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Bayesian hybrid Kalman filter auto-regressive for smarter electricity load forecasting

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Abstract: Energy management efficiency requires highly accurate electricity load forecasting, especially in dynamic and complex environments. This study presents the Bayesian Hybrid Kalman Filter Auto-Regressive (BAR-KF) model as an advanced technique for improving load forecasting accuracy. This hybrid framework addresses the fundamental limitations of the autoregressive model and the Kalman filter model in previous works by better handling non-stationarity and model uncertainty through Markov Chain Monte Carlo (MCMC) methods in estimating the posterior of AR parameters, which are subsequently integrated into the Kalman filter framework. The analysis of hourly electricity consumption data demonstrates the model's ability to capture temporal dependencies and provide probabilistic forecasts that offer a better understanding of possible load ranges. The results offer valuable insights into the dynamics of electricity consumption, aiding policymakers and grid experts in building greater operational resilience, distributing load more effectively, and consequently improving forecast accuracy. The interaction between the MCMC-derived model parameters and their adaptive mechanisms enhances the robustness of the Kalman filter, making the forecast model more responsive to innovative approaches for electricity demand.

Keywords: *Autoregressive modelling, Electricity load forecasting; Kalman filter, Markov chain monte Carlo, Probabilistic forecasting.*

1. Introduction

Electricity load forecasting plays an important role in energy management systems for reliable power supply, optimization of energy resources, and reduction in operational costs. In these dynamic and complex environments, the relevance of appropriate forecasting models, which can predict the future demand for electricity, becomes highly significant. So far, the Bayesian Auto-Regressive Kalman Filter BAR-KF has emerged as an advanced technique in which Bayesian estimation is integrated with auto-regressive modeling and Kalman filtering to improve the accuracy of load forecasting. This introduction covers the theoretical basics, advantages, and applications of BAR-KF in the context of load electricity forecasting, referencing relevant works. Electricity load forecasting involves the prediction of future electrical demand from historical data and a variety of factors that determine it [1, 2].

The Kalman filter was originally developed by Kalman [3] to give an optimum estimate of the state of a linear dynamic system from noisy observations [4, 5]. It predictively updates the state estimates recursively with minimum error covariance. The traditional Kalman filter is reasonably effective when working with linear systems that assume Gaussian noise; however, it may fall short in performance related to non-stationary data or when model parameters are not well known [6, 7].

Bayesian methods update the incrementing probabilities of a hypothesis when evidence is acquired and have provided a robust framework for incorporating uncertainty and prior knowledge into

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forecasting models [8, 9]. In load forecasting, Bayesian inference dynamically adjusts based on both historical data and current observations to enable adaptiveness in the forecasting model [10, 11].

In general, time series forecasting employs an autoregressive (AR) model that predicts future values based on previous observations alone [12, 13]. Even though AR models capture temporal dependencies effectively, they assume that in most cases the data follows a linear structure, which may not hold in realistic cases. Merging AR models with Kalman filtering and Bayesian inference will surmount these deficiencies by modeling model uncertainty and adjusting to potential non-stationarity in the data [14, 15]. The Bayesian Auto-Regressive Kalman Filter or BAR-KF combines features of Bayesian inference, AR modeling, and Kalman filtering to improve the accuracy of load forecasting. The BAR-KF framework considers the AR model parameters to be random variables with assigned prior distributions, thus enabling a more robust and adaptive estimation [16, 17]. This Bayesian approach explicitly takes into account model uncertainty and automatically adapts to changing data patterns. In this regard, it overcomes the limitations of previous AR and Kalman models [18, 19].

In BAR-KF, the Kalman filter recursively projects forward and updates the state, while Bayesian inference is used to estimate parameters of the AR model. Incorporating these into a single algorithm enables the filter to dynamically adapt the predictions with the incoming data and prior information, thereby improving its robustness and accuracy [20, 21]. BAR-KF will also be able to capture the time-evolving nature of a non-stationary load pattern and model the uncertainty in the forecasting process through modeling prior distributions and updating them based on new data [22] and Liu and An [23].

One of the biggest advantages of BAR-KF is that it can provide probabilistic forecasts, not just point estimates. In fact, this offers quantification of uncertainty in load forecasting that is, better decisions and risk management can be informed by understanding the range of possible demands in the future [24, 25]. More importantly, external factors and domain knowledge can be encapsulated into the Bayesian framework to improve the model's forecast performance accordingly [26, 27]. BAR-KF has been used in many domains under the heading of load forecasting, which includes residential, commercial, and industrial sectors. In residential load forecasting, it is performed using historical data of electricity consumption and weather variables to predict consumption patterns [28, 29]. In the case of commercial and industrial purposes, the filter optimizes energy usage by correctly estimating peak load demand and identifying possible opportunities for energy savings [30, 31].

Advancements in computational techniques and algorithms have been very effective in making BAR-KF more efficient. Some of the methods employed to achieve these improvements are particle filtering and MCMC methods that better evaluate the posterior distribution of the AR parameters, which further refine the filtering process [32, 33]. Corresponding challenges in high-performance computing and parallel computation also made the real-time application of BAR-KF with large amounts of data possible [34, 35].

Fusing machine learning algorithms with BAR-KF is another promising development that warrants further improvement. This may help to enhance the sophisticated yet probabilistic adaptive creeping behavior of BAR-KF by capturing non-linearities and feature interactions present in the load series [36, 37]. This is the approach that quite interestingly combines both traditional, statistical approaches and modern, machine learning techniques to produce accurate load forecasting [38, 39]. The BAR-KF is a generic linear model in electricity load forecasting, in light of the great innovation that it possesses: Bayesian approaches combining modeling with Kalman. In this manner, the BAR-KF resolves the illustrated limitations by fixed forecasting techniques in power prediction and adds some average probabilistic and adaptive mechanics for the prediction of future electricity requirements. That is, constant theories and the enhancement of technology keep the grounds of the system developing more and more. It has grown to be quite a beneficial tool in optimizing energy management and decision-making in complex and dynamic environments.

2. Literature Review

2.1. Bayesian Model in Load Electricity Forecasting

As much as there are vital tasks that resemble electricity load forecasting, one specific task stands out, and that is inferring from the previous data, taking into consideration the demands that will be made in the coming days based on several factors influencing that basic economic need. It has been identified that, more often than not, conventional methods of load forecasting, which are most commonly used, fall short in tracking internal variations and the time dimension in electricity load data. Bayesian equations provide a powerful framework in which prior knowledge can be incorporated, and the quantification of uncertainty in the predictions is enabled. This section discusses Bayesian equations, their application in electricity load forecasting, and the advantages of such an approach over traditional methods [40].

It has been mentioned above that Bayesian equations find their roots in Bayesian inference. It is due to Thomas Bayes that the term is derived from. The term Bayesian inference involves a way to modify the likelihood of a certain hypothesis based on obtaining further corroborative evidence. It presents a mechanism for revising the estimate of a given parameter's probability based on prior knowledge and the observed data, through the application of Bayes' theorem [41].

Bayes' theorem is mathematically expressed as:

$$P(\theta \mid y) = \frac{P(y \mid \theta) \cdot P(\theta)}{P(y)} \tag{1}$$

where:

- $P(\theta \mid y)$ is the posterior probability of the parameter θ given the data y.
- $P(y \mid \theta)$ is the likelihood of the observed data y given the parameter θ.
- $P(\theta)$ is the prior probability of the parameter θ.
- $P(y)$ is the marginal likelihood or evidence, ensuring that the posterior probabilities sum to one

2.2. The Kalman Filter

The Kalman filter is an intricate computation procedure employed in estimating the parameters of a dynamic linear system through the successive acquisition of a set of measurements, which may be affected by some form of noise. This makes it particularly attractive for real-time systems, which require a constant estimation of the state. In the case of electricity load forecasting, the Kalman filter with a comprehensive model makes for a good arrangement that attempts, relying on historical records and a handful of other variables, to compute the future demand for power. This paper presents a brief overview of the Kalman filter and its basic mathematical concepts, as well as its implementation in load forecasting of electricity [42].

2.3. The Auto Regressive Model AR (1):

Time series analysis can also be performed using the AR(1) model, which is both simple and effective in associating an observation with its preceding one. This relationship can be expressed in a mathematically straightforward manner, as Yang et al. [43] and Roy and Karmakar [44].

2.4. Markov Chain Monte Carlo (MCMC)

Markov Chain Monte Carlo (MCMC) methods are a broad category of computational approaches used to generate posterior samples and estimate integrals. In Bayesian analysis, MCMC methods are frequently employed to create simulated samples in order to approximate the posterior distribution. For generating posterior samples, the Metropolis-Hastings (MH) algorithm is a popular principle in Bayesian analysis according to Khidir et al. [45].

3. Methodology

This study utilized the recorded dataset on electricity load for 2024, provided by the Erbil Electricity Control Directorate. The dataset consists of 8,760 observations, with each observation representing the daily electricity load in Erbil, the capital of the Kurdistan region of Iraq. Before training the model, several preprocessing steps were carried out on the dataset. First, an inspection for missing values indicated that none were present. Additionally, the original dataset was not stationary, so a first-difference transformation was applied to achieve stationarity.

3.1. Bayesian Hybrid AR-Kalman Filter Model

3.1.1. State and Observation Models

Using Kalman filter methodology, the state of the system vector is defined as the electricity load at time t, and the measurement model describes how this state, the so-called system state, relates to the measurements [46]. The state transition equation for load forecasting can be written as

$$X_t = F_t X_{t-1} + W_t \quad (2)$$

Where X_t is the Current State, F_t is the transition matrix and W_t is the process noise with covariance Q_t i.e., $W_t \sim N(0, Q_t)$.

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

$$Z_t = H_t X_t + V_t \quad (3)$$

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

3.1.2. Integration of Auto Regressive with Kalman Filtering Algorithm:

AR (1) can be expressed mathematically as below:

$$Z_t = \phi X_{t-1} + \epsilon_t \quad (4)$$

Z_t is the load value at t.

ϕ is the AR coefficient.

ϵ_t is white noise distributed with (mean= 0 and variance= σ_ϵ^2

in order to introduce the AR model in the framework of the Kalman Filter, we consider AR coefficients to be the state variables. Definition of a State Vector [47].

$$F = \begin{bmatrix} \boldsymbol{\phi_i} \\ 1 \end{bmatrix}$$

3.1.3. Prediction Step (State and Covariance)

State Prediction:

$$\hat{X}_{t|t-1} = \phi_i \hat{X}_{t-1|t-1} \quad (5)$$

Here, ϕ_i is the sample from the posterior distribution of ϕ_i.

- Covariance Prediction

Similarly, the covariance prediction depends on ϕ_i (from the posterior) and the process noise Q:

$$\hat{P}_{t|t-1} = \phi_i^2 \hat{P}_{t-1|t-1} + Q \quad (6)$$

Where Q is the process noise, and ϕ_i is sampled from the posterior distribution.

- Update Step (State and Covariance)
- Kalman Gain:

The Kalman gain K_t is computed based on the predicted covariance and the measurement noise covariance R, as usual:

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$$K_t = \frac{\hat{P}_{t|t-1}}{\hat{P}_{t|t-1} + R} \quad (7)$$

- State Update

The state estimate $\hat{X}_{t|t-1}$ is updated based on the predicted state and the observation data Z_t

$$\hat{X}_{t|t-1} = \hat{X}_{t|t-1} + K_t\left(Z_t - \hat{X}_{t|t-1}\right) \quad (8)$$

- Covariance Update:

The Covariance estimate is updated as follows:

$$\hat{P}_{t|t} = (1 - K_t)\hat{P}_{t|t-1} \quad (9)$$

3.2. Model Implementation and Parameter Tuning

The suggested technique offers a reliable way to analyze dynamic time series data by combining the estimation of the AR (1) parameter using MCMC with its integration into the Kalman Filter architecture. An accurate AR (1) parameter (ϕ), which is a crucial input for the state prediction equation in the Kalman Filter, is produced by the MCMC-based estimate step, which also captures the temporal dependencies and uncertainty in the data. The filter can now balance real-time observations and past dependencies owing to this connection, producing accurate state estimations and increased forecast accuracy. As more observations are added, state estimates closely match the actual dynamics of the system because of the Kalman Filter's iterative nature, which guarantees convergence over time.

4. Results

The dataset's Bayesian AR (1) MCMC analysis shows important new information about the patterns of electricity use over a 24-hour period, including its acceptance rate, variability, and temporal dependencies. This research reveals subtle predictability and variability influenced by temporal and external influences by highlighting important correlations between autoregressive coefficients (ϕ), noise variances (σ^2), and acceptance rates.

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Table 1.
Descriptive statistics of the posterior distribution.

Hour	Phi				Sigma2				Acceptance Rate
	Mean	SD	CI Lower	CI Upper	Mean	SD	CI Lower	CI Upper	
1	0.8004	0.0321	0.7369	0.8631	0.363	0.0275	0.3132	0.4207	31%
2	0.8440	0.0285	0.7881	0.9001	0.2901	0.0215	0.2517	0.3354	29%
3	0.8676	0.0266	0.815	0.9194	0.2504	0.0188	0.2155	0.2892	27%
4	0.8811	0.0245	0.8328	0.9292	0.2221	0.0162	0.1925	0.2559	25%
5	0.9064	0.0223	0.8623	0.9501	0.1762	0.0133	0.1522	0.2042	23%
6	0.8806	0.0251	0.8315	0.9292	0.2252	0.0167	0.1945	0.2603	26%
7	0.8839	0.0244	0.836	0.9317	0.2171	0.016	0.1879	0.2502	25%
8	0.8406	0.0285	0.7857	0.8961	0.2907	0.0215	0.2514	0.3358	28%
9	0.8103	0.0311	0.7487	0.8705	0.3432	0.0257	0.296	0.3968	30%
10	0.8099	0.0306	0.7497	0.8694	0.3425	0.0256	0.2956	0.3955	30%
11	0.7708	0.0337	0.7046	0.8365	0.4052	0.0299	0.3511	0.4675	32%
12	0.7513	0.0353	0.6824	0.8208	0.4398	0.0329	0.3798	0.5088	33%
13	0.7115	0.0369	0.6393	0.7836	0.4981	0.0369	0.4311	0.576	34%
14	0.716	0.0366	0.6448	0.7883	0.4842	0.0363	0.4173	0.561	34%
15	0.7015	0.0379	0.6276	0.7758	0.5064	0.0376	0.4368	0.5837	35%
16	0.7264	0.0358	0.6554	0.7966	0.4681	0.0352	0.4043	0.5421	34%
17	0.7517	0.0344	0.6847	0.8185	0.427	0.0322	0.3685	0.4936	33%
18	0.7090	0.0366	0.637	0.7814	0.4867	0.0359	0.4207	0.5632	34%
19	0.7420	0.0351	0.6735	0.811	0.4403	0.0331	0.3798	0.5097	33%
20	0.7936	0.0317	0.7311	0.8558	0.3594	0.0270	0.3111	0.4171	31%
21	0.8193	0.0298	0.7613	0.8775	0.3186	0.0238	0.275	0.3689	30%
22	0.8034	0.031	0.7425	0.8639	0.3453	0.0258	0.2983	0.3991	29%
23	0.8239	0.0296	0.7661	0.8818	0.3137	0.0237	0.2708	0.3638	28%
24	0.8473	0.0278	0.7928	0.9020	0.2763	0.0204	0.2394	0.3195	28%

Strong temporal dependencies were shown by periods with high autoregressive coefficients (ϕ), where the usage of electricity during the preceding hour had a considerable impact on power consumption. For example, there was substantial autoregressive behavior during hours 24 ($\phi = 0.85$) and 23 ($\phi \approx 0.82$), indicating great predictability. Hours 4 ($\phi = 0.88$), and 5 ($\phi \approx 0.91$), also exhibited significant autocorrelation, indicating recurring reliance on previous spending. Moderately high ϕ values were displayed by hours, such as 8 ($\phi \approx 0.84$) and 9 ($\phi \approx 0.81$), which showed a balance between temporal dependence and outside effects. Periods with poor secure reliability, such as 13 (($\phi = 0.71$) and Hour 14 ($\phi \approx 0.72$), have lower coefficients, which makes the period less predictable and more affected by outside variables.

Unaccounted-for variability is more commonly used by noise variances (σ^2). Periods with rich values σ^2 values, as Hour 13 ($\sigma^2 \approx 0.50$) and Hour 15 ($\sigma^2 \approx 0.51$), indicated significant variability that the model was unable to account for, which might be a result of environmental factors or outside disturbances. On the other hand, smaller σ^2 values were observed during times such as Hour 5 ($\sigma^2 = 0.18$) and Hour 6 ($\sigma^2 \approx 0.23$), which indicated more steady and regular consumption habits.

The convergence and sampling efficiency were assessed through the acceptance rate of the Bayesian MCMC model. A slower mixing process was suggested by the research; however, it became evident that the acceptance rate fluctuated throughout the day. For instance, lower values were observed during hours such as Hour 5 (Acceptance Rate ≈ 0.26) and Hour 6 (Acceptance Rate ≈ 0.25). In contrast, a more effective sampling procedure was indicated by higher acceptance rates during hours like Hour 13 (Acceptance Rate ≈ 0.34) and Hour 15 (Acceptance Rate ≈ 0.35). Although the intricacy of the underlying temporal connections and the model's ability to adapt to shifting consumption patterns may be reflected in these variances in acceptance rates, this complexity warrants further investigation.

Credible intervals (CIs) for ϕ provided valuable insights into the reliability of the model's estimates. Narrow intervals, such as those for Hour 6 (ϕ CI: [0.83, 0.93]) and Hour 24 (ϕ CI: [0.79, 0.90]), indicated high confidence in the estimates. In contrast, wider intervals, like those for Hour 13 (ϕ CI: [0.64, 0.78]) and Hour 18 (ϕ CI: [0.64, 0.78]), suggested greater uncertainty, possibly due to increased variability or the influence of external factors.

The MCMC analysis showed that acceptance rates across all hours ranged between 0.235 and 0.346, comfortably within the recommended range of 20–40% for Metropolis-Hastings algorithms. This balance ensured that the sampler was neither overly cautious nor overly aggressive when proposing new states. As a result, the MCMC algorithm efficiently explored the parameter space, striking a good balance between computational speed and thoroughness.

The findings shed light on the complex and dynamic nature of electricity consumption patterns. High predictability and stability were evident during periods with low noise, consistent acceptance rates, and strong autoregressive coefficients. Conversely, variability in acceptance rates, larger noise levels, and weaker coefficients highlighted the importance of incorporating additional external factors into the models. These insights are critical for effectively managing periods of high uncertainty, optimizing grid operations, and improving forecasting accuracy.

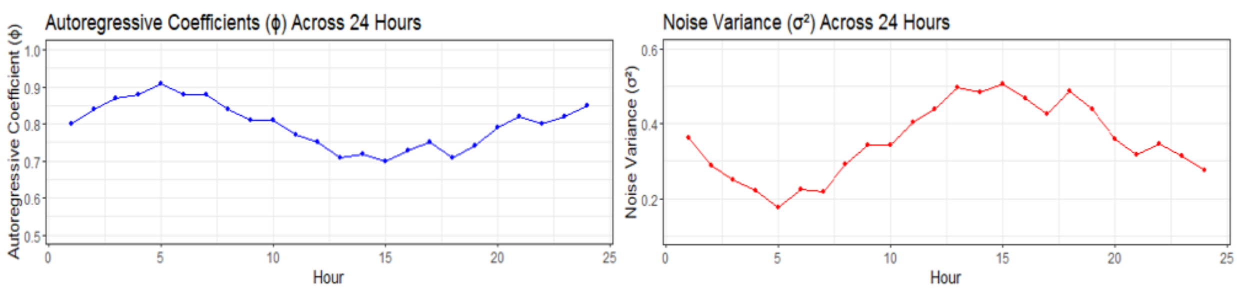

Figure 1.
a) Phi mean value from posterior dist.
b) Sigma2 mean value from posterior dist.

The results revealed how electricity usage changes over the day. During peak hours, there were clear and consistent patterns, reflecting predictable behavior. In contrast, off-peak hours showed more variation, indicating less predictable and more scattered usage. The AR (1) model worked well when autocorrelation was high, but it might need to be enhanced or additional variables, such as weather or day type, added to improve accuracy during periods of increased unpredictability. All things considered, the Bayesian AR (1) Kalman Filter provided grid managers and energy providers with valuable data to enhance operational resilience, control load distribution, and improve demand forecasting, particularly when temporal dependencies were significant. The mean values taken from the posterior distribution over a 24-hour period are displayed in Figures 1. a and 4. b.

Before using the posterior distribution in the Kalman Filter state estimate, it was worth investigating its distribution with trace plots as well as density plots. Thus, the trace plot of phi shows the evolution of the parameter over MCMC iterations.

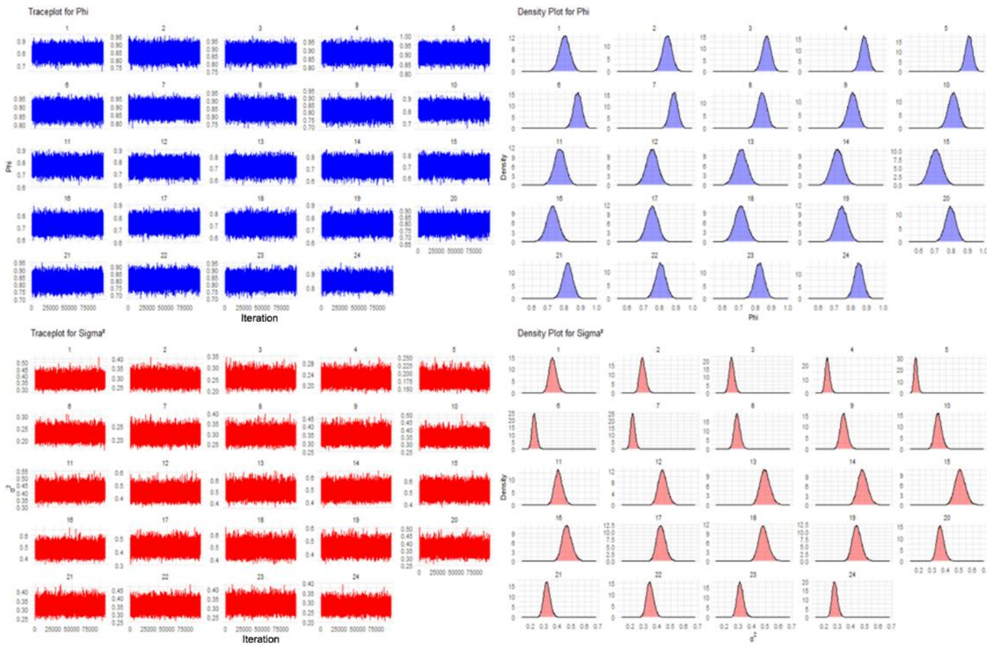

Figure 2.
Traceplot and density plot illustration for phi as well as sigma square values per hour.

Figure 2. As shown, they were all well-behaved traces and exhibited random walk patterns, which indicated good mixing and that the sampler should lead to exploring the parameter space adequately. Since they were all stable and showed no trends, this suggested convergence and reliable estimates. Furthermore, the density plot for phi showed the posterior distribution, with a narrower peak indicating more precise estimates and a wider peak reflecting higher uncertainty. A clear peak suggested the most probable value of phi, which was the case for most of them, while its spread shows the uncertainty in the estimate. Similarly, the trace plot for sigma^2 showed random fluctuations without trends, indicating good mixing, and had a narrow peak.

4.1. Kalman Filter Analysis of Electricity Consumption: A Detailed Explanation

An indispensable tool for determining the actual level of electricity usage is the Kalman Filter, particularly in cases where the data is ambiguous or noisy. By taking into account both past forecasts and observed data, it continuously improves estimations of the underlying state. The performance of the Kalman Filter over a 24-hour period is examined in this investigation by applying it to actual hourly electricity usage data, as seen in Table 2.

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Table 2.
Summary output of the Bayesian Kalman filter.

Hour	Time Convergence	Observed Load	Prediction Load	Kalman Gain	Error Covariance	Residuals
1	5	1116.99	1010.5456	0.622	2713.5484	106.4444
2	6	1176.63	1049.3009	0.5906	3131.1345	127.3291
3	6	1167.39	1073.4791	0.6255	3850.5173	93.9109
4	5	1164.765	1088.0967	0.6244	4522.8805	76.6683
5	6	1190.49	1096.0235	0.5784	5580.256	94.4665
6	6	1154.7774	1060.2747	0.5602	5547.5257	94.5027
7	6	1179.9774	1084.0228	0.5996	6091.4368	95.9546
8	6	1154.16	1051.1724	0.6016	5422.6017	102.9876
9	6	1159.62	1040.8104	0.6202	4460.057	118.8096
10	5	1150.8	1042.9467	0.6205	4311.2771	107.8533
11	7	1150.17	1004.7106	0.5922	3336.1508	145.4594
12	6	1179.36	1021.9977	0.624	3272.0486	157.3623
13	5	1161.048	973.8374	0.5993	2939.6201	187.2106
14	6	1186.29	996.8078	0.6152	2668.878	189.4822
15	5	1137.528	971.7136	0.6373	2695.3352	165.8144
16	6	1144.71	997.3896	0.6548	2971.2608	147.3204
17	5	1145.34	990.1312	0.6132	2945.9253	155.2088
18	5	1194.606	1023.0315	0.6375	2771.4142	171.5745
19	6	1163.19	1005.9839	0.6232	2896.3575	157.2061
20	5	1179.486	1063.15	0.6386	3140.748	116.336
21	5	1187.466	1073.185	0.6411	3080.769	114.281
22	6	1166.76	1027.1909	0.6013	2972.2881	139.5691
23	5	1147.608	1025.5494	0.5952	3377.6932	122.0586
24	6	1125.18	1017.5682	0.5635	3094.4716	107.6118

The Kalman Filter predicted a marginally lower value of 1010.55 at Hour 1 than the measured load of 1116.99. This initial disparity arose because the filter makes a cautious forecast at first, since it had little prior knowledge. The Kalman Gain of 0.622 indicated cautious confidence in the first observation, while still leaving room for doubt about the data. This initial uncertainty was further highlighted by the substantial error covariance of 2713.55. However, as time progressed, the Kalman Filter gradually refined its understanding of the system, using this initial observation as a starting point to improve its future predictions.

As more observations were analyzed, the Kalman Filter adjusted its state prediction, making it increasingly accurate. By Hour 6, this refinement was evident, with the prediction state reaching 1060.27 compared to the observed load of 1154.78, showing a clear improvement in precision. The fact that the Kalman Gain had dropped to 0.5602 suggests that the filter was updating its state more consistently by utilizing both historical data and the most current observation. As the filter improved its understanding of the system, the error covariance also decreased, going from 2713.55 in Hour 1 to 5547.53 in Hour 6.

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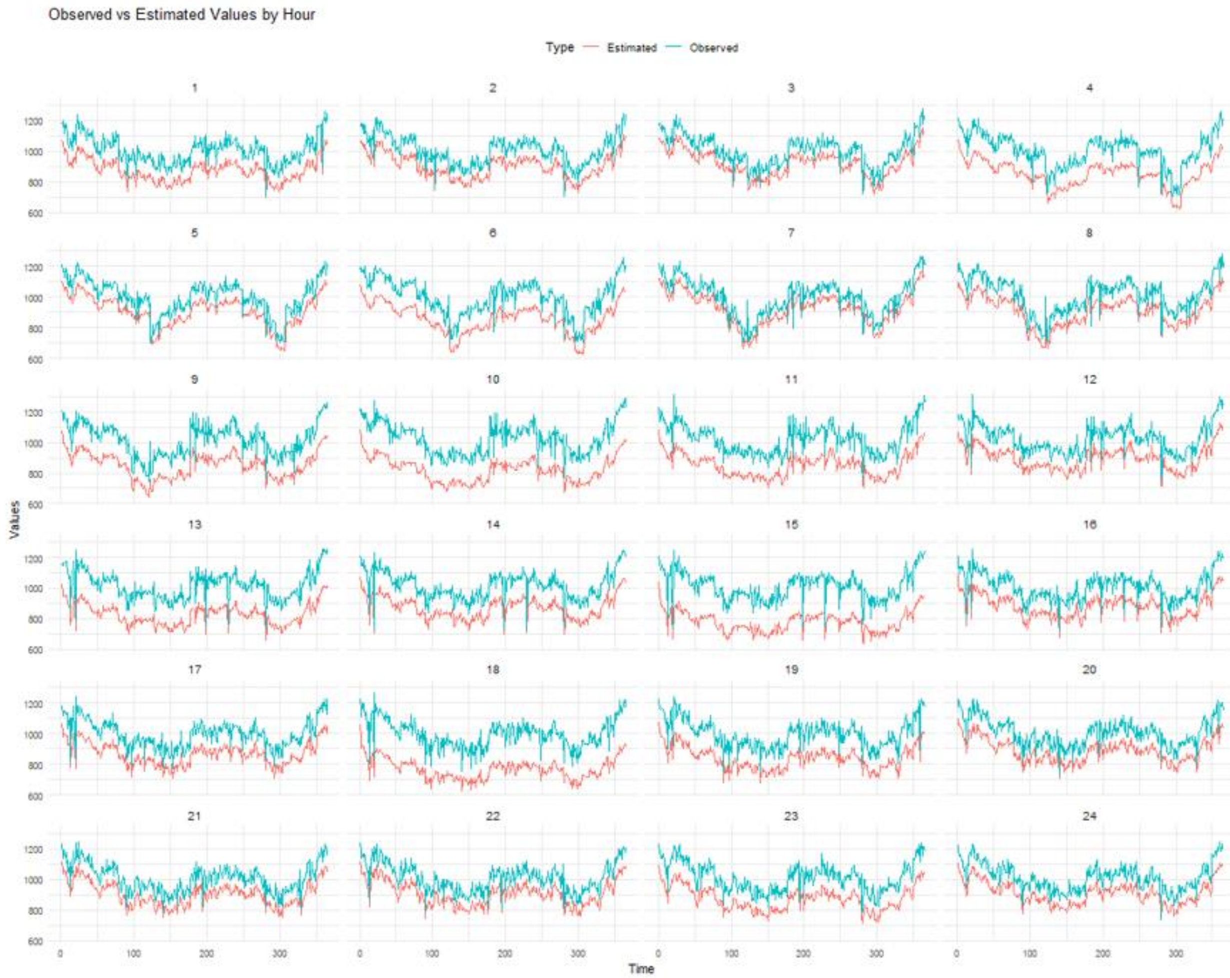

Figure 3.
Observed Load against State Prediction Values.

The Kalman Filter is continuously adjusted throughout the day. At Hour 14, the predicted state was 996.81, the measured load was 1186.29, and the residual between the predicted and observed values was 189.48. By assigning more weight to the most recent observation (as indicated by the Kalman Gain of 0.6152), the filter compensated for the larger residual, which reflected a significant variation in consumption. These residuals decreased as the filter processed more data, indicating an increase in accuracy. The lines were parallel, suggesting a well-fitted estimated model, as shown in Figure 3, which compared the observed dataset to the state estimate from the Bayesian Kalman Filter.

5. Dissection

The filter provided the initial observation with a substantial amount of weight at Hour 1, as indicated by the Kalman Gain of 0.622. The Kalman Gain varied from 0.5635 at Hour 24 to 0.6373 at Hour 15 when more data points were added. This range demonstrated how the filter modifies its dependence on fresh observations in response to the system's volatility. The Kalman Gain increased during hours with greater variation, such as Hour 14, giving the current data point more weight. This ensured that the filter would swiftly adjust to major system changes.

Over time, the error covariance also evolved, reflecting changes in the level of uncertainty. At Hour 1, the error covariance was 2713.55, indicating significant uncertainty in the initial estimates. However,

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as the filter processed more observations and refined its state estimates, the uncertainty decreased. By Hour 24, the error covariance had dropped to 3094.47, demonstrating that the filter's predictions had become more reliable and accurate.

The dissimilarities observed in the state estimate and the actual load, known as the Kalman Filter residuals, clarified the extent to which the Kalman Filter represented the system dynamics. For instance, in the early hours, say hour 1, the residual for this time period was noted to be 106.44, which indicated a significant difference between the estimated and actual load observed in that hour. However, as expected, the residuals tended to decrease over time. According to this observation, the residual dropped by 107.61 by hour 24, implying that the filter had managed to reduce errors and improve the accuracy of the system condition estimates.

It was this property of the Kalman Filter that was one of its most powerful features: the ability to smooth observed data. Fluctuations in electricity usage could be caused by a number of factors, including abrupt increases or decreases in demand. These variances were reduced through the Kalman filter, which provided a much cleaner estimation of actual consumption. For example, in Hour 8, when the measured load spiked to 1154.16, the estimate provided by the filter was 1051.17. This demonstrated how the filter could help control outliers and provide a more reliable picture of the underlying trend.

The Kalman Filter estimate of 997.39 during Hour 16, while the observed load was 1144.71, again demonstrated its smoothing capability by absorbing small variations in the observed load and yielding an improved state prediction.

With the inclusion of the Kalman Filter in developing the Markov Chain Monte Carlo results, with the use of temporal structure presented in MCMC output for correction of real-time prediction, the integration yielded a better estimation of power consumption. Some important parameters developed from MCMC were ϕ- Phi, showing autoregressive dependence between hourly consumptions, and σ^2 - sigma squared, depicting uncertainty within the model. These helped the correction procedure of the Kalman Filter.

The ϕ values in the MCMC results show how different the consumption is at one hour from the hour before. For instance, the value ϕ is 0.8004 for Hour 1, indicating strong temporal correlation, while for Hour 24, it increased to 0.8473, which means it became even more stable. The σ^2 values were representative of uncertainty; the lower this value, the greater the confidence in the model's predictions. This allowed the Kalman Filter to correct its predictions with greater accuracy, depending on how well the system could be predicted at any given time.

These values of ϕ and σ^2 were then used by the Kalman Filter to update its prediction of the state. Indeed, for highly uncertain hours σ^2, the observed data is weighted higher, while during hours of low uncertainty, the filter relies more on its predictions. The adjustments get smoothed out as the ϕ values increase, giving more confidence to long-term trends. When ϕ decreases, the filter is more responsive to observed data and changes in response to transient variations rapidly.

We created a dynamic model that adjusts in real-time while maintaining a strong understanding of patterns in electricity usage by integrating the MCMC and Kalman Filter. The MCMC provided the Kalman Filter with the context it needed to modify its estimates, resulting in an accurate and responsive model.

6. Conclusion

Only by integrating the Kalman Filter and MCMC analysis could a better understanding of the dynamics of electricity use be acquired. Considering some hours had strong and others weaker ϕ -values showing autoregressive correlations, temporal dependencies in consumption were underlined by means of MCMC results. For example, ϕ values were small during such hours as Hour 13 (0.7115), which shows less predictability, whereas Hour 8 (0.8406) and Hour 24 (0.8473) had higher ϕ values, indicating solid correlations between hours.

These findings from MCMC analysis helped the Kalman Filter because they provided context for how it should adjust its state estimates. In hours whose ϕ value was low, the filter gave more weight to new data; during hours with a high ϕ value, it paid more attention to historical observations. This flexibility ensured the Kalman Filter effectively balanced short-term fluctuations against long-term trends.

Uncertainty needed to be added to both models. With wider credible intervals and higher error covariances, the σ^2 values from MCMC point toward times of greater uncertainty. In these times of increased uncertainty, the model is not as confident about projections of the future. This is updated in real-time by the ability of the Kalman Filter to adapt its state predictions based on new observations.

Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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