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RESEARCH ARTICLE

A Hybrid Fuzzy-Kalman Filtering Approach for Short-Term Electricity Load Forecasting in the Kurdistan Region of Iraq

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ABSTRACT

Accurate short-term load forecasting is vital for maintaining the reliability and stability of electricity supply systems. This study examines forecasting methods for the Kurdistan region of Iraq, where electricity demand is steadily rising. Historical hourly load data and relevant exogenous variables were used to develop and compare two models: A standalone Fuzzy Logic model and a Hybrid Fuzzy-Kalman Filter (KF) model. Although both Fuzzy Logic and KFs have been used separately for load forecasting, there has been a lack of literature directly comparing a standalone Fuzzy Logic model with a Hybrid Fuzzy-KF approach, especially using data from the Kurdistan region. The Fuzzy Logic model was designed to capture non-linear relationships and apply human-like reasoning in predicting load demand. The hybrid approach integrated a KF to refine initial fuzzy estimates by reducing noise and updating predictions based on recent observations. Both models were evaluated using mean absolute percentage error and root mean square error (RMSE). The outcomes show that standalone fuzzy logic prediction is not as effective as the Hybrid Fuzzy–KF. The hybrid technique lowers the average mean absolute error and RMSE of the fuzzy model to 95.13 MW (−3.75%) and 109.89 MW (−10.46%), respectively, compared to the fuzzy model's average of 98.84 MW and 122.73 MW. This enhancement demonstrates how well noise filtering and recursive state estimation work, especially when load circumstances are steady. Results show that the hybrid model consistently outperformed the standalone Fuzzy Logic model. The findings highlight that the Hybrid Fuzzy-KF provides a more effective solution for short-term load forecasting in Kurdistan's electricity sector.

Keywords: Short-term load forecasting, fuzzy logic model, Kalman filter, hybrid modeling, electricity demand

INTRODUCTION

Electrical load forecasting stands at the core of planning and administration of contemporary power systems. The precise forecasting of load is essential for ensuring the reliability of the electrical grid, enhancing the efficiency of power generation, regulating energy markets, and reducing operational expenses.[1,2] Conventional statistical methods, including exponential smoothing and autoregressive models have seen extensive applications in load forecasting, but their shortcomings are apparent when dealing with issues of nonlinearity, non-stationary, and environmental variables such as temperature.[3-5] This has given rise to the development of hybrid and intelligent models, such as fuzzy logic and Kalman filtering, to improve forecasting efficiency under dynamic and uncertain conditions.[6-8] The Kurdistan region of Iraq faces significant challenges with its unstable electricity supply and rapidly growing demand, making accurate short-term load forecasting a crucial priority.

Fuzzy logic systems (FLS) are based on human cognitive processes and linguistic rules, making them well-suited to represent uncertain or imprecise relationships.[9] These systems are data-driven and can embody expert knowledge through conditional statements, which enables them to flexibly accommodate complex, nonlinear trends in load behavior.[10] Kalman Filters (KF), on the other hand, offer an optimal recursive estimation for linear dynamic systems with Gaussian noise assumptions.[11] Though they are widely used in signal and control processing, standard KFs perform inadequately when the noise characteristics are nonstationary or in cases where system dynamics are nonlinear.[12]

To overcome these limitations, Fuzzy Adaptive KFs (FAKF) have been established as a hybrid approach. In FAKF schemes, fuzzy logic is used to adaptively adjust the measurement

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noise covariance (R) and, occasionally, the process noise covariance (Q), based on contextual variables such as temperature, time factors, or historical trends of error.[13] This capability makes the KF adaptable and responsive to changing operating conditions, thereby enhancing its predictive capability and robustness.[14]

This work presents a comparison of two techniques for electric load forecasting: A fuzzy logic model by itself and a FAKF. The goal is to contrast the predictive capabilities of each approach and point out the possible benefits of hybrid methodologies. To the best of our knowledge, few works have explicitly compared these approaches with a unique dataset under controlled simulation conditions.[15]

LITERATURE REVIEW

Traditional Methods of Load Forecasting

Initial approaches to load forecasting depended primarily on statistical techniques, encompassing methods such as autoregressive integrated moving average, regression analyses, and exponential smoothing.[16-18] These models are effective where the underlying data are stationary and the relationships are linear. Nevertheless, electric load is influenced by numerous nonlinear factors, such as weather conditions, human activities, and economic constraints.[19] Thus, conventional models need to be frequently retrained and are not very generalizable in dynamic environments.

Fuzzy Logic in Load Forecasting

Fuzzy logic was first proposed by Zadeh (1965) to deal with the imprecision present in most real-world problems.[20] Fuzzy logic models have been used in electric load forecasting to incorporate human knowledge and heuristic rules, such as "if temperature is high, then load is likely to be high." Such models are highly interpretable and can perform well even with noisy or limited data.[21] Fuzzy logic forecasting has been shown to outperform the traditional linear models, especially for short-term instances of varying demand.[22]

Various types of fuzzy systems have been studied, including the Mamdani and Sugeno models. The Mamdani models make use of fuzzy sets for input and output variables, while the Sugeno models incorporate crisp outputs and are more computationally efficient. The selection of the two models is based on the complexity of the application and whether interpretability is required.[23]

Kalman Filtering in Forecasting

KFs, which were suggested by Kalman in 1960,[24] are an optimum recursive linear system estimation algorithm for Gaussian noise. KFs have been used in energy systems for filtering measurement noise from loads and estimating real-time system states.[25] Extended KFs and Unscented KFs have been suggested to allow handling nonlinear dynamics,[26] but the performance degrades as the noise statistics change with time.[27]

A significant drawback of conventional Kalman filtering is its assumption of constant and fixed noise covariances (R and Q). In practice, such parameters are rarely stable, particularly in situations influenced by external variables such as temperature, weather conditions, and human activity.[28,29]

Hybrid Models: Fuzzy Adaptive Kalman Filtering

Hybrid approaches of Kalman filtering and fuzzy logic have received much attention due to their adaptation capabilities under varying conditions. In such approaches, fuzzy inference systems adaptively change the noise covariance's R and/or Q in real-time, depending on auxiliary variables. For instance,[30] R is considered to be regulated by a fuzzy logic controller according to load and temperature changes, resulting in better tracking performance. The same hybrid models have been applied in other areas, including finance and robotics, and their applicability is attested.[31]

Studies have shown that FAKF models can outperform both FLS and conventional KFs, particularly in systems with highly varying and nonlinear dynamics[32] Good fuzzy rules and membership functions remain challenging to design and generally require expert insight or tuning using optimization algorithms.[33]

Despite the extensive discussions about hybrid models, there is still a notable lack of studies comparing pure fuzzy logic with FAKF in the field of load forecasting applications. This gap underscores the need for further research, which our current study intends to explore.[34] Thus, this study aims to address the existing gap by developing and evaluating a hybrid fuzzy-KF model specifically designed for the electricity load profile of the Kurdistan region, and comparing its performance to that of a standalone Fuzzy Logic model.

METHODOLOGY

The methodology of this study is structured in a systematic sequence. It begins with dataset preparation, followed by the implementation of a Fuzzy Logic model to produce initial load forecasts. Subsequently, a KF is incorporated to enhance these forecasts. Finally, the performance of both the standalone and hybrid models is assessed using standard accuracy metrics.

By combining fuzzy logic with the KF, the study develops a hybrid modelling approach that provides more stable predictions for electricity load. There are four fundamental phases in the methodology:

1. Data preparation
   Data on electricity loads over 24 h was collected, along with temperature data. Load values were used as the target variable, and temperature was added as an input to the fuzzy model to adjust for external influences on demand.
2. Fuzzy logic load estimation
   A system that relied on fuzzy inference was developed to estimate the load by analysing temperature variations. The initial load estimates were obtained through fuzzy regression after designing triangular membership functions for the temperature variable.
3. KF integration
   The outputs were fuzzy and then subjected to a KF to smooth out fluctuations and improve the stability of the time series. The filter was set to the mean and variance

of the actual load per hour. By performing the prediction and update steps every hour, the KF produced an adjusted estimate. Several crucial statistical data were reported, including:

- Kalman gain (K): Balancing the validity of fuzzy measurements with the filter's predictions.
- Error covariance (P): Defining the uncertainty of the state estimates.
- Residuals: Identifying the dissimilarities between fuzzy outputs and Kalman estimates.

4. Evaluation and analysis
For model performance, two accuracy measures, mean absolute error (MAE) and root mean squared error (RMSE), were calculated by utilizing fuzzy outputs and Kalman-filtered estimates. Time Convergence was also documented to determine how many times the filter had to be adjusted for each hour. Hourly load profiles and the error plotted are use to illustrate the results in performance tables per hour.

Fuzzy Logic (Takagi–Sugeno) Estimator

Memberships (three terms: L, C, R)

A triangular membership function is defined by three parameters:

- L (left): left endpoint - the membership starts to rise from 0.
- C (centre): peak point - the membership is 1 (full membership).
- R (right): right endpoint - the membership falls back to 0.

$$\mu_i\ (Tk)\in[0,1], \qquad i\in\{L,C,R\}$$

Linear consequents (fuzzy regression)

$$y_i(Tk) = a_{0,i} + a_{1,i}Tk \tag{1}$$

Defuzzification (TS-weighted average)

$$y_k^f = \sum_i \bar{w}_i(Tk)y_i(Tk) = \frac{\sum_i \mu_i(Tk)y_i(Tk)\,[a_{0,i}+a_{1,0}Tk]]}{\sum_i \mu_i(Tk)} \tag{2}$$

The defuzzification step is vital, as it transforms the fuzzy output into a single, clear value that represents the estimated load demand.

State and observation models

We treat the true load as a latent state x_k and the fuzzy output as the measurement.

$$X_t = F_t X_{t-1} + W_t \tag{3}$$

Where $X_t = \begin{bmatrix} \text{Load}_t \\ \text{Temperature}_t \end{bmatrix} \in \mathrm{R}^2$ are the Current State, $F_t = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$ is the transition matrix, and W_t is the process noise with covariance , i.e., $W_t \sim N(0,Q_t)$.

The predicted load to the actual measurements to the observation model is:

$$Z_t = y_k^f = H_t X_t + V_t \tag{4}$$

Where Z_t = fuzzy logic output = estimated load are the measurements of true state X_t, H_t = (1 0) is the measurement function or (matrix), and V_t is the measurement noise with covariance R_t, i.e., $V_t \sim N(0,R_t)$.

Initialization (per hour)

$$x_{0|0} = \bar{y}_{actual,hour} \quad , \quad P_{0|0} = Var(y_{actual,hour}) \tag{5}$$

$$\hat{X}_{0|0} = \begin{bmatrix} \text{Mean load}_0 \\ \text{Mean temp}_0 \end{bmatrix}, \quad P_{0|0} = \begin{bmatrix} \text{Var(load)} & 0 \\ 0 & \text{Var(temp)} \end{bmatrix}$$

Forecasting:

$$x_{k|k-1} = Fx_{k-1|k-1}, \quad P_{k|k-1} = FP_{k-1|k-1}F^T + \mathrm{Q} \tag{6}$$

Innovation (residual) and its variance

$$\hat{y}_k = z_k - Hx_{k|k-1} \quad , \quad S_k = HP_{k|k-1}H^T + R \tag{7}$$

Kalman gain, update of state and covariance

$$K_k = P_{k|k-1}H^T S_{k-1} \tag{8}$$

With $H = 1 \quad K_k = \dfrac{P_{k|k-1}}{P_{k|k-1} + R}$

Hence:

K_k ↑ when $P_{k|k-1}$↑ (high state uncertainty) or R↓ (trust the fuzzy measurement more).

K_k↓ *when* $P_{k|k-1}$↓ or R↑ (trust prediction more)

the Kalman Gain serves as a dynamic weighting factor, determining the extent to which the new fuzzy measurement adjusts the state prediction.

Time convergence (per-hour iteration)

If you iterate the filter within hour until stability, stop when $\left|x_{k|k}^{t} - x_{k|k}^{(t-1)}\right| < \varepsilon \Rightarrow iterations = Time\,Convergence$.

MAE/RMSE (for fuzzy and for Kalman estimates)

Given actual load y_k, fuzzy $\hat{y}_k^f$, and Kalman forecasting $\hat{y}_k^K$

$$MAE_F = \frac{1}{N}\sum_{k=1}^{N} |y_k - \hat{y}_k^f|, RMSE_F = \sqrt{\frac{1}{N}\sum_{k=1}^{N}(y_k - \hat{y}_k^f)^2} \tag{9}$$

$$MAE_K = \frac{1}{N}\sum_{k=1}^{N} |y_k - \hat{y}_k^K|, RMSE_k = \sqrt{\frac{1}{N}\sum_{k=1}^{N}(y_k - \hat{y}_k^K)^2} \tag{10}$$

RESULTS

Descriptive Statistics

Table 1 displayed each period's mean consumption, which ranges from 996 to 1026 units, and was comparatively constant. For example, the average hourly use of electricity fluctuated between 996 and 1026 units during the day, while the minimum hourly load was between 700 and 792 units. Maximum loads could reach up to 1263 units at 1 AM, while average consumption was slightly lower during the early morning hours (1 AM–5 AM), with mean values between 998 and 1008 units. The demand for electricity steadied throughout the day, with a discernible uptick beginning at 8 AM. Midmorning to early afternoon (9 AM–12 PM) was when power consumption was at its highest. During this time, the mean load was continuously higher than 1023 units, and at noon, the maximum recorded values were higher than 1311 units. During these peak hours, the third quartile (Q3) continuously exceeded 1080 units, suggesting persistently high electricity consumption.

Moreover, with mean values between 1010 and 1017 units, power consumption in the afternoon (1 PM–5 PM) was still strong but somewhat tapered down. The fact that maximum loads during this time still surpassed 1250 units indicated that demand was still high even after peak hours. A slow decrease was noted in the evening (6 PM–9 PM), with maximum loads continuously surpassing 1229 units and mean values ranging from 996 to 1007 units. With upper quartiles continuing to be above 1060 units, late-night (10 PM to midnight) hours exhibited a little recovery in mean consumption (1005–1011 units), suggesting that some users continued to consume at high levels. With notable peaks in the morning and consistent high consumption throughout the day and evening, the overall pattern indicated that the demand for power stayed strong throughout the 24-h cycle. These insights were essential for predicting peak load demand and optimizing the energy supply.

Regarding to the variation inspected through standard deviation, which might be a sign of seasonal patterns, population activity shifts, or outside events that impact the demand for power. The existence of fluctuating consumption periods highlighted the dynamic character of power demand, even when the overall trend of mean consumption was steady as shown in Figure 1.

In conclusion, the data points to a pattern of electricity use that was largely steady, with sporadic fluctuation spikes and this might be due to hourly usage.

The study's findings demonstrate the enhanced performance of the Hybrid Fuzzy-KF model in comparison to the standalone Fuzzy Logic model for 24-h power demand forecasting in the Kurdistan Region of Iraq. A thorough comparison of the hourly performance metrics, including MAE and RMSE, is provided in Table 2.

Table 2 The data consists of hourly measurements of electricity load with convergence times between 9 and 32 units, representing different computational complexities in different hours of the day. The load values themselves range from 842 MW to 1223 MW, exhibiting normal daily variation patterns in power grids. The fuzzy logic approach produces estimates based on membership functions and rule-based reasoning, whereas the hybrid Fuzzy-Kalman method fuses the fuzzy estimates with Kalman filtering principles. The values of the Kalman gain (0.1321–0.6395) represent adaptive weighing between forecasted states and measurements, where higher gains reflect greater reliance upon new observation. The values of error covariance (0.8921–15.0214) reflect quantification of uncertainty inherent in the Kalman formulation, representing a measure of confidence in estimation that changes based upon system behavior and quality of measurement.

The analysis of performance clearly indicates merits of the Hybrid Fuzzy-KF over Fuzzy Logic prediction alone. For Fuzzy Logic prediction, MAE ranges from 87.27 to 110.13 MW, averaging 98.84 MW, and RMSE ranges from 111.14 to 137.14 MW, averaging 122.73 MW. For its own part, though, better accuracy is evidenced by the Hybrid Fuzzy-KF, where higher and lower limits of MAE are 82.48 MW and 108.03 MW, averaging 95.13 MW, and RMSE is 101.85 MW to 137.04 MW, averaging 109.89 MW. Reduction of mean MAE by approximately 3.75% and RMSE by 10.46% verifies that mitigation of prediction error is efficacious by means of recursive state estimation and filtering out measurement noise by means of the KF. Notably, improvement is most effective during stable load patterns, where dynamic tracking of the

Table 1: Descriptive statistics of electricity usage per hour

Time (hour)	Min	Q1	Median	Mean	Q3	Max
1	715.95	943.74	1004.98	1007.72	1057.35	1262.62
2	705.45	936.33	1010.9	1006.83	1070.79	1247.29
3	718.47	937.07	1012.2	1005.02	1068.96	1273.33
4	707.36	943.61	1010.72	1004.17	1075.83	1260.31
5	700.35	932.69	1010.31	997.9	1073.4	1233.22
6	701.06	919.61	1006.41	997.63	1080.44	1256.32
7	700.77	916.82	1016.19	998.78	1079.33	1266.82
8	707.15	921.12	1031.5	1011.42	1092.34	1277.95
9	743.57	932.5	1029.84	1016.37	1089.69	1257.37
10	763.7	935.84	1034.25	1024.11	1089.99	1292.36
11	775.46	939.12	1025.39	1022.95	1082.66	1316.06
12	748.79	957.35	1028.08	1025.59	1084.27	1310.61
13	732.83	946.5	1022.12	1015.88	1071.51	1257.62
14	733.41	952.01	1023.05	1016.78	1076.13	1246.87
15	737.1	946.89	1014.84	1010.02	1070.97	1249.71
16	719.25	941.5	1014.18	1009.27	1067.1	1256.43
17	774.69	934.58	998.31	998.97	1051.98	1245.09
18	757.89	930.86	999.97	996.21	1046.79	1263.78
19	746.55	929.5	999.02	996.85	1050.69	1242.78
20	735.21	940.46	1006.46	1005.68	1063.23	1229.34
21	781.41	938.57	998.55	1005.41	1061	1246.77
22	788.97	941.85	1003.36	1007.19	1066.8	1233.96
23	791.76	939.33	1010.06	1010.06	1075.62	1239.73
24	745.79	946.47	1007.79	1010.95	1066.51	1244.56

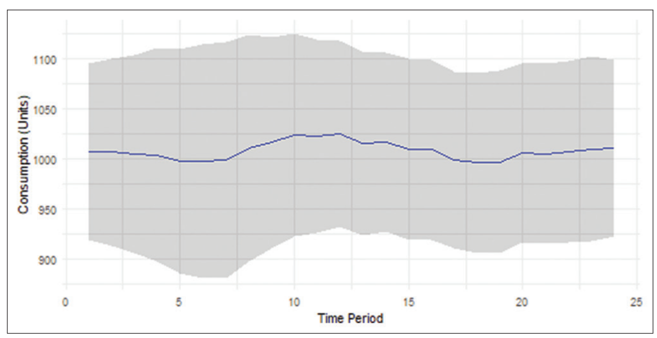

Figure 1: Mean value electricity consumption along the standard deviation

Table 2: Comparative performance of fuzzy logic and Kalman filter in hourly electricity load forecasting

Hour	Time convergence	Actual load	Fuzzy estimate	Hybrid fuzzy Kalman estimate	Kalman gain	Error covariance	MAE fuzzy	RMSE fuzzy	MAE hybrid fuzzy Kalman	RMSE hybrid fuzzy Kalman
1	18	869	993.5175	994.2120	0.3666	9.3148	99.7513	126.4092	96.9012	116.5078
2	19	913	993.5688	992.8582	0.3588	9.0806	93.8269	120.4091	91.9222	110.4947
3	11	1125	989.8345	998.8921	0.1321	2.3912	99.9843	125.4510	91.1241	110.6721
4	20	942	987.0795	987.3470	0.3317	7.9133	105.3296	128.9729	103.2337	128.8743
5	10	937	990.0841	990.0517	0.6395	15.0214	110.1316	137.1414	108.0257	137.0420
6	9	957	991.2938	988.5844	0.6388	14.8233	108.3457	135.4950	102.2415	135.3820
7	13	970	985.4966	983.6682	0.5041	11.6609	98.0972	120.8465	91.0112	120.7222
8	15	1019	998.9841	991.7821	0.2131	0.8921	97.3198	111.6521	91.2145	111.1356
9	12	911	969.5256	968.6863	0.5019	12.3685	87.3745	114.4130	83.4176	104.5622
10	11	920	972.5506	973.9142	0.5477	13.7590	87.2726	112.3233	82.4764	102.5188
11	13	933	981.8118	980.8849	0.4984	12.6171	88.5465	111.6972	85.6648	101.8515
12	14	974	997.1779	997.1924	0.4525	11.7432	90.6179	114.0169	89.8102	104.2056
13	17	931	1004.3805	1003.9539	0.3845	9.9920	101.9171	126.5612	100.1427	106.7305
14	32	1223	1010.0128	1009.2449	0.2375	6.1291	102.9925	127.2011	101.1941	107.3971
15	19	910	1003.4640	1002.2439	0.3561	9.1703	102.8988	126.4447	101.9947	106.5636
16	29	966	999.7001	998.9355	0.2776	7.0489	99.3463	123.0828	87.4779	103.2102
17	14	911	978.0435	978.3640	0.4699	11.7828	95.3139	116.7649	93.4216	106.8494
18	13	842	975.8941	974.8487	0.4858	12.1119	94.6491	117.2003	91.7241	107.2476
19	13	847	975.6425	974.7775	0.4796	11.9167	95.7082	118.5607	91.8665	108.6998
20	12	895	978.8031	978.6536	0.5384	13.5677	95.6425	119.2586	92.7773	109.2960
21	17	865	984.2127	983.6644	0.4042	10.1428	102.3556	125.4825	99.5326	105.5813
22	12	896	975.7212	978.6232	0.5357	13.5517	100.1922	123.5975	98.3706	103.7136
23	11	1000	981.3080	983.9600	0.5462	13.9360	99.7326	124.1023	92.8354	104.1944
24	11	968	988.3236	990.0097	0.5732	14.6578	99.1915	123.8975	94.2848	103.9962

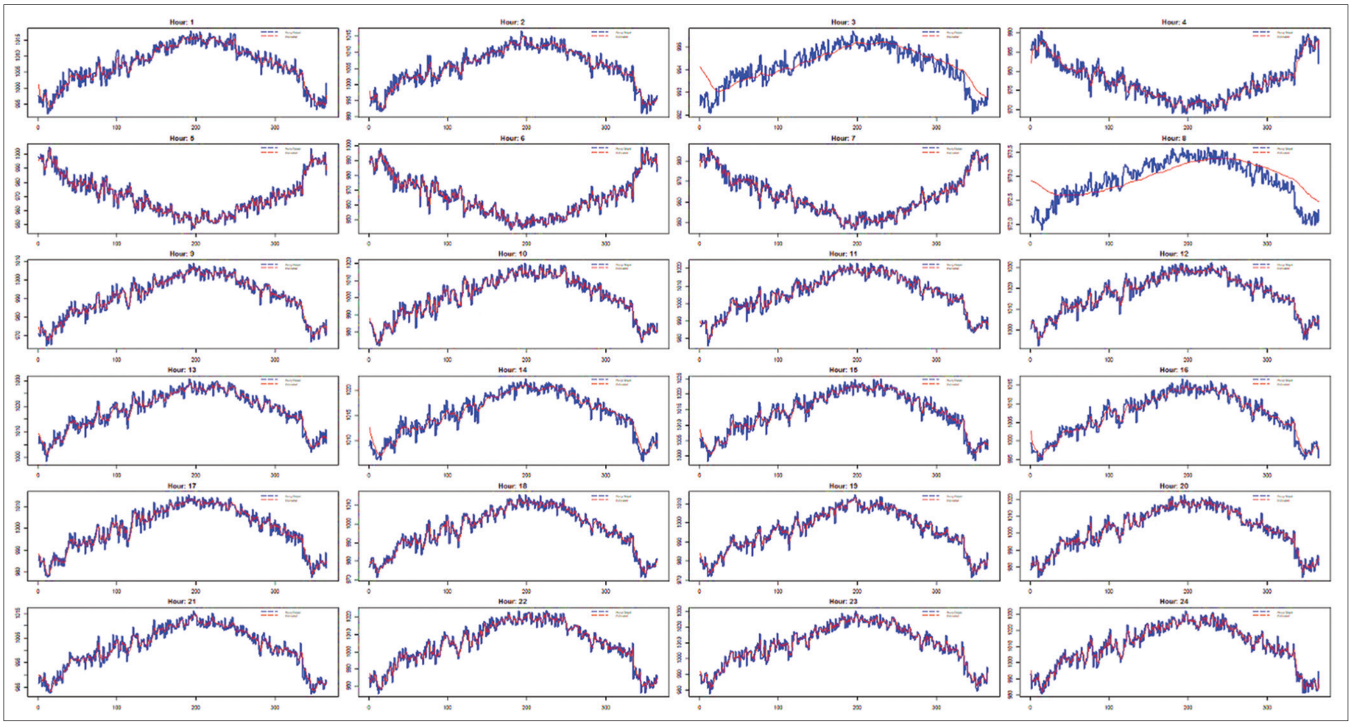

Figure 2: Hourly electricity load forecasting using fuzzy logic and hybrid fuzzy-Kalman filter models

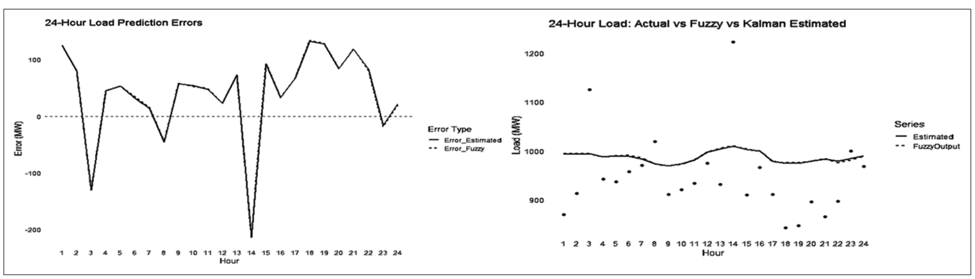

Figure 3: Error analysis and forecast comparison of 24-h electricity load using fuzzy logic and hybrid fuzzy-Kalman filter

system along with filtering out measurement noise is aided by means of the KF.

The consistently lower MAE and RMSE values for the hybrid model, as indicated in Table 2, clearly demonstrate that the integration of the KF effectively mitigates forecasting errors. This enhancement is particularly evident during periods of high load volatility, illustrating the filter's ability to refine the noisy predictions generated by the fuzzy logic component.

By examining the 24-h load profile, it is evident that clear patterns exist in both fuzzy outputs and Kalman-filtered estimates when compared to the actual load. Higher fuzzy outputs than the actual load are observed during the early morning period, hours 1–6, which is probably due to temperature-based changes in the fuzzy model. Despite being somewhat biased towards smoothing short-term fluctuations, the hybrid Fuzzy-KF estimates do not address the systematic overestimation of outputs.

The temperature effect in the fuzzy model is reflected in both the moderate differences between the noon period, hours 7–14, as well as their fuzzy outputs and Kalman estimates, which remain slightly below or above the actual load. Hours 15–24 exhibit comparable behavior, with the highest residuals occurring in hours 22–24. The KF somewhat reduced fluctuations but still tracks the ambiguous outputs. This is also true for the evening period, hours 15–24. The KF maintains temporal consistency and reduces noise, whereas it fails to significantly enhance alignment with the actual load. Despite the filter's improved stability, predictive accuracy is primarily determined by the quality of the fuzzy model itself, as demonstrated in this trend analysis as shown in Figures 2 and 3.

CONCLUSION

For a region facing electricity supply instability and rapid demand growth, such as Kurdistan, the improved accuracy provided by the Hybrid Fuzzy-KF offers a more dependable tool for grid management and operational planning.

The findings showed that while the Fuzzy Logic model captured the non-linear relationship between temperature and electricity demand, it was also prone to noise and uncertainty. The addition of the KF significantly improved forecasting accuracy by reducing estimation errors and smoothing short-term fluctuations, as evidenced by a consistent decrease in the RMSE over the 24-h forecast period. However, the performance of the hybrid model still relied heavily on the initial fuzzy estimate, and the KF did not address systematic overestimation biases found in the fuzzy model's output.

This research validates the effectiveness of the hybrid model; however, its reliance on the initial fuzzy estimate suggests that future efforts should focus on refining the core Fuzzy Logic component. Potential enhancements include the integration of additional external variables and the optimization of fuzzy membership functions, aiming to improve forecasting accuracy further and mitigate the systematic overestimation biases observed in the current model.

In conclusion, this research validates the hybrid Fuzzy-KF as an effective method for STLF in the Kurdistan-Iraq electricity system, providing a practical solution for better power grid management and operational planning.

Limitations and Recommendations

This study has several limitations that should be acknowledged. First, the application of the KF was based on fuzzy model outputs derived from actual load data, which limits the filter's potential to substantially enhance prediction accuracy, as the observation model is already closely aligned with the target values. Second, the current framework does not incorporate exogenous variables such as weather, seasonal effects, or socio-economic indicators that are known to influence electricity demand. Finally, the model assumes relatively simple noise structures, which may not fully capture the complex stochastic behavior inherent in real-world load patterns.

For future research, it is recommended to extend the model by integrating exogenous predictors to improve robustness, exploring alternative state-space formulations, and considering adaptive or hybrid filtering approaches such as advanced Kalman variants. Additionally, comparative evaluations with other estimation techniques, including particle filters and Bayesian methods, would provide further insights into the trade-offs between model interpretability, computational efficiency, and forecasting accuracy.

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