [12], [8].

Traditional STLF methods, such as regression and time series models (e.g., ARIMA [20]), often struggle to fully capture the complex nonlinearities and interdependencies present in load data [5], [48]. Artificial Intelligence (AI) techniques have emerged as powerful alternatives. Artificial Neural Networks (ANNs) [4], [42], [48], and more recently Deep Learning (DL) models, particularly Long Short-Term Memory (LSTM) networks [11], [14], [47], [71], have demonstrated significant success due to their ability to learn complex patterns and long-range dependencies directly from data.

Fuzzy Logic Systems (FLS) offer a complementary approach, excelling at handling the inherent vagueness and linguistic uncertainty in load forecasting problems [19], [52], [56]. Techniques like Adaptive Neuro-Fuzzy Inference Systems (ANFIS) [1], [22], [56], interval type-2 FLS [7], and fuzzy time series [4], [9] have been successfully applied. Hybrid approaches combining fuzzy logic with other methods (e.g., Neuro-Fuzzy [1], [52], [56]) aim to leverage the strengths of both paradigms. Clustering techniques, such as Fuzzy C-Means (FCM) [3], [11], are also employed to group similar load profiles, potentially improving model accuracy by training specific models for different patterns [4], [11].

This report explores a hybrid approach that enhances a Bidirectional LSTM network for STLF by incorporating features derived from fuzzy logic principles and FCM clustering. The core idea is that explicitly representing input features (like time, temperature, lagged load) using fuzzy membership degrees and identifying typical load patterns via clustering can provide richer, more descriptive information to the LSTM model, improving its ability to learn complex relationships and ultimately enhancing forecasting accuracy. This study utilizes the publicly available Tetouan City power consumption dataset to compare the performance of a baseline LSTM model against the proposed hybrid Fuzzy-LSTM model.

The report is structured as follows: Section II provides a brief review of relevant concepts in fuzzy logic, clustering, and LSTM for load forecasting. Section III details the methodology, including data preprocessing, feature engineering (standard, fuzzy, and cluster-based), model architectures, and evaluation metrics. Section IV presents and discusses the experimental results based on the obtained metrics. Section V concludes the report and suggests potential future work.

II. BACKGROUND

Short-Term Load Forecasting (STLF)

STLF aims to predict electricity load for horizons ranging from one hour to one week [15]. Accurate STLF is crucial for operational efficiency and grid stability [1]. Diverse methods exist, from classical statistical models like ARIMA [20] to AI techniques like ANNs [42], [48], SVM [16], [7], and LSTMs [11], [14].

Fuzzy Logic Systems (FLS)

FLS, pioneered by mathematician Dr.Lotfi A. Zadeh [6], [32], provide a mathematical framework for dealing with imprecise and uncertain information, often expressed using linguistic terms. Unlike crisp sets, where an element either belongs or does not belong, a fuzzy set A defined over a universe of discourse U is characterized by a membership function μA(x) which assigns each element x ∈ U a degree of membership in A, μA(x) ∈ [0, 1] [56]. These functions define the degree of membership for each element in a fuzzy set. Common shapes include triangular, trapezoidal, Gaussian, and generalized bell functions [1], [10], [33]. For example, a simple triangular MF for a fuzzy set 'Medium' centered at 'c' with width 'w' might be represented as:

$$\mu Medium(x) = \max\left(0{,}1 - \frac{2|x-c|}{w}\right)$$

FLS use IF-THEN rules (e.g., IF Temperature is Hot THEN Load is High) and fuzzy logic operations (AND, OR, NOT) to map fuzzy inputs to fuzzy outputs [10], [48]. Defuzzification converts the fuzzy output back to a crisp value [8]. ANFIS is a popular neuro-fuzzy approach that learns rules from data [1], [22], [56]. Crisp data can be transformed into fuzzy features by calculating their membership degrees in predefined fuzzy sets. For instance, a temperature of 28°C might be transformed into features like {temp_cold: 0.0, temp_mild: 0.2, temp_warm: 0.9, temp_hot: 0.6}. This provides a richer representation than the single crisp value.

Fuzzy C-Means (FCM) Clustering

FCM is a partitioning clustering algorithm where each data point belongs to multiple clusters with varying degrees of membership, unlike K-Means where each point belongs to only one cluster [3], [11], [31]. It is particularly useful when clusters overlap or are not well-defined. FCM aims to minimize the objective function:

$$J_m = \sum_{i=1}^{N}\sum_{j=1}^{C}(u_{ij})^m \left|\left|x_c - c_j\right|\right|^2 \ \text{ for } 1 \le \mathrm{m} \le \infty$$

Where N is the number of data points, C is the number of clusters, x_i is the i-th data point, c_j is the center of the j-th cluster, u_ij is the degree of membership of x_i in cluster j (∑(j=1 to C) u_ij = 1), m > 1 is the fuzzifier exponent (typically m=2) and ||.|| is a distance norm (e.g., Euclidean) [4]. The membership u_ij is updated iteratively:

$$u_{ij} = \frac{1}{\sum_{k=1}^{C}\left(\frac{\left||x_c - c_j|\right|}{\left||x_c - c_k|\right|}\right)^{\frac{2}{m-1}}}$$

Cluster centers c_j are updated as the weighted average:

$$c_j = \frac{\sum_{i=1}^{N}(u_{ij})^m x_i}{\sum_{i=1}^{N}(u_{ij})^m}$$

In this work, FCM is used to identify typical load patterns; membership degrees (u_ij values) become LSTM input features. IFCM is an improvement addressing imbalanced data [4], [11]. LSTMs are RNNs designed for long-range dependencies via internal gates [11], [14]. Bidirectional LSTMs process sequences in both directions. Combining methods like Fuzzy Logic and ANNs/LSTMs often improves performance [1], [7], [11], [29], [34], [52], [56]. This work focuses on a Fuzzy-LSTM hybrid enhanced with FCM features.

III. METHODOLOGY

Software Implementation and Dependencies

The analysis and modeling were implemented using the Python programming language. Key libraries utilized include:

- **Pandas:** For data loading, manipulation, time series resampling, and DataFrame management.
- **NumPy:** For numerical operations, array handling, and mathematical functions (e.g., sine/cosine for cyclical encoding).
- **Scikit-learn:** For data preprocessing (MinMaxScaler, StandardScaler), model evaluation metrics (mean_absolute_error, mean_squared_error, r2_score).
- **Scikit-fuzzy:** For implementing fuzzy logic concepts, specifically defining membership functions (trapmf, trimf), calculating membership degrees (fuzz.interp_membership), and performing Fuzzy C-Means clustering (skfuzzy.cluster.cmeans, skfuzzy.cluster.cmeans_predict).
- **TensorFlow/Keras:** For building, training, and evaluating the deep learning models (Bidirectional LSTM). Core components used include Sequential API, LSTM, Bidirectional, Dense, Dropout, BatchNormalization layers, and the Adam optimizer.
- **Matplotlib:** For generating plots to visualize results (training loss, daily forecasts)
- **Math:** Standard Python library used for constants like pi (for cyclical encoding) and sqrt (for RMSE).

Dataset Description

The study utilizes the publicly available “Tetouan City power consumption” dataset from the UCI Machine Learning Repository. Tetouan, a major city in northern Morocco near the Mediterranean, has a Mediterranean climate (hot, dry summers; mild, wet winters) and a mixed economy of commerce, tourism, light industry, and agriculture. Its power consumption exhibits strong seasonality—with summer cooling peaks and potential winter heating peaks—distinct daily residential and commercial load profiles (overnight lows and morning/evening peaks), and a high dependence on weather variables, especially temperature. The dataset’s completeness, multivariate time-series structure, nonlinearity, and multi-zone outputs, together with its public availability, make it a reproducible, real-world benchmark for load-forecasting research.

The CSV is first read into a DataFrame and its column names are standardized. The timestamp column is converted to pandas datetime, and the data are resampled to an hourly frequency by taking the mean. Next, basic time-based features—hour of day, day of week, month, day of year, and day of month—are engineered, and any missing weather values are imputed via forward-fill, backward-fill, or global mean. A binary holiday indicator is added, and sine/cosine transformations of the cyclical time features are created. Rolling averages over 6- and 24-hour windows are then computed, and lagged load predictors at lags of 1–6 hours, 24 hours, and 168 hours are constructed. Finally, the initial rows containing NaNs resulting from those rolling and lag operations are dropped.

Fuzzification was performed on the variables hour_original, dayofweek, month, temperature, and zone_X_lag1. Membership functions for categories such as “night,” “morning,” “weekday,” “weekend,” “spring,” “summer,” “autumn,” “winter,” “cold,” “mild,” “warm,” “hot,” “low,” “medium,” and “high” were defined using skfuzzy.trapmf and skfuzzy.trimf. For each row, membership degrees were then computed via fuzz.interp_membership and appended to the dataset as new features.

Relevant features such as zone 1 power consumption lag1, _lag24, _lag168, temperature, hour_sin/cos, and dayofweek_sin/cos—were first selected. These features were then scaled using StandardScaler. Next, fuzzy C-means clustering was applied to the scaled training subset via skfuzzy.cluster.cmeans, yielding seven cluster centers (with fuzzifier m = 2.0, error threshold < 0.005, and a maximum of 1,000 iterations). Membership degrees for all observations were subsequently predicted using skfuzzy.cluster.cmeans_predict with the trained centers. Finally, the resulting membership columns (fcm_cluster_0 through fcm_cluster_6) were added to the main DataFrame as new features.

The final preprocessed DataFrame was first filtered to include only the target months (April, July, October, and December), with days 1 – 7 designated for training and days 8 – 14 for testing. Then, the final numerical feature set was extracted, excluding the target variables and any original columns created during fuzzy, cyclical, or FCM feature engineering. A MinMaxScaler was fitted exclusively on the training features and applied to both splits, and a StandardScaler was fitted on the training targets, used to transform them, and retained for subsequent inverse transformation.

LSTM Model Architecture

A 3-layer Bidirectional LSTM network was implemented in Keras as the core predictor (see Figure 1). Three stacked Bidirectional (LSTM) layers—each comprising 192 units—were employed, with return_sequences=True specified for the first two layers and return_sequences=False for the final layer. After each BiLSTM layer, Dropout (0.25) and BatchNormalization() were applied for regularization. Subsequently, a Dense layer of 128 units with ReLU activation was added, followed by a final Dense output layer configured with N_Zones units and a linear activation. Training was conducted using the Adam optimizer (tf.keras.optimizers.Adam) with a learning rate of 0.001, and Mean Squared Error ('mean_squared_error') was used as the loss function.

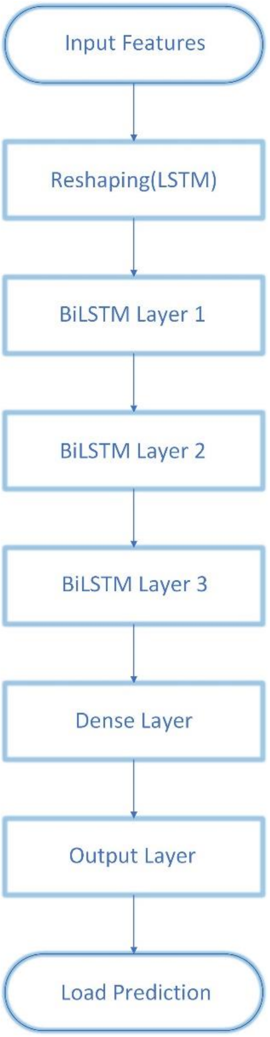

Figure 1 - Architecture of Baseline LSTM Model

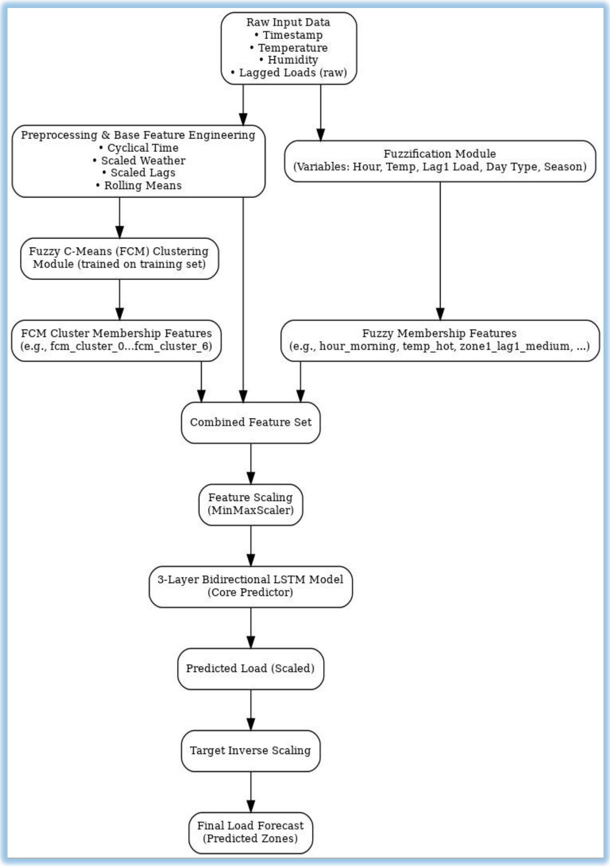

Figure 2 - Architecture of Hybrid Fuzzy-LSTM Model

Training and Evaluation

Model training was conducted using Keras's model.fit for up to 150 epochs with a batch size of 32 or 64 and a 20% validation split. Two callbacks were applied via tf.keras.callbacks:

- EarlyStopping monitored val_loss with a patience of 15–20 epochs and restore_best_weights=True.
- ReduceLROnPlateau monitored val_loss, reduced the learning rate by a factor of 0.2, and used a patience of 7–8 epochs.

After training, predictions were generated on the test set using model.predict and then inverse-scaled with the saved target StandardScaler. Any resulting negative values were clipped to zero.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i|$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{N}(y_i - \bar{y})^2}$$

$$Tolerance\ Accuracy(15\%)$$

$$= \frac{1}{N}\sum_{i=1}^{N}1(|y_i - \hat{y}_i| \le \max(0.15|y_i|, 10)$$

The training process utilized Early Stopping based on validation loss and learning rate reduction on plateau. The resulting learning curves for the baseline and hybrid models are shown in Figure 3 and Figure 4, respectively. Both models show successful convergence, with the training loss consistently decreasing and the validation loss stabilizing or decreasing until the stopping criterion was met. Notably, the final validation loss achieved by the hybrid model (Figure 4) appears lower than that of the baseline model (Figure 3), suggesting better generalization learned during the training phase itself before evaluation on the final test set.

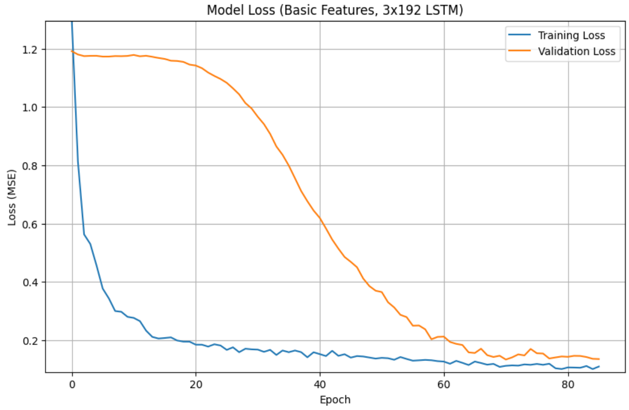

Figure 3 - **Training and validation loss curves (MSE vs. Epoch) - Baseline LSTM model**

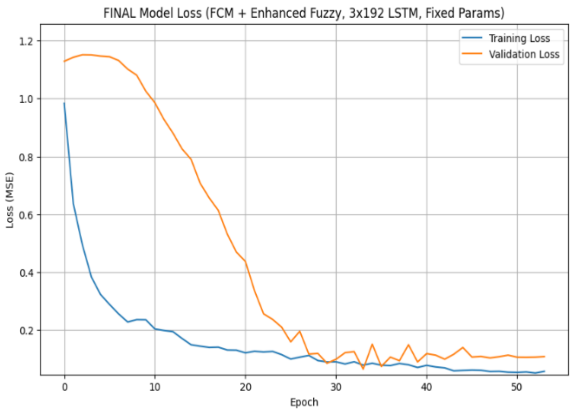

Figure 4 -**Training and validation loss curves (MSE vs. Epoch) - Hybrid Fuzzy-LSTM model**

IV. PERFORMANCE

Metrics

The overall test set performance comparison is summarized in Table 1, using the metrics calculated from the simulation outputs. The hybrid Fuzzy-LSTM model demonstrates substantial improvements over the baseline. Overall RMSE and MAE decreased by 22.22% and 20.41% respectively. The R^2 score improved, indicating a better model fit. The 15% tolerance-based accuracy saw a significant increase of 8.64 percentage points, suggesting enhanced practical reliability. Per-zone results also showed consistent improvements, particularly notable in Zone 2 (RMSE reduction ~32.9%).

Metric	Base	Hybrid	Difference
RMSE	2114.79	**1644.95**	**22.22%**
MAE	1624.38	**1292.79**	**20.41%**
R^2	0.9457	**0.9671**	**2.26%**
Accuracy	85.71%	**94.35%**	**+8.64%**

Table 1 – **Simulation Output (Base Model vs Hybrid Model)**

Visual Comparison

Visual analysis of the hourly forecast plots further supports the quantitative findings. Figures 5 and 6 compare the baseline and hybrid model forecasts against the actual load for Zone 1 on Saturday, April 8, figures 7 and 8 provide a similar comparison for Zone 2 and figures 9 and 10 provide the comparison for Zone 3 on the same day. Consistently, the hybrid model's predictions (orange bars) track the actual load (black bars) more accurately, especially around peak times and during load ramps, compared to the baseline model. Similarly, the forecasting is done for July 9, October 11 and December 12 by both the models on the 3 Zones.

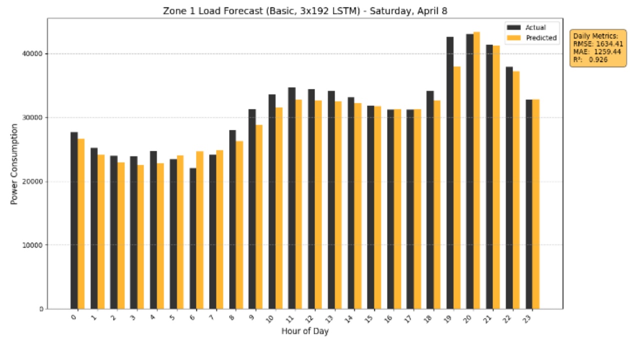

Figure 5 - **Baseline LSTM Daily Plot - Zone 1, April 8**

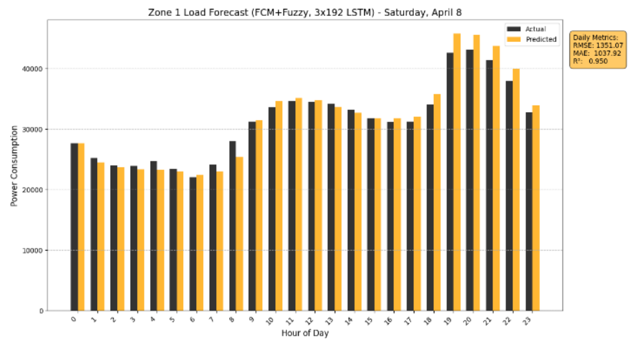

Figure 6 - **Hybrid Fuzzy-LSTM Daily Plot - Zone 1, April 8**

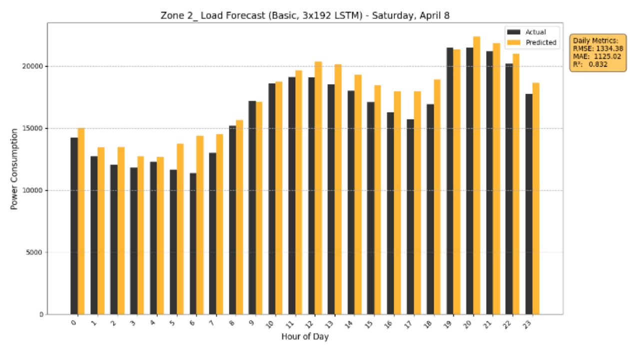

Figure 7 - **Baseline LSTM Daily Plot - Zone 2, April 8**

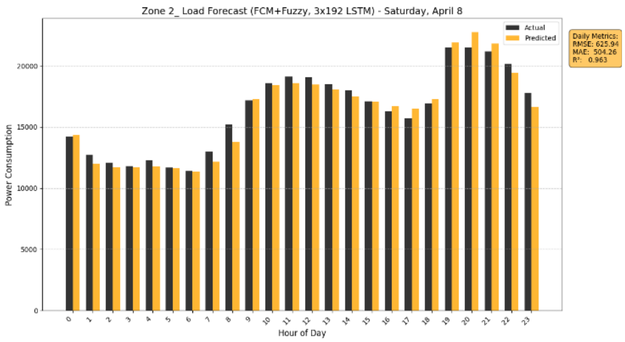

Figure 8 - **Hybrid Fuzzy-LSTM Daily Plot - Zone 2, April 8**

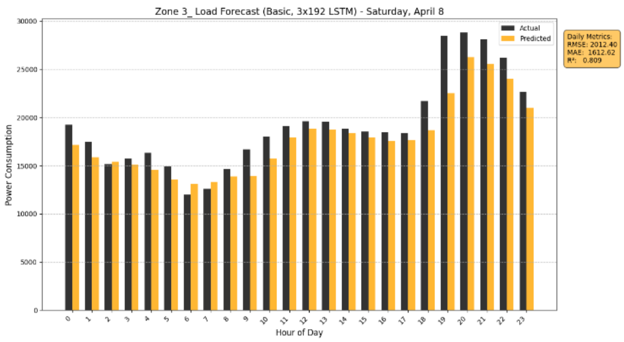

Figure 9 - **Baseline LSTM Daily Plot - Zone 3, April 8**

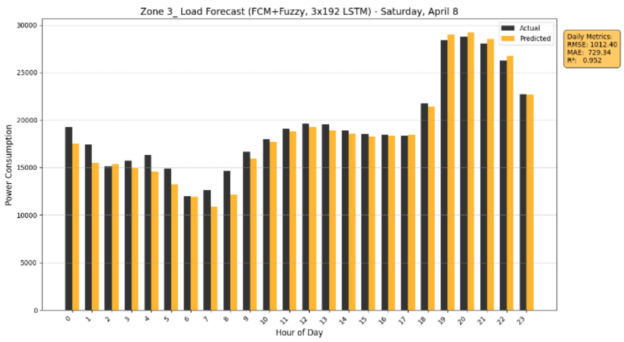

Figure 10 - **Hybrid Fuzzy-LSTM Daily Plot - Zone 3, April 8**

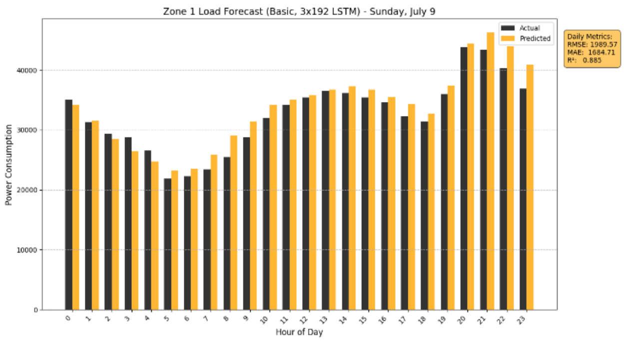

Figure 11 - **Baseline LSTM Daily Plot - Zone 1, July 9**

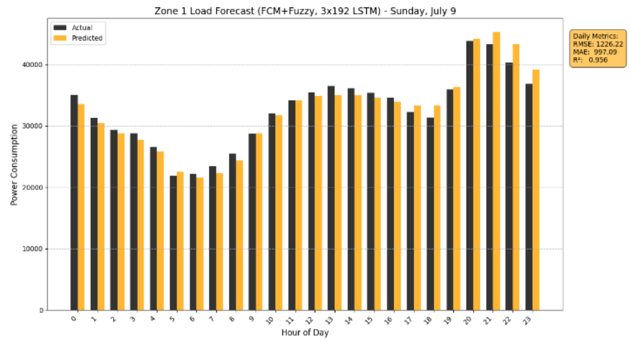

Figure 12 - **Hybrid Fuzzy-LSTM Daily Plot - Zone 1, July 9**

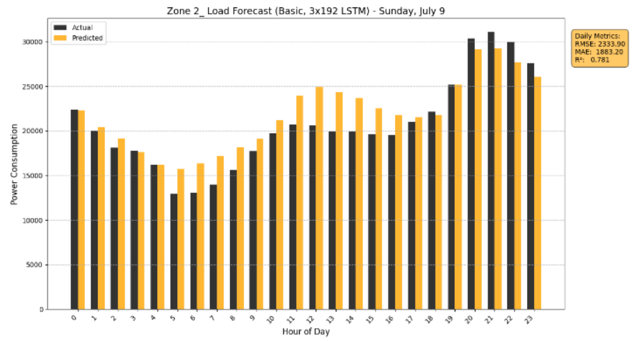

Figure 13 - **Baseline LSTM Daily Plot - Zone 2, July 9**

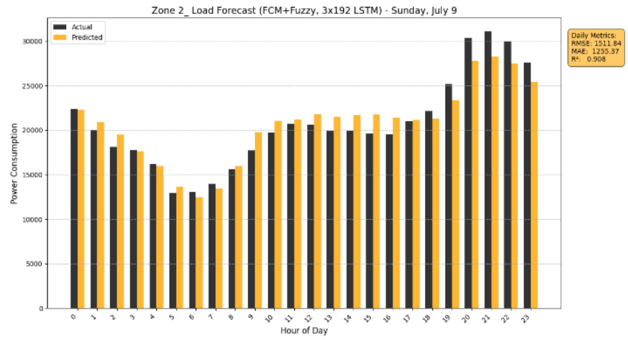

Figure 14 - **Hybrid Fuzzy-LSTM Daily Plot - Zone 2, July 9**

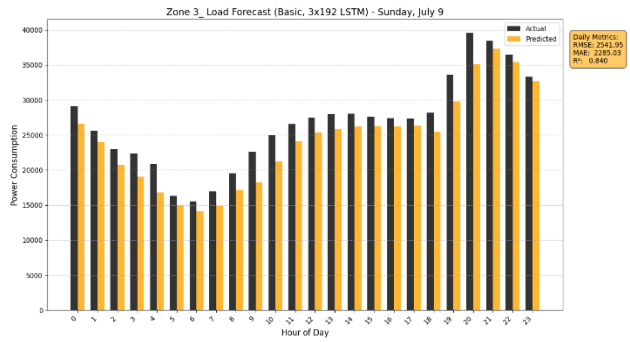

Figure 15 - **Baseline LSTM Daily Plot - Zone 3, July 9**

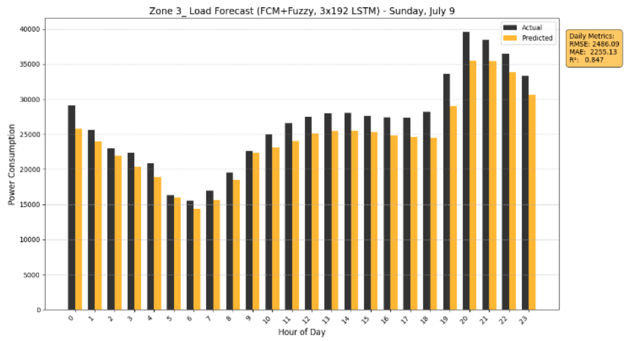

Figure 16 - **Hybrid Fuzzy-LSTM Daily Plot - Zone 3, July 9**

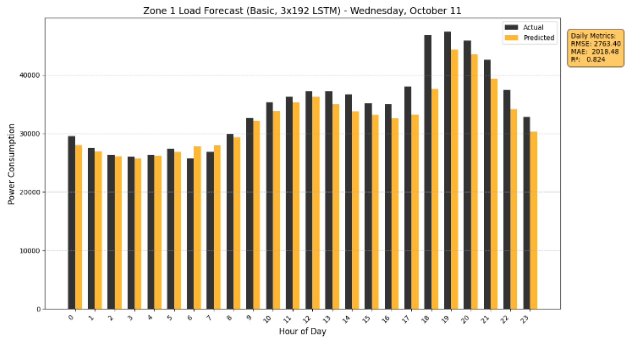

Figure 17 - **Baseline LSTM Daily Plot - Zone 1, Oct 11**

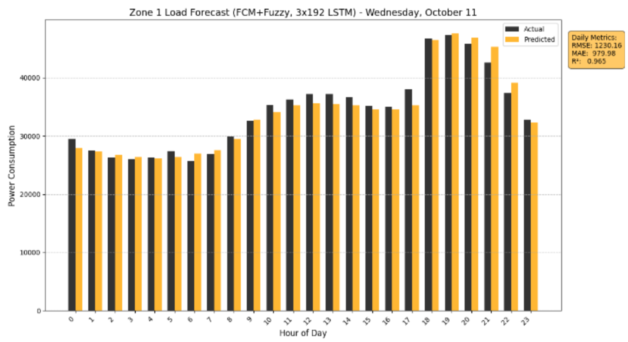

Figure 18 - **Hybrid Fuzzy-LSTM Daily Plot - Zone 1, Oct 11**

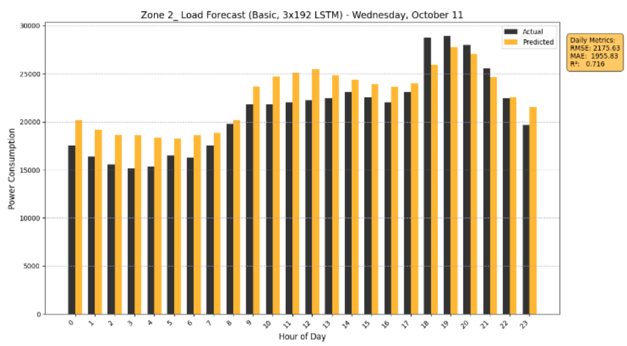

Figure 19 - **Baseline LSTM Daily Plot - Zone 2, Oct 11**

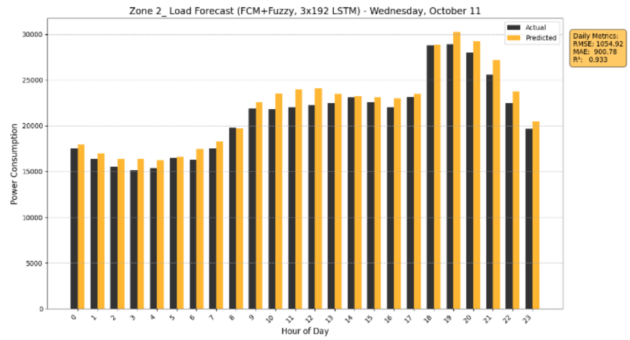

Figure 20 - **Hybrid Fuzzy-LSTM Daily Plot - Zone 2, Oct 11**

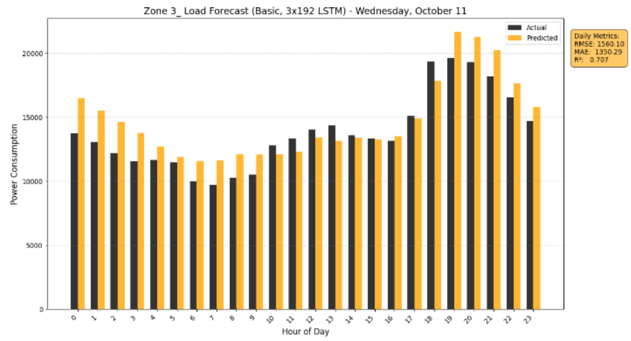

Figure 21 - **Baseline LSTM Daily Plot - Zone 3, Oct 11**

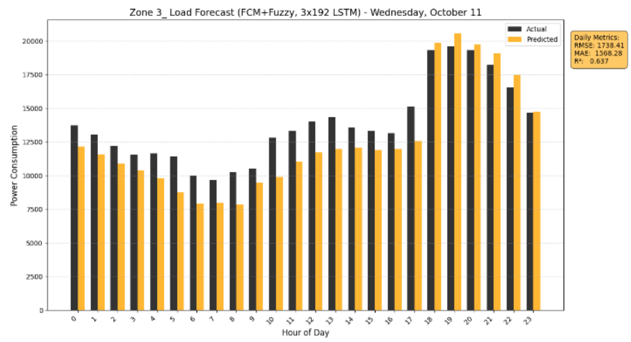

Figure 22 - **Hybrid Fuzzy-LSTM Daily Plot - Zone 3, Oct 11**

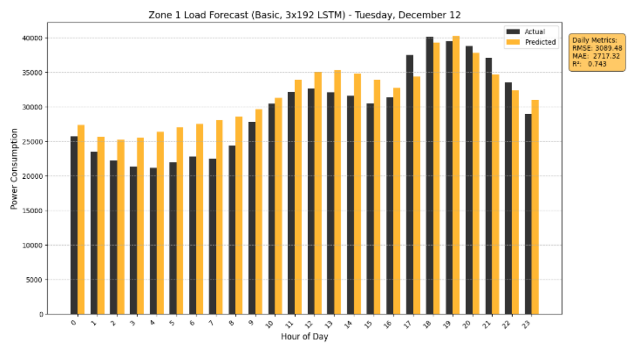

Figure 23 - **Baseline LSTM Daily Plot - Zone 1, Dec 12**

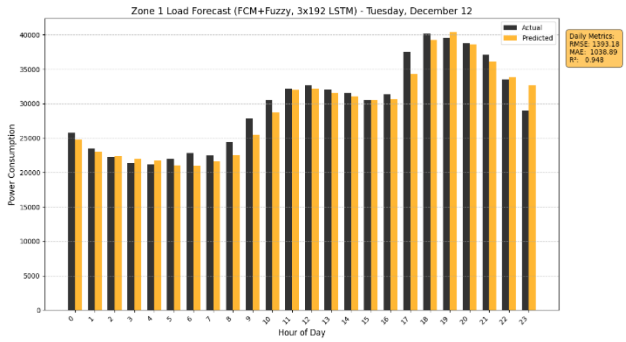

Figure 24 - **Hybrid Fuzzy-LSTM Daily Plot - Zone 1, Dec 12**

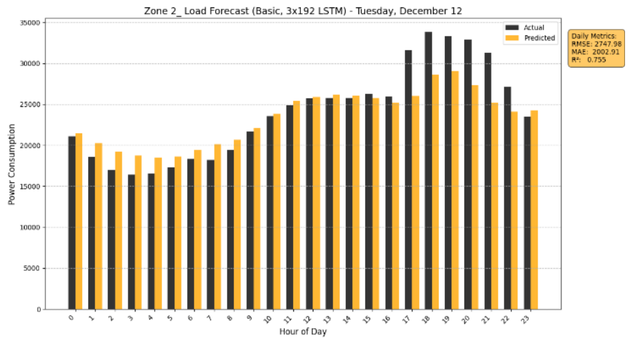

Figure 25 - **Baseline LSTM Daily Plot - Zone 2, Dec 12**

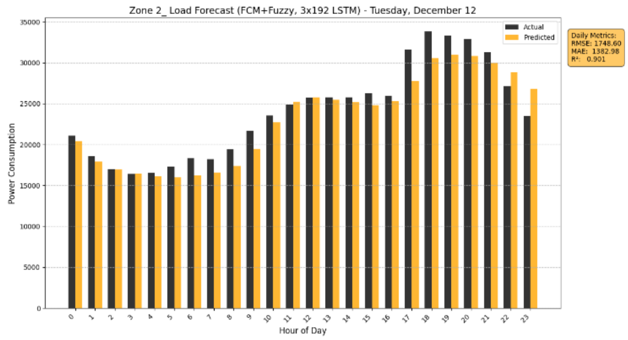

Figure 26 - **Hybrid Fuzzy-LSTM Daily Plot - Zone 2, Dec 12**

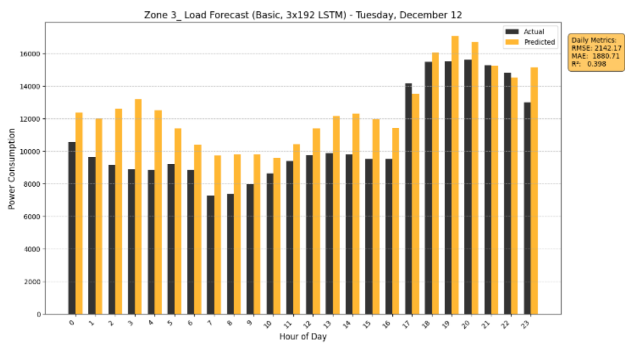

Figure 27 - **Baseline LSTM Daily Plot - Zone 3, Dec 12**

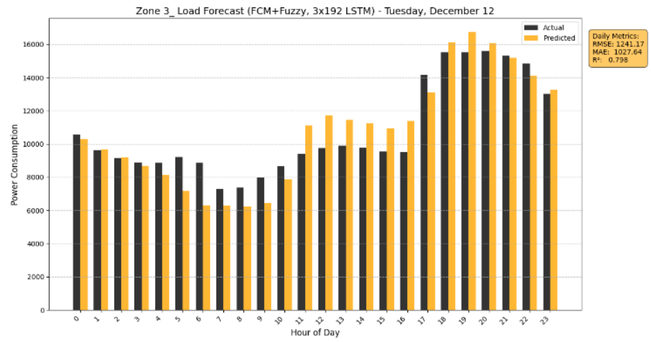

Figure 28 - **Hybrid Fuzzy-LSTM Daily Plot - Zone 3, Dec 12**

The superior performance of the hybrid model is attributed to the enhanced feature representation provided by the fuzzy logic and FCM clustering steps. Fuzzy features transform crisp inputs into linguistic representations (e.g., degree of 'hotness', 'morning-ness'), capturing nuances and nonlinear effects potentially missed by raw numerical values [1], [8]. FCM cluster membership features provide crucial context about the typical daily pattern the current hour belongs to, allowing the LSTM to differentiate its predictions based on expected overall daily behavior [4], [11]. This combination provides a richer, more context-aware input space, simplifying the learning task for the LSTM and leading to more accurate forecasts.

V. CONCLUSION

This report successfully demonstrated the effectiveness of a hybrid approach combining fuzzy feature engineering, Fuzzy C-Means clustering, and a Bidirectional LSTM network for short-term load forecasting. Evaluated on the Tetouan City dataset, the hybrid model significantly outperformed a baseline LSTM model trained on standard features, achieving substantial reductions in RMSE (22.2%) and MAE (20.4%), and a notable increase in 15% tolerance-based accuracy (to 94.35%). The results validate the hypothesis that integrating fuzzy logic concepts and clustering via feature engineering enhances the ability of deep learning models to capture the complex dynamics and uncertainties inherent in electricity load forecasting.

VI. FUTURE WORK

Future research should focus on **optimizing the fuzzy and clustering components**, potentially using automated techniques or metaheuristics to define membership functions and determine the optimal number of clusters. Comparing **FCM with alternative clustering methods** robust to imbalanced data, such as IFCM [4], [11], is recommended. Exploring **Interval Type-2 Fuzzy Logic Systems [7]** for feature generation could further improve uncertainty handling. Investigating **different deep learning architectures** (GRUs, Transformers) and implementing **automated feature selection** could refine the model. Finally, **evaluating the hybrid approach on diverse datasets** with varying load characteristics and across different forecast horizons is necessary to establish its broader generalizability.

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