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# Design an Electricity Consumption Prediction Information System Using the Monte Carlo-Based Regression Tree Method

**Junira Merrylin Ng[1]*, Genrawan Hoendarto[2], Thommy Willay[1]**

[1]Departement of Information System, Universitas Widya Dharma Pontianak, Jl. H.O.S. Cokroaminoto No. 445, Darat Sekip, Pontianak Kota, Pontianak, Kalimantan Barat 78243, Indonesia
[2]Departement of Informatics, Universitas Widya Dharma Pontianak, Jl. H.O.S. Cokroaminoto No. 445, Darat Sekip, Pontianak Kota, Pontianak, Kalimantan Barat 78243, Indonesia

*Correspondence: juniramerrylin14200@gmail.com

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**ABSTRACT:** Electricity became an essential component in every industry and was widely used in organizations and households. Improper handling of electricity consumption resulted in unnecessary energy loss and increased costs. The objective of this study was to develop an online electricity consumption prediction information system that was efficient, reliable, and capable of rapid forecasting. The system used IoT sensor data from Universitas Widya Dharma Pontianak, and the Monte Carlo based Regression Tree (MCRT) method was employed to mitigate the unpredictability of the data. Feature selection was conducted using Monte Carlo simulation to identify the most important features, which in this case were the year, month, and day, and these were used in the regression tree model. The developed system was able to provide estimations of hourly and daily energy consumption and the associated costs based on the MCRT model. The MCRT model predicted daily energy consumption with an accuracy of 91.61%, outperforming the Monte Carlo simulation (85.39%) and the Regression Tree method (84.29%). The results demonstrated that the MCRT model was the most efficient in capturing non-linear relationships and regression patterns in the energy consumption data. The constructed system featured an easy-to-use web interface that captured real-time data inputs and visualized predicted consumption for operational use. The system was suitable for public and private sectors, as well as educational and household applications. This approach improved effectiveness in energy management and streamlined resource allocation decision-making. The study highlighted the potential of integrating the Internet of Things (IoT) with predictive analytics to provide actionable, reliable, and precise energy management and monitoring services.

**KEYWORDS:** Electricity consumption prediction; Monte Carlo simulation; regression tree; Internet of Things; web-based information system

## 1. Introduction

Electricity was most often used for heating and cooling spaces, lighting, cooking, and running industrial equipment [1, 2]. Continued rapid economic growth, industrialization, and population increase created higher demand for global electricity supply. The International Energy Agency anticipated consumption would rise nearly 4% annually through 2027 [2]. This sustained demand highlighted the critical need for capacity and demand management. Inefficient use of heterogeneous blocks of electricity contributed to energy waste, increased costs, and negative side effects. Houses and industrial facilities were the most significant sources of inefficiency, emphasizing the need for effective energy consumption monitoring. The development of real-time electricity usage monitoring technologies emerged as a response to this need [3].

Although energy management systems advanced, progress remained limited by several challenges. Traditional monitoring systems had restricted capacity for administrative decision support, relying heavily on stored historical data [4]. Additionally, real-time electricity usage data was often imprecise or stagnant due to insufficient sensor coverage, transmission delays, and interference from distributed Internet of Things (IoT) devices [5–8]. These limitations created gaps in providing real-time estimations of electricity costs and loads, which were critical for optimizing energy retention and consumption.

The advent of IoT technologies and machine learning in the early 2020s enhanced the ability to gather, analyze, and predict energy consumption patterns [9–11, 13, 15, 16]. Integration of IoT systems with predictive analytics enabled targeted energy savings and helped managers optimize electricity scheduling [10, 11, 13, 15, 16]. Applications of IoT within smart cities, combined with techniques such as transfer learning, further improved energy efficiency and reduced overconsumption [12].

Advanced stochastic methods, including machine learning, Monte Carlo simulations, and regression trees, have been widely applied to consumption forecasting [14, 17–19, 21, 22]. The Monte Carlo method was particularly effective, as it provided probabilistic predictions based on random sampling, enhancing reliability and reducing system uncertainty in IoT-based systems [13, 14, 20, 23]. However, integrating these methods with real-time monitoring systems remained challenging due to the distributed nature of sensor networks [24].

This study presented a web-enabled IoT-powered Real-time Electricity Consumption Forecasting Information System [15, 16, 25]. The system aimed to forecast daily power consumption, predict associated costs, and implement a Monte Carlo Regression Tree (MCRT) approach [17, 18]. Accurate forecasting of electricity load facilitated efficient power management and optimal distribution across multiple tiers of users [26].

Previous studies demonstrated the advantages of integrating Monte Carlo simulations with regression trees. Darmanto et al. [17] applied the MCRT algorithm to small datasets, achieving enhanced predictive accuracy. Hoendarto et al. [18] employed MCRT for daily electricity usage forecasting and real-time anomaly detection. BIM-oriented performance simulations using Monte Carlo and regression methods reported prediction errors under 5%, validating their support for design and operational decisions [19]. Additionally, MCRT has been applied to assess energy load uncertainty, improving scheduling adaptation and system responsiveness [20, 23, 24, 27].

The incorporation of real-time IoT data with MCRT represented the most novel aspect of this research [15, 26]. Unlike systems that rely solely on historical data, this system generated predictive information to assist users in optimal electricity usage [3]. Predictive energy modeling in smart buildings has been the focus of multiple studies, employing methods such as machine learning, artificial neural networks (ANN) [28], Random Forest (RF) [27], Gradient Boosting (GB) [29], and time-series models (ARIMA, LSTM) [30–34], demonstrating the ongoing pursuit of prediction accuracy [35].This study aimed to develop a web-based model that used IoT sensor data to estimate daily power consumption and associated costs, and to evaluate the model's effectiveness in operationalizing efficient energy management.

## 2. Materials and Methods

This study was conducted through systematic and structured stages to ensure that each step was carried out efficiently, accurately, and consistently. The research process was designed to minimize errors and obstacles during implementation, ensuring reliable results while maintaining data quality. The implementation of structured stages also supported efficient management of time and resources, allowing the research to be completed according to schedule.

### *2.1. Materials.*

The research conducted utilized several materials: IoT-based hardware and software components, computing devices, and ready-made datasets. Several IoT devices, such as smart energy meters, and current and voltage sensors, were utilized to measure, in real time, the energy consumption information across several electrical devices [3, 6, 15]. These devices recorded the current (A), voltage (V), and total power (kWh) of the connected loads. Their outputs were sent to a processing unit for further analysis [4, 25]. The processing unit was maintained on a server with an Intel Core i7 processor and 16GB RAM with a 512GB Solid State Drive (SSD). Software used for the implementation of the Monte Carlo Regression Tree (MCRT) model was Python 3.10 and the following libraries: Pandas, NumPy, Scikit-learn, and Matplotlib for data processing and manipulation, model building, and data visualization. Users' interaction with the system was facilitated through a web interface developed with HTML, CSS, and JavaScript and a Flask-based backend [26, 36, 37].

The dataset contained 11,373 records from smart energy meters installed in multiple rooms across Universitas Widya Dharma Pontianak, Indonesia. The sensors measured real-time electricity consumption of numerous devices like lights, air-conditioning, lab instruments, and general-purpose sockets. The sensors monitored and measured energy consumption and current availability in real-time. The attributes measured and stored included the year, month, date, time, energy usage in three load categories (kWh1, kWh2, kWh3), total energy consumed (kWh), and current drawn (A). Table 1 shows a sample from the dataset with some of the raw entries captured by the IoT sensors. The dataset was then split into 70 and 30 percent for training (7961 records) and testing (3412 records) the prediction model.

### *2.2. Methods.*

There were multiple stages to the methodology that started with system requirement analysis, to system architecture design, to predictive model implementation, to user interface design and integration, to system testing, and to evaluation and improvement of the results. Each stage achieved the specific research objectives, and provided the opportunity to gather data that could be processed to enable real-time prediction, as shown in Figure 1. In system requirement analysis, the focus was on user need and core system function definition. This step also analyzed the necessary data, information requirements, and objectives to help users make more informed decisions regarding electricity usage. The results of this step directed focus on system design in the next stage and the design of focal features [38].

**Table 1**. Sample of IoT sensor dataset.

| Year | Month | Date | Time | kWh1 | kWh2 | kWh3 | Total kWh | Current (A) |
|---|---|---|---|---|---|---|---|---|
| 2024 | 5 | 23 | 08:00 | 0.142 | 0.255 | 0.31 | 0.707 | 3.21 |
| 2024 | 5 | 23 | 09:00 | 0.15 | 0.26 | 0.295 | 0.705 | 3.18 |
| 2024 | 5 | 23 | 10:00 | 0.165 | 0.28 | 0.312 | 0.757 | 3.44 |
| 2024 | 6 | 20 | 14:00 | 0.13 | 0.21 | 0.25 | 0.59 | 2.87 |
| 2024 | 6 | 20 | 15:00 | 0.145 | 0.265 | 0.3 | 0.71 | 3.26 |

In System Architecture Design, the focus was on developing an integrated framework of IoT sensors and the predictive MCRT model with the user interface. The data gathered by the sensors were checked for completeness and accuracy, and then, in a predictive model, processed data that was captured by the sensors and was accessed by users, as shown in Figure 2. The design accommodated effective data flow and system integration, which enables improvement and scalability for the system [26].

For the purpose of implementing the predictive model, the next step is the use of the Monte Carlo Regression Tree (MCRT) technique which aids in daily consumption prediction [17, 18]. This model combines the Monte Carlo simulation approach and regression tree to capture the uncertainty and address the non-linearity of the data [13, 22]. The probabilistic leaf values generated by the Monte Carlo simulation provided greater frame dependency and regression tree prediction accuracy as illustrated in the literature [17, 19, 27].

In regards to User Interface Design and Integration, the purpose was to create and develop a web interface that allows users to view the predictions in an engaging format [26]. Specifically, users are able to view prediction data and input different days to retrieve predictions. Along with predictions, users also see estimated costs for the predicted values. The user interface contains a reset/clear button as demonstrated by the Figures 3 and 4 for new date predictions.

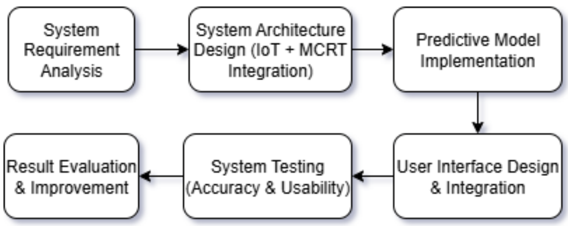


**Figure 1.** Research flow.

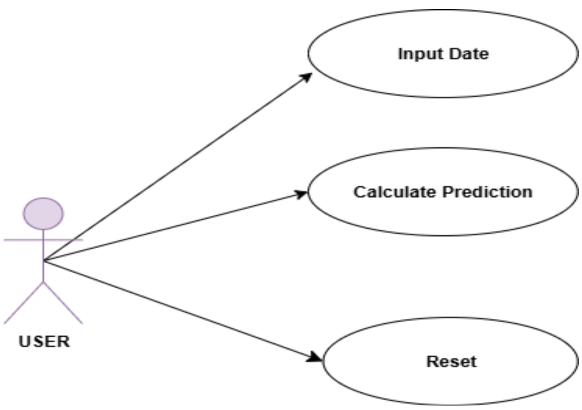


**Figure 2.** Use case diagram.

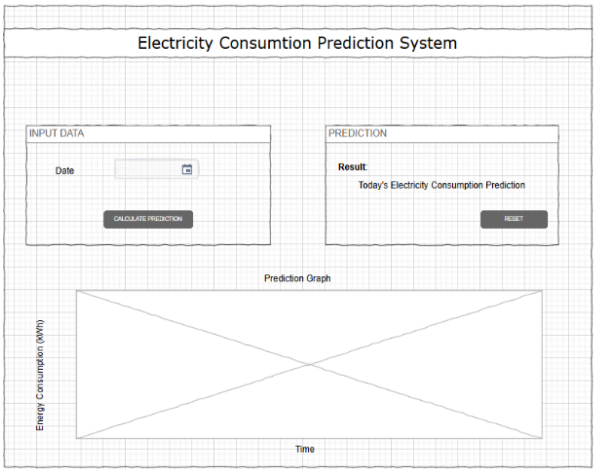


**Figure 3.** Wireframe of Electricity Consumption Prediction System.

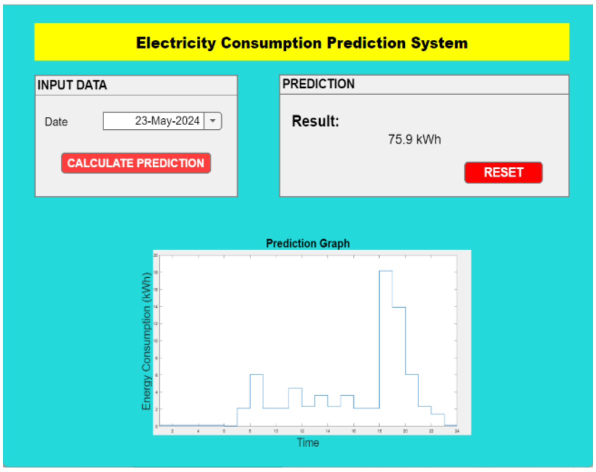


**Figure 4.** Electricity consumption prediction interface design.

System Testing verified both the predictive model's accuracy and the interface's functionality. Criteria for accuracy involved the use of Root Mean Square Error (RMSE), Normalized Root Mean Square Error (NRMSE), and accuracy levels to compare and contrast obtained outcomes to predicted values [17]. Testing the interface for usability and functionality included the collection and analysis of data on ease of system use, clarity, and responsiveness, which was subsequently used to enhance system refinement and optimization. Assessing Outcome Evaluation and Enhancement evaluated measurable components of system functioning like accuracy of models, computation efficiency, and system usability at user interface levels. Additional recommendations were made towards improving interfaces, adding more sustaining features, and eluding more flexible and efficient systems. User Interaction Flow was designed to be smooth and seamless. Users set a date, and the system ran the MCRT model to predict daily energy usage and provide graphs of the prediction. Users were also equipped with a reset button, enabling them to remove old information and re-predict for other days [35].

## 3. Results and Discussion

The prediction system for daily electricity consumption was developed and tested employing data acquired from IoT sensors [15]. The system incorporated components discussed in Chapter II, such as the Monte Carlo Regression Tree (MCRT) model, which is used to predict energy consumption and to calculate electricity consumption costs [17, 18]. The overall implementation of the system is shown in Figure 4, which displays the system's final user interface.

*3.1. System implementation.*

The user interface functions as the primary point of contact between users and the system. The interface for the prediction of electricity consumption displays when users log onto the platform, which is designed to be streamlined and accessible [26]. Users enter the prediction data by inputting the day, month, and year in the "Input Data" panel and pressing the "Calculate Prediction" button which displays the prediction results. The prediction results include a breakdown of hourly electricity consumption and the estimated costs for the day in a chart, as well as the total daily consumption in the "Prediction" panel. A "Reset" button is also available to delete the previous inputs and results to enable new predictions to be made. Figure 4 shows these interface elements and their functionalities.

*3.2. System testing.*

System testing was performed to determine whether the developed system functioned as designed and whether it produced the correct results and outputs. Testing was focused on the features and functionalities as well as the evaluation of the prediction model for precision.

*3.2.1. Functional testing.*

The purpose of functional testing was to determine whether the system was performing the required functions related to the different units that made up the system. The basic steps and results of the functional testing are summarized in Table 2, in respect of web access, date input, and reset functionalities. The functional testing results indicate that the system is operational, and the functions of the features tested are correctly performed. There were no issues encountered in input prediction or prediction display, which means the system is ready for testing accuracy.

**Table 2**. Functional Testing Results

| Test Scenarios | Test Steps | Test Results | Status |
|---|---|---|---|
| Web Access | The user logs into the system | The system promptly displays the main menu | Valid |
| Enter Date | Enter the date, then click the "Process Data" button | The system validates the data and displays graphs of electricity consumption and costs | Valid |
| Reset | Click the "Reset" button | The system clears input data, predictions, and graphs | Valid |

*3.2.2. Accuracy of prediction.*

The system's predictive capabilities were verified with hourly electricity usage data from the system for specific dates represented in Figures 5 (2024, May 23) and 6 (2024, June 20). The MCRT method was used to estimate the total electricity consumption for given variables such as year, month, day, and hour. Predictions were made for all the 24-hours in a day and the total daily consumption in kWH was derived. MCRT predictions were very accurate. The figure indicates the MCRT methodology was accurate 91.61% of the time [15]. The forecasting accuracies are shown in Table 3, where the prediction accuracies, the Root Mean Square Error (RMSE) along with the Root Mean Square Error normalized (NRMSE) for several algorithms are compared: Monte Carlo (MC), Regression Tree (RT), Random Forest (RF) with 10 (RF10) and 100 trees (RF100), Gradient Boosting (GB) and the modified MCRT method which was proposed as a solution [17, 18].

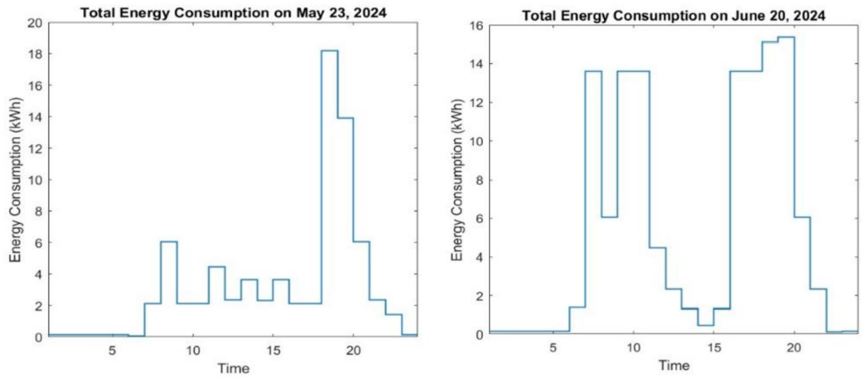


**Figure 5.** Electricity consumption prediction interface design.

**Table 3**. Accuracy comparison of prediction models.

| Algorithm | RMSE | NRMSE | Accuracy (%) |
|---|---|---|---|
| MC | 6.08 | 0.14 | 85.39 |
| RT | 6.54 | 0.16 | 84.29 |
| RF-10 | 8.05 | 0.19 | 80.66 |
| RF-100 | 8.18 | 0.2 | 80.37 |
| GB | 6.63 | 0.16 | 84.07 |
| MCRT | 3.49 | 0.09 | 91.61 |

Analysis comparison indicates that the MCRT model had the least RMSE (3.49) and NRMSE (0.09) values, thus registering less predictive error than the rest methods [17]. MCRT model also achieved better predictive accuracy than the traditional regression models, including MC (85.39%) and RT (84.29%) and than the ensemble models such as RF-100 (80.37%) and GB (84.07%) [17, 27, 29]. Results also indicate that the MCRT model, which involves the use of a Monte Carlo simulation and regression tree, increases predictive improvements due to the non-linearities and uncertainties characterizing the electric consumption data [19, 22]. The model's accuracy indicates that MCRT can be applied reliably to the prediction of real time electricity consumption. The model offers the ability to help users monitor, predict, and better manage their electricity consumption, thus better informing electricity consumption decisions [38].

## 4. Conclusions

In this project we created a web-based electricity consumption prediction system that combines IoT sensor data and a Monte Carlo based Regression Tree (MCRT) method to determine the daily electricity consumption and costs based on a prediction model. The system had an accuracy of 91.61%; a result that surpassed Monte Carlo and simple Regression Tree prediction methods. The new method that combines Monte Carlo with regression trees addresses the non-linear energy consumption and the uncertainties present in the data to provide reliable real-time predictions. The web-based system has a simple interface that allows users to enter control data to see the predicted consumption for each of the controlled devices on an hourly and daily basis. The system provides a time and cost saving tool for energy management and the optimal allocation of resources for all users such as. the general public, schools, businesses, and government agencies. The system can be improved further by increasing the area covered by the sensor network, additional prediction parameters and the use of adaptive algorithms. These changes will make the system more accurate and easier to use in a variety of situations.

## Author Contribution

Junira Merrylin Ng contributed to the conceptualization of the research, design of the methodology, development of the predictive model, and drafting of the manuscript. Genrawan Hoendarto was responsible for data collection, integration of IoT sensor data, and assistance in the implementation of the system. Thommy Willay provided guidance and supervision throughout the research process, contributed to data analysis, and reviewed and edited the manuscript. All authors have read and approved the final version of the manuscript and agree to be accountable for all aspects of the work.

## Competing Interest

All authors should disclose any financial, personal, or professional relationships that might influence or appear to influence their research.

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