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Electrical Consumption Forecasting for Boarding Rooms with Kalman Filter and PZEM-004T Integration

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Abstract— ***Electricity is a fundamental necessity for humans in conducting daily activities. The electricity consumption in Indonesia rises annually. Moreover, the overestimation of electrical energy consumption is a challenge encountered by consumers, as they lack control over electricity usage and are unaware of the power consumption associated with each regularly utilized electrical load. A research system was implemented to estimate electricity usage utilizing the Kalman Filter Algorithm. The Kalman Filter may forecast future conditions using limited data. This system utilizes the PZEM-004T sensor to collect data on electrical parameters from loads, including voltage, current, active power, and energy. The results obtained from this investigation pertained to electronic loads associated with the electricity consumption of the boarding room. The electrical load was recorded every 15 minutes for a period of 60 days. The data was partitioned in an 80:20 ratio, with 80% designated as training data and 20% as test data. The accuracy numbers from each test are derived using RMSE, MSE, and MAPE. Additionally, one of the assessments involves the fan load, utilizing RMSE to achieve an error percentage of 0.077% on the training data and 0.076% on the test data. Furthermore, the error percentage derived from the MSE equation attains 0.006% for the training data and 0.005% for the test data. Simultaneously, the error percentage derived by MAPE attains 0.789% on the training dataset and 0.202% on the testing dataset. The results indicate that the Kalman Filter prediction approach is highly effective in forecasting electrical load usage.***

Keywords—Electricity, Kalman Filter, PZEM-004T, Forecasting, Accuracy.

I. Introduction

In the modern era of technological advancement, the utilization of electrical energy is an essential component that underpins numerous actions in daily life, encompassing industry, residences, education, transportation, illumination, and communication. A prevalent issue with electrical energy consumption is the inefficient usage by individuals, stemming from a deficiency in awareness regarding their daily electricity consumption. Consequently, to forecast electricity consumption for the upcoming month, an estimation is conducted to ascertain the electricity utilized by each load[1]. Many methods exist for forecasting power use, including machine learning and statistical approaches. Although the Kalman Filter has previously been employed to estimate relatively stable variables such as atmospheric temperature[2], its application in this study pertains to the highly volatile and stochastic characteristics of household electrical consumption. The algorithm is chosen for its recursive estimation capability, enabling it to effectively filter sensor noise from the PZEM-004T and deliver precise load forecasting even in the presence of intermittent data patterns marking a notable improvement over static estimation approach. Monthly investigation and analysis of electrical power in boarding rooms can facilitate the prediction of power use. This study employs the PZEM004T sensor to gather data on the electrical load of electronic equipment in boarding rooms, including lights, fans, smartphone chargers, and laptop chargers, as well as measurements of voltage, current, power, energy, frequency, and power factor. The sensor data will be automatically stored in a database utilizing Microsoft SQL Server[3]. Diverse algorithms have been employed to forecasting, estimate and anticipate electricity consumption.

Study [4] investigated the application of the SARIMA approach for forecasting residential electricity consumption based on electricity load utilization patterns. The findings indicated a Mean Square Error (MSE) of 0.0095081. Study [5] employed Support Vector Regression and Fruit Fly methods to compute monthly electricity consumption. The findings indicated that the proposed method is a feasible alternative to employing power consumption predictions[6]. The support vector regression method was employed to forecast energy usage using pre-generated data. The outcomes from Support Vector Regression had a success rate of 85.7%, representing the optimal result. The application of the Ensemble Kalman Filter can diminish the variance and estimation error produced by pre-forecasting, as elaborated in [7]. Supplementary research [8] discusses the development of an application capable of calculating electricity use to provide more accurate power estimations. The Kalman filter algorithm method can be employed to conduct optimal electricity power estimation. In the domain of real-time monitoring hardware, the research conducted by Abdillah et al. showcased the efficacy of employing the PZEM-004T sensor within an IoT-based system to continuously monitor energy consumption parameters, including voltage, current, and power[9]. Furthermore, research on intelligent campus infrastructure has employed microcontroller-based automatic regulation of lighting and air conditioning systems to improve energy efficiency [10]. While these existing systems establish a foundation for automated control and monitoring, this research advances the field by incorporating the Kalman Filter algorithm to enhance the stochastic data obtained from PZEM-004T sensors, resulting in more stable and accurate load estimations in comparison to traditional monitoring techniques.

Research Methodology

A. Prediction and Forecasting

Prediction involves using present and historical data to forecast potential future events. The objective is to minimize the discrepancy between actual occurrences and expected outcomes[11]. Numerical prediction refers to the forecasting method that aims to estimate continuous (sequential) values based on input data.

B. Kalman Filter

The Kalman filter combines a measuring methodology and a model. The most recent measurement data significantly impacts the projected outcomes of future measurements, ensuring that the estimated results consistently represent the current data condition, hence rendering this measurement data essential in the Kalman filter. The Kalman filter, being an autoregressive filtering model, enables the optimal estimation of the present state by utilizing the optimal estimates derived from prior system observations alongside the current system observations[12].

The fundamental equation of the Kalman Filter is:

$$\hat{X}_k = K_k \cdot Z_k + (1 - K_k) \cdot \hat{X}_{k-1}$$

Where:

$\hat{X}_k$: Present estimation

K_k : Kalman Gain

Z_k : Measured value

$\hat{X}_{k-1}$: Prior estimate

The value of k will consistently fluctuate in conjunction with the Kalman Filter procedure.

Determine the initial value of the Kalman Gain:

$$K_k = \frac{P_{k.k-1}}{P_{k.k-1} + r_k}$$

Where:

$P_{k.k-1}$: Estimation Uncertainty

r_k : Measurement Uncertainty

The Kalman Gain is a value ranging from 0 to 1, inclusive: $0 \leq K_k \leq 1$.

The initial step is to identify the Kalman Filter model.

1. The Dynamic Model (state transition model) is represented by

$$\hat{X}_k = Ax_{k-1} + q_{k-1}, \qquad q_{k-1} \sim N(0, Q)$$

2. The Measurement Model (observation model) is represented by

$$y_k = Hx_k + r_k, \qquad r_k \sim N(0, R)$$

The concealed state (hidden variable) of the system is represented by the vector k in both models, while the observation process is represented by *y*. The noise covariance matrix is positively defined by q and r, and the matrices *A* and *H* have forms that correspond to *q* and *r*. The Kalman Gain value will approach zero when the measurement and estimation uncertainties are extremely tiny. In contrast, the Kalman Gain value will approach one when the estimation and measurement uncertainties are extremely high. The subsequent action is to determine the uncertainty of the measurement[13].

The process for updating existing uncertainty estimates:

$$p_k = (1 - K_k)\, p_{k-1}$$

Where:

P_k : Current Uncertainty Estimate

K_k : Kalman Gain

$P_{k,k-1}$: Preceding Uncertainty Assessment

A singular function is generated by the iteration process, which predicts one point at a time. This function is then repeated, with the standard error of the previous value being considered to predict future values. Eleven the Kalman Filter estimation system is divided into two components: update and predict. The predict component operates by utilizing the results of previous predictions of the system's state to forecast the current state. In contrast, the update section employs data from a previous period to forecast the results at the current state.

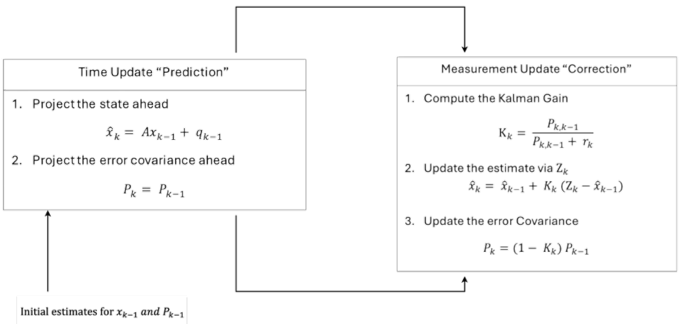

Figure 1 Kalman Filter Process[14]

For evaluating the accuracy of predictions, various model selection criteria are employed, and the optimal models are identified by their minimal error values. Greater error levels signify diminished forecasting accuracy. The standards employed to attain elevated forecast precision encompass the evaluation of Mean Square Error (MSE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE).

C. Data Collection Techniques

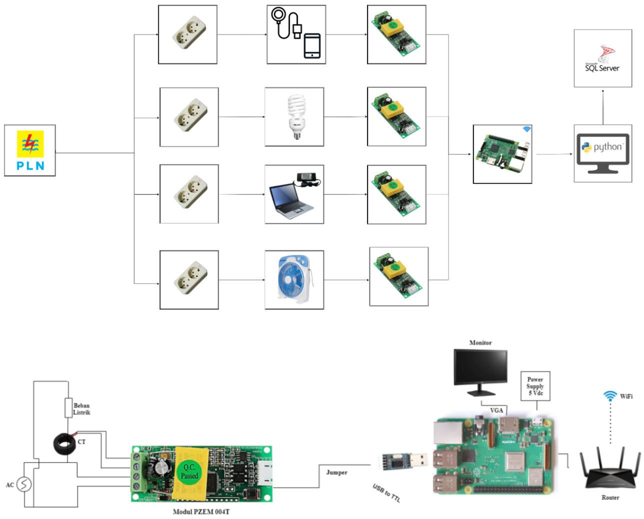

Figure 2 Hardware Design Scheme[15]

The previously mentioned design illustrates that when the electrical load from cellphone chargers, lamps, laptop chargers, and fans is supplied by a voltage source, the PZEM-004T sensor will detect data based on its electrical characteristics, including voltage, power, current, energy, frequency, and power factor. Subsequently, the Raspberry Pi simulates the sensor data using the Python programming language, which presents the data regarding the magnitude of the electrical load. The data will be presented on the monitor, after which the Raspberry Pi will transmit the electrical load data to the SQL Server database for storage, enabling the assessment of power consumption for each electrical load. The subsequent estimate of usage is predicated on the energy value (KWh), which will thereafter be employed to forecast energy consumption.

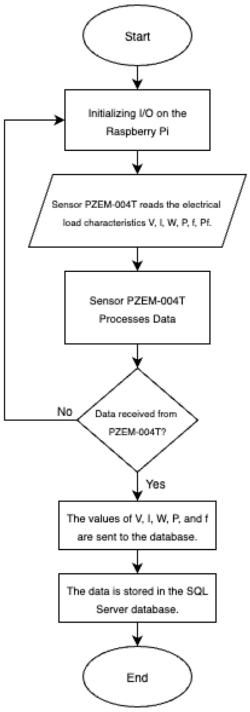

Figure 3 Workflow System

The system workflow for the electric load consumption data collecting tool is illustrated in *Figure 3*. Before moving on to the PZEM-004T sensor, make sure to initialize each load individually. So far, the sensor has been able to read power, energy, voltage, current, frequency, and power factor, among other load characteristics. The data is then processed by the sensor and shown on the monitor via USB to TTL after each electrical load has been measured. After startup, the process goes on to the next phase if the sensor receives the data; otherwise, it goes back to the beginning. After that, in order to make that data program input, the data shown on the screen which originates from the PZEM-004T sensor will be saved in a SQL server database. To facilitate data processing within the software, the data will then be exported as a CSV file. The operation of the system tool is finished once the data is saved.

Results and Discussion

A. System Design

The hardware used in this Project is a Raspberry Pi 3B+, a PZEM-004T sensor, jumper wires, a USB to TTL converter, and an electrical terminal. To install the PZEM-004T sensor and begin measuring electrical load data, simply attach it to the terminals where the coil was put before. The pre-assembled terminals are linked to the electrical load of the boarding house room, and the sensor reads the parameters of each load.

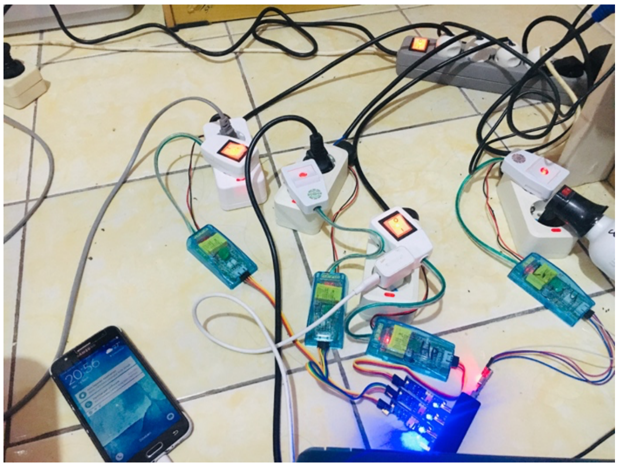

Figure 4 Electrical Load Measuring Device

Four PZEM-004T sensors were employed to collect data for this endeavor. Data was acquired over a 24-hour period for 60 days using four electrical loads or electronic devices. Phone chargers, laptop chargers, lights, and fans comprise the burden or electronic devices. Each 15 minutes, data regarding the utilization of these electronic devices is captured, updated, and transmitted to the database. This data is then stored in a database that was previously established. The Kalman Filter methods will be employed to predict electricity consumption using the data that is currently recorded in the database as input data.

B. Kalman Filter Process

The Kalman Filter algorithm is a statistical estimation and prediction model that integrates estimating and update models based on observations. Continuously updated data is crucial for Kalman Filter computations since it indicates the degree to which the outcomes align with the actual conditions. This study used the Kalman Filter technique to forecast electrical energy consumption in boarding rooms, utilizing data from the previous month's electricity load utilization. The Kalman filter can execute the prediction process utilizing a single parameter; in this analysis, the parameter in focus is the energy consumption of each electrical load.

Table 1 Collected Load Data

Fan Load	Laptop with Charger Load	Handphone with Charger Load	Lamp Load
Energy (kWh)			
2,10069444	0,15	0.038	0.28918
0.600577	0.411731	0.109216	2,89930556
0.837108	0.57359	0.14875	0.519344
1.282.742	0.709836	00.15	0.64322
1.579.828	0.860345	0.175263	0.846207
2.091.771	109.625	00.18	0,67638889
2.762.021	1.398.636	0.21117	1.169.559
3.417.708	1.653.125	0.244839	1.394.921
4.105.556	1.884.366	0.314167	1.616.047
4.596.129	2.151.828	0.365495	1.753.922
5.193.293	2.454.868	0.394342	1.959.444
5.929.138	2.824.737	0.468571	2.128
6.584.706	3.115.294	0.508824	02.39
7.204.265	3.417.941	0.532794	2.627.907
7.756.528	3.745.556	0.614085	0,14027778
8.484.583	4.062.222	0.656944	3.013.939
9.158.229	4.285.484	0.713368	3.202.917
996.075	4.590.375	0.767867	NaNN
10.413.012	4.865.301	0.806049	0,16875
11.109.024	05.19	0,05763889	3.874.615
11.304.286	5.278.571	5,85069444	39.425
12.105.588	5.680.625	0.885588	4.215
12.532.688	5.810.978	0.922717	4.399.661
13.331.316	6.220.789	6,78819444	4.637.105
13.805	6.461.333	1	4.800.333
15.994.375	6.726.562	1.025.625	5.548.438
16.544.107	6.980.714	1.078.214	5.736.964
17.131.642	7.261.525	1.132.879	5.937.612
17.613.393	7.432.222	1.173.929	6.103.929
18.345.319	7.728.723	1.224.894	635.837
18.965.618	8.024.205	1.256.786	6.572.273
1.966.275	8.298.537	1.315.854	6.812.927
20.207.111	8.561.778	1.347.159	7.006.778
20.790.494	8.858.272	1.384.198	721.679
21.433.307	9.182.131	1.446.385	7.447.874
22.045.104	9.606.667	1.496.176	7.665.729
22.660.787	9.741.573	1.558.068	7.885.281
23.280.833	10.056.979	1.622.043	8.107.187
239.025	10.384.375	1.689.271	8.328.333
24.653.103	10.771.609	0,09375	0,37569444
25.171.875	11.039.792	178.129	8.774.947
25.822.198	11.358.352	1.822.093	9.033.231
26.444.316	11.677.789	1.867.234	9.219.158
2.708.449	11.919.388	190.125	9.444.694
27.645.104	12.163.299	193.617	9.640.313
28.261.368	12.486.737	1.985.833	9.859.574
28.875	12.808.632	2.048.421	10.081.368
29.495.579	13.131.158	2.144.105	10.300.632
30.161.688	13.418.831	2.195.946	10.535.844
30.751.042	13.775.729	2.240.957	10.743.958
31.377.813	14.259.583	2.276.889	10.965.937
320.075	14.765.521	229.914	11.187.604
32.638.298	15.255	2.384.681	11.409.894
33.220.864	15.720.864	2.445.802	11.616.667
33.871.368	16.253.684	2.509.255	11.849.579
34.487.065	16.741.176	2.552.619	12.060.319
35.075.946	17.241.029	2.606.364	12.271.923
35.746.628	17.824.186	2.671.977	12.505.814
36.370.833	18.395.521	273.625	12.725.104
36.848.163	18.801.633	2.781.915	12.892.449

The process of estimation or prediction using the Kalman Filter algorithm is as follows:

a. Determining the initial values for the Kalman Gain and Gaussian Noise, with the Gaussian noise maintained as a constant and the Kalman Gain subject to variation during the iterative process.
b. The program will process the input of daily power energy data, which will subsequently be utilized in the prediction algorithm. The program will ascertain the initial measurement date of electrical energy for each day till the final measurement day using this approach.
c. Following the successful reading of the input data for processing by the Kalman Filter, the program will also ascertain the number of days for which predictions will be made, as specified, to terminate the estimating process.
d. Subsequently, the application will initiate the prediction process utilizing the Kalman Filter, aiming to forecast electricity usage for the months of May and June. The initial step involves establishing the Kalman filter framework, which includes a dynamic model (state transition model) and a measurement model (observation model). In equation (3), $\hat{x}$ represents the system's latent variable, while p denotes an observation, namely the electrical load energy in this case. At this juncture, the noise process (Gaussian noise) is executed, during which the prior covariance error value is determined, subsequently utilized to compute the Kalman Gain value. The input value for the noise process is 0.1, which will subsequently be utilized for model observation and noise processing.
e. Subsequently, the test data will serve as a benchmark for forecasting electricity consumption in the ensuing days and months. Following a successful prediction in May, the iteration will persist until the last intended month. The program incorporates 10 iterations, indicating that the looping process will execute 10 times to achieve prediction results that approximate the real number.
f. Subsequently, after executing 10 iterations, the software will present the daily prediction outcomes for May and June. It will also display graphs of the training data, test data, and the program's predictive outcomes.

In this experiment, the Kalman Filter method uses only one parameter, which is energy. In the original dataset, there is a considerable amount of data for each day because the sensor is set to store data every 15 minutes. Therefore, to make it easier for the Kalman Filter program to predict the energy data, it is averaged to a daily basis. Using the analysis process above, prediction can begin using the Kalman Filter. Prediction using this Kalman Filter method can predict the usage of each load for the next 2 months. The results can be seen in the image on Figure 5

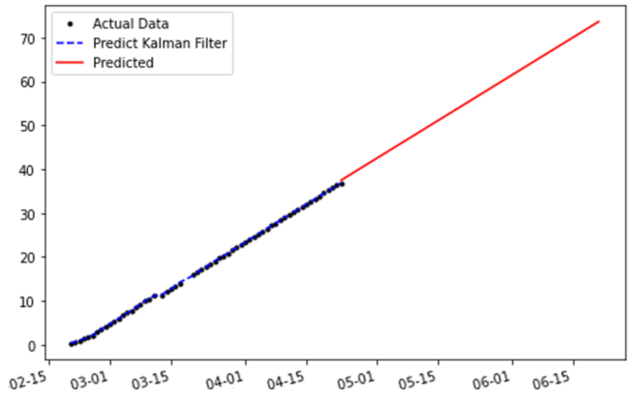

Figure 5 Kalman Filter Prediction Result Fan Load

The Kalman Filter prediction results were derived using a program employing the *simdKalman* documentation in Python, utilizing a one-dimensional Kalman Filter model. This final project utilizes a singular parameter: energy. Consequently, *simdKalman* was selected to forecast electricity consumption for the forthcoming two months.

C. Accuracy Test of Kalman Filter Prediction

The system's prediction capabilities will be evaluated in this accuracy test experiment by utilizing both training and test data. Testing for data errors will be conducted on each data point from each transaction. The magnitude of the error rate derived from each predicted training and test data point will be demonstrated by this accuracy test. The RMSE (Root Mean Square Error) and MAPE (Mean Absolute Percentage Error) methods can be employed to determine the error rate.

Table 2 Kalman Filter Prediction Testing Results

Data	Training Data	Testing Data
Laptop with Charger Load		
RSME	0.020	1.074
MSE	0.001	1.154
MAPE	0.432	5.030
Data	Training Data	Testing Data
Phone with Charger Load		
RSME	0.004	0.171
MSE	1.744	0.029
MAPE	1.087	6.105
Fan Load		
RSME	0.077	0.076
MSE	0.006	0.005
MAPE	0.789	0.202
Lamp Load		
RSME	0.027	0.052
MSE	0.001	0.002
MAPE	0.510	0.366

According to Table 2, the results that the Kalman Filter algorithm achieves high precision in estimating electrical loads measured by the PZEM-004T sensor. By effectively mitigating the impact of measurement noise and data fluctuations, the algorithm produces stable estimations that closely align with actual consumption patterns. The evaluation, utilizing RMSE, MSE, and MAPE metrics, confirms that most tested loads exhibit minimal error rates frequently below 1% particularly for appliances with consistent power such as fans and lighting. These results underscore the effectiveness of the Kalman Filter in maintaining robust estimation stability under steady-state load conditions. Nevertheless, under dynamic loads, such as laptops and smartphones when charging, the error rate is marginally elevated. This condition arises from fluctuations in current and inconsistent alterations in power consumption, necessitating more modifications to the Kalman Filter model, especially regarding the covariance matrix parameters, to more precisely accommodate the power variations that transpire.

D. Comparison of Predictions using Linear Regression and Kalman Filter Methods

Three methods were used to compare prediction results: sensor tool measurement (actual data), linear regression, and Kalman Filter. To compare these predictions, 8-day data from April 23rd to April 30th was used. This data allows the program's prediction findings to be compared to the first tool's measurements.

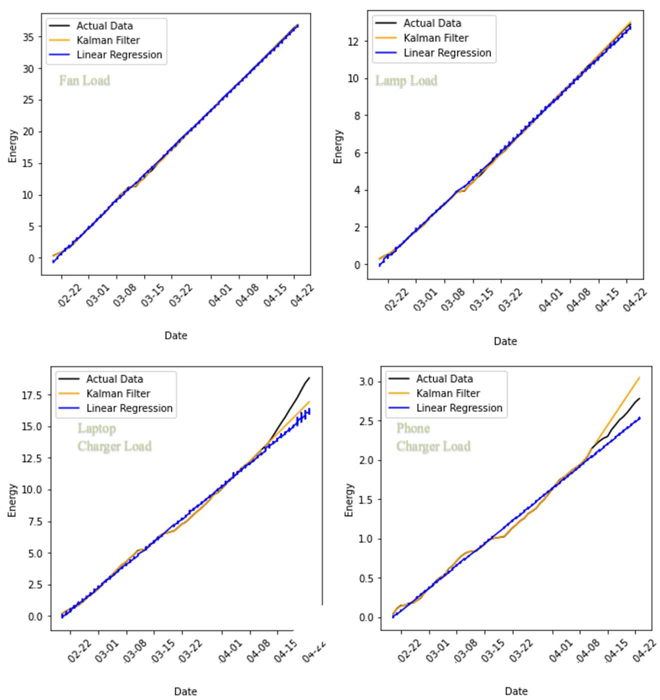

Figure 6 Comparison of results Prediction

The Kalman Filter's prediction results are superior to those of linear regression, as evidenced by the diagrams in Figure 6 for each load mentioned above. This is evident in the graphs, where the actual data predicted using the Kalman Filter method is more closely aligned with the actual data. The prediction results will consistently improve as the data that has been previously trained and tested is used. The data that most closely aligns with the actual data is the Fan load. In cases where the predicted energy values are comparable to the actual data. The results for that burden on the training data were 0.077%, and on the test, data were 0.076%, as determined by the RMSE approach to accuracy testing.

Conclusion

From the analysis of the results and discussion, it can be inferred that:

1. The collection of electrical load data over 60 days utilizing four electronic devices indicates that this information can serve as a dataset or input for forecasting electrical load consumption.
2. The outcomes of evaluating electricity consumption prediction in boarding rooms utilizing the Kalman Filter, with accuracy assessed via RMSE for loads approximating actual data, are as follows: Electric Fan, yielding results of 0.077% for training data and 0.076% for test data. Additionally, the error percentage for the Lamp load is 0.027% for the training data and 0.052% for the test data. The error percentage for the phone charger load is 0.004% for the training data and 0.171% for the test data. The accuracy level for the laptop charger load is 0.020% for the training data and 1.074% for the test data.
3. The prediction results of the Kalman Filter are more accurate and closely aligned with actual data compared to those of Linear Regression. The results of assessing both techniques using the RMSE, MSE, and MAPE metrics demonstrate.
4. The time series model employed to forecast the electrical load of boarding rooms, specifically utilizing the Kalman Filter prediction approach, yields predictions that closely align with the actual data.

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