Sustainable Energy Management System for AIoT Solutions Using Multivariate and Multi-Step Battery State of Charge Forecasting

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Abstract: The convergence of Artificial Intelligence (AI) with Internet of Things (IoT) technologies, known as AIoT, is revolutionizing industries, including smart cities. However, this transformation introduces challenges in energy management. Addressing this issue while upholding responsible AI principles requires prioritizing the sustainability of AIoT solutions through using renewable energy sources. While renewable energy offers numerous advantages, its intermittent nature necessitates an effective power management system. Developing a power management system serving as a decision-making platform for AIoT-driven solutions is the goal of this study. This platform contains two critical components: accurate forecasts of battery "State of Charge" (SoC), and the implementation of appropriate control strategies, including energy consumption adjustments. This study focuses on accurate battery SoC forecasts, to this end, an experiment has been designed, and a data logging system has been developed to produce suitable data since publicly available datasets do not match the specific characteristics of this research. The SoC forecasting in this paper has been addressed as a multivariate and multi-step time series forecasting problem, benchmarking various models. Comprehensive evaluations on datasets with varying time intervals showed the Bi-GRU model outperforming others based on MAE and RMSE metrics.

1 INTRODUCTION

In our increasingly interconnected world, the Internet of Things (IoT) has emerged as a transformative technology, changing how data is collected and used across various domains. As a result of this widespread adoption of IoT technology, many remarkable innovations have taken place, particularly in the areas of smart cities and healthcare. These innovations are, however, accompanied by significant challenges. The extensive volume of data collected from different sensors and devices during the advancement of IoT solutions poses privacy issues that affect their widespread adoption, as this data often contains sensitive information (Lipford et al., 2022). The transmission of large amounts of data from IoT devices requires a high bandwidth, and not all environments support it (Fetahu et al., 2022). Additionally, IoT data is often unstructured, large-scale and unclean, which poses challenges in extracting meaningful insights (Krishnamurthi et al., 2020). On the other hand, a valuable application of Artificial intelligence (AI) is its capability to uncover insights and opportunities through data analysis. It is imperative to emphasize the principles of Responsible AI when it comes to AI-driven solutions, which include privacy, ethics, and sustainability. Responsible AI ensures that AI technologies are developed and used in ways that protect individual privacy, maintain ethical standards, and reduce environmental impact by promoting energy-efficient practices and energy management (Barredo Arrieta et al., 2020). AI integration with IoT ecosystems has empowered them with the capability to analyze vast amounts of data, derive insights, and facilitate autonomous decision-making. The convergence of AI and IoT technologies, known as AIoT, is introducing a new era of smart and adaptive systems, accelerating innovation and increasing efficiency across a variety of industries (Zhang and Tao, 2021). Smart cities are one of the sectors where AIoT is bringing significant innovation. In order to leverage the full power of AIoT, it is important to address IoT challenges and adhere to responsible AI principles, in which pri-

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vacy, ethics, and sustainability are all taken into account. As a result, BusPas Inc., a Montreal-based company, is offering a smart platform using AIoT in order to tackle these challenges and meet the current demand for smart mobility. Their idea involves replacing regular bus stop signs with intelligent and interconnected displays named “SCiNe” which stands for “**S**mart **Ci**ty **Ne**twork”. Besides showing real-time information regarding bus schedules, this device is equipped with several IoT sensors, including a light sensor, environment sensors, an Infrared sensor, microphones, speakers, and a fisheye camera. These sensors enable the intelligent display to collect valuable data at bus stops, making them strategic hubs for gathering information on passenger and vehicle flows, environmental conditions, traffic patterns, ridership, and more. This data contributes to enhancing mobility and optimizing transportation services. Despite this, what truly distinguishes this intelligent display is its embedded computational capabilities. Through the use of AI at the edge, this device enables real-time data processing at bus stops while preserving user privacy by only transmitting descriptive information, not only safeguarding privacy but also streamlining data transmission due to the reduced data volume after processing. The advancement of AI technologies has resulted in larger and more powerful models capable of performing complex tasks. However, these larger models are energy-intensive, which poses a challenge. Furthermore, IoT technologies are developing rapidly, creating new challenges, one of which is managing energy resources efficiently (Guenfaf and Zafoune, 2023). This challenge is further compounded when integrating AI with IoT in AIoT-driven solutions. To address these challenges and uphold the principles of responsible AI, it is important to ensure the sustainability of these solutions. The use of renewable energy sources is a promising approach to addressing this challenge. Following this approach, SCiNe is powered by a lithium-ion battery that derives its charge from a solar panel, showcasing its dedication to sustainability. Renewable energy sources, like solar panels, offers benefits such as reducing reliance on fossil fuels and cutting costs. It can be harnessed in various locations, reducing dependence on centralized grids and increasing energy self-sufficiency. However, challenges exist in managing the intermittent nature of renewable sources for a consistent energy supply for AIoT devices (Rathod and Subramanian, 2022). Moreover, when renewable energy sources are not producing enough power, energy storage is required to ensure a reliable energy supply. However, current storage technologies have capacity and efficiency limitations (Bharatee et al., 2022). Therefore, an effective power management system is essential to mitigate these challenges. In systems based on renewable energy sources, predictive control techniques have recently been offered as a way to cope with uncertainty and intermittency of energy production and consumption (Elmouatamid et al., 2020). The State-of-Charge (SoC) of batteries, which indicates the amount of energy stored in them, is one of the main parameters for the development of these techniques. Consequently, effective power management of renewable energy systems involves two key aspects: accurately forecasting batteries SoC, and the implementation of appropriate control strategies such as adjusting energy consumption patterns, to ensure stable and reliable system operation. This power management system serves as a decision-making system, defining different service levels for the device. At each service level, certain functionalities of the device are limited to control power consumption. Based on the predicted SoC of the battery, and considering weather and solar conditions in the future, the system switches between these service levels dynamically. The main objective of this study is to develop such an effective power management system for AIoT solutions, exemplified by our work on SCiNe, with a specific focus on accurate battery SoC forecasting. This SoC forecasting plays a central role within the broader decision-making system, all while making efficient use of renewable energies to ensure the practical sustainability of AIoT solutions. The majority of previous work in battery SoC forecasting has focused on microgrid systems, electric vehicles, and grid ancillary services. This study fills a gap in battery SoC forecasting by focusing on a unique application domain: developing a power management system for a battery-powered AIoT device charged through a solar panel. Additionally, the characteristics and scale of this project are different from previous work, so publicly-available datasets are not applicable. The remainder of this study is structured as follows: We begin by presenting the state of the art in studies on battery SoC forecasting in different domains and the forecasting models employed for this purpose. Then, the Design of Experiment section introduces our experimental design and data gathering process, emphasizing the custom data logging system developed to collect relevant data. Finally, we exhibit the evaluation results and finish with conclusions and avenues for future research.

2 LITERATURE REVIEW

Energy storage becomes necessary as a consequence of using renewable energies when they fail to generate sufficient power. Batteries are commonly used for energy storage in Renewable Energy Source systems and Lithium-ion batteries are often used in this context. The SoC of batteries is one of the main parameters can be used in predictive control algorithms in power management of systems using renewable energies. The process of determining the current state of charge of a battery is known as SoC estimation, whereas SoC forecasting involves predicting the future state of charge based on past data and other factors. While numerous methods exist for SoC estimation in batteries, limited research has been conducted specifically on SoC forecasting which is an important aspect of battery management systems (BMS) reliant on renewable energy sources, as it enables the development of effective power management strategies (NaitMalek et al., 2021). Unlike other battery parameters, such as voltage, current, and temperature, SoC cannot be directly measured. Researchers have studied various methods for accurate SoC estimation, which can be divided into three categories: conventional methods, model-based methods, and data-driven methods (Park et al., 2020). The focus of this study is on SoC forecasting rather than estimation. Several studies have investigated SoC forecasting across different domains, employing various models and techniques. Researchers have used several time series methods to forecast battery SoC in the field of grid ancillary services. For instance, (Ardiansyah et al., 2021) developed an approach for multi-step SoC forecasting of battery energy storage systems (BESS) in grid ancillary services, using Long Short-Term Memory (LSTM) neural networks. This model considers dynamic grid conditions and varying power demand, enabling accurate and reliable predictions of the battery SoC over multiple time steps. (Ardiansyah et al., 2022) proposed a Seq2Seq regression approach for multivariate and multi-step forecasting of BESS in frequency regulation service. The model showed promising results in accurately predicting SoC, enabling efficient use of BESS. Another domain in which SoC forecasting has been studied, is in Micro grids, such as (NaitMalek et al., 2021). That paper developed an embedded system for real-time forecasting of battery SoC, enabling effective energy management and decision-making in microgrid systems. In (Elmouatamid et al., 2020), MAPCAST, an adaptive control approach enhanced by predictive analytics, one of which is SoC forecasting, is used to achieve energy balance in microgrid systems. By combining predictive analytics with adaptive control techniques, the proposed method optimizes energy usage and ensures a stable energy balance, leading to improved energy management and reliable operation in microgrid systems. One of the key concerns of electric vehicle (EV) customers is the driving range which depends mainly on battery capacity. Forecasting battery SoC is therefore useful in this context as well. In (NaitMalek et al., 2022) Youssef NaitMalek et al. introduced a hybrid method for accurate SoC forecasting in EVs. The approach combines a machine learning algorithm with an EV model to forecast battery SoC. The machine learning algorithm predicts vehicle speed, which is then used as input for the EV model to determine the battery SoC. The work presented in (NaitMalek et al., 2019) also explored the integration of predictive analytics techniques for multi-horizon forecasting of battery SoC and contributes to the development of an intelligent management system for battery-powered electric vehicle. A variety of forecasting techniques and algorithms have been applied in battery SoC forecasting. (NaitMalek et al., 2022) used linear regression for SoC forecasting, which offered simplicity and interpretability, making it suitable for real-time SoC forecasting in battery-powered electric vehicles. However, to address the limitation of not capturing complex nonlinear patterns in linear regression, alternative algorithms such as decision trees (DT) were employed in (Mashlakov et al., 2019). It is worth noting that decision trees can be prone to overfitting, and ensemble methods like random forests (RF) or gradient boosting can be employed to mitigate this issue and further enhance SoC forecasting performance. In light of this, (Mashlakov et al., 2019) also applied random forest and Light Gradient Boosting Machine (LightGBM), whereas (NaitMalek et al., 2019) leveraged the power of Extreme Gradient Boosting (XGBoost). Moreover, in (Ardiansyah et al., 2021), advanced deep learning architectures including LSTM, Gated Recurrent Unit (GRU), Bidirectional Long Short-Term Memory (Bi-LSTM), and Bidirectional Gated Recurrent Unit (Bi-GRU) were investigated. These recurrent neural network variants demonstrated their ability to capture temporal dependencies and long-term patterns in SoC data, enabling more accurate and the multi-step forecasting of battery SoC. (Ardiansyah et al., 2022) proposed a solution to the challenges of multi-step SoC forecasting by using a sequence-to-sequence (seq2seq) model in deep regression learning. This model has demonstrated its effectiveness and robustness in various scenarios, making it a reliable approach for accurate multivariate and multi-step forecasting, as supported by previous studies (Hewamalage et al., 2021). In summary, prior research on battery SoC forecasting has been mostly centered around domains such as microgrid systems, electric vehicles, and grid ancillary services. This research focuses on battery SoC forecasting which serves as the foundation for the intelligent power management system designed to optimize the operation of a battery-powered AIoT device using solar panel energy, addressing a crucial gap in the field of SoC forecasting - specifically for this unique application. Considering the specific characteristics and scale of this study, a custom dataset was required and created since public data did not meet the study's needs. Three contributions were made in this paper: the design of an experimental setup and the development of a data logging system, handling the problem as a multi-step and multivariate time series forecasting, and conducting a comprehensive model evaluation. In order to overcome the shortage of suitable datasets in this domain, an experimental setup was designed and a custom data logging system was devised to ensure acquisition of relevant and accurate data. Data collection is an essential part of the study because it provides essential data for analysis and model development. The paper uses various forecasting models, including machine learning and deep learning approaches, to forecast SoC as a multivariate and multi-step time series problem. Furthermore, the paper conducts a comprehensive evaluation of the forecasting models, providing valuable insights into their performance.

3 DESIGN OF EXPERIMENTS

To gather data for this project, a comprehensive experimental setup was designed to capture and analyze the relevant parameters of the battery system of the device. This system comprised essential components, including a lithium-ion battery, a solar panel (substituted with a programmable power supply for lab environment purposes), a load representing the device with various subsystems, and an MPPT (Maximum Power Point Tracking) solar charge controller. The battery, power supply, and load were interconnected through the MPPT charge controller, while a computer served as the central control unit for data collection and control of the power supply. The computer was connected to both the MPPT charge controller and the power supply, allowing for real-time monitoring and control of the power supply's parameters.

Figure 1 illustrates the setup configuration. The collected parameters from the MPPT charge controller are presented in Table 1, with the data acquisition facilitated by the MPPT controller's software.

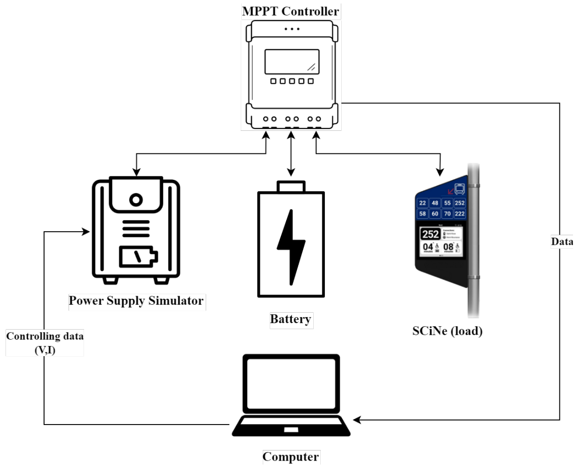

Figure 1: Setup Configuration.

Table 1: Description of Parameters from MPPT Controller.

Category	Parameters
Solar Info.	Voltage, Current, State, Power
Battery Info.	Voltage, Current, Temperature, SoC
Load Info.	Current, Voltage, Power
Controller Info.	Temperature, State

An experimental plan was designed to observe and analyze the behavior of the battery system. The battery charging and discharging methodology were the two crucial aspects that the experimental plan focused on. Since the experiment was conducted in a controlled lab environment without direct sunlight, a programmable power supply was used to charge the battery instead of solar panel. To simulate the charging effect of the solar panel, solar radiation data for the desired location were obtained from publicly available sources. Based on solar radiation values for each hour, Equation 1 was used to calculate the voltage and current settings for the power supply simulator. The device's solar panel specifications indicated a power output of 50W under standard test conditions (STC) with solar radiation at $1000W/m^2$. This information was used to calculate the amount of power that the solar panel would deliver to the battery based on the actual solar radiation data.

$$\text{Charge Power} = \frac{\text{SR}}{\text{STC SR}} \times \text{SP} \tag{1}$$

where: SR = Solar Radiation, STC SR = Solar Radiation at STC, SP = Solar Panel Power at STC.
For instance, if the solar radiation for a particular hour was measured as $300\,\text{W/m}^2$, the power supply's voltage and current were adjusted to deliver 15W to the battery during that hour. This approach facilitated the simulation of solar charging within the lab environment. One of the device's functionalities is to

send sensor data to the cloud at five-minute intervals which is called telemetry data. This data is reflecting the activation and deactivation of various subsystems of the device. In this study, for the discharging methodology, the telemetry data for the month of February 2023 was used. The collected telemetry data were employed to precisely reproduce the activation and deactivation patterns of the subsystems to simulate real-world scenarios throughout the experiment. To ensure consistency in the data gathering process, the experiment was initiated with a fully charged battery and incorporated a repetitive cycle. When the battery SoC reached a critical level close to zero, the experiment was temporarily paused. The battery was then charged back to its full capacity, and the experiment was resumed from the point at which the battery had reached the critical level. This process of discharging, pausing, recharging, and resuming was repeated multiple times throughout the experiment, ensuring a reliable and controlled data collection approach. Through the carefully planned experiments, which encompassed the simulated solar charging and the replication of real-world subsystem activation and deactivation, a comprehensive dataset was obtained. This dataset serves as the foundation for the subsequent analysis and enables accurate battery SoC forecasting.

4 EXPERIMENTS

The dataset produced for this study consists of 40,320 observations, which corresponds to the number of minutes in 28 days. The data was collected at one-minute intervals to ensure a high level of detail in capturing the behavior of the battery system. To assess the impact of different time intervals on forecasting accuracy, the dataset was resampled into three subsets. This resampling makes a balance between data granularity and computational efficiency, as the original dataset contained a large volume of one-minute interval observations. Based on the resampled datasets, time series forecasting models were evaluated and results were compared across different temporal resolutions. The subsets consisted of 2,688 observations (15-minute interval), 1,344 observations (30-minute interval), and 672 observations (1-hour interval). This approach enables a comprehensive analysis of the dataset and provides insight into the effect of temporal granularity on forecasting accuracy.

4.1 Data Preprocessing

An exploratory data analysis (EDA) is performed to preprocess the dataset and select the important features to include in the SoC forecasting model. In Figure 2, the correlation heatmap, which is based on Pearson correlation coefficients, clearly shows that the battery voltage and SoC are positively correlated, with a correlation coefficient of 1. This high correlation is not surprising, considering that the MPPT controller relies on the battery voltage as a crucial factor in determining the SoC. The pearson correlation coefficient r is calculated using Equation 2:

$$r = \frac{S_{xy}}{\sqrt{S_{xx} \cdot S_{yy}}} \tag{2}$$

where S_{xy} represents the covariance between variables X and Y, S_{xx} is the variance of X and S_{yy} is the variance of Y.

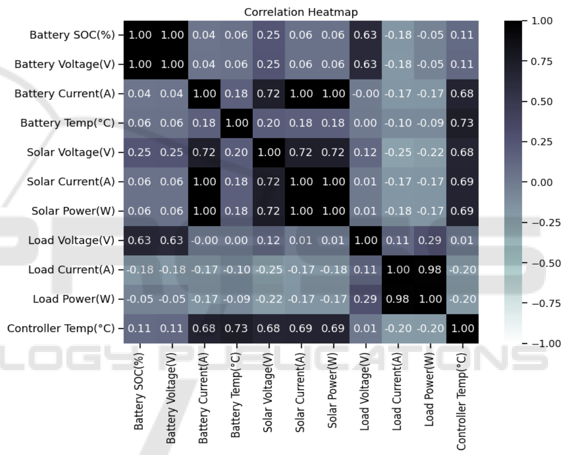

Figure 2: Pearson correlation heatmap displaying the relationship between the gathered features and the SoC of the battery.

According to the correlation values, the SoC is more correlated with load voltage, solar voltage, and load current. Therefore, these features become crucial factors to consider in order to improve the SoC forecasting model. To further improve the feature selection process, mutual information (MI) is employed alongside correlation analysis. While correlation focuses on linear relationships between variables, MI takes into account both linear and nonlinear dependencies. It quantifies the amount of information one variable provides about another, capturing a broader range of relationships beyond what correlation alone can reveal. The MI is calculated as:

$$\mathrm{MI}(X,Y) = \sum\sum P(X,Y) \log_2 \left(\frac{P(X,Y)}{P(X) \cdot P(Y)} \right) \tag{3}$$

where $P(X,Y)$ represents the joint probability distribution of variables X and Y, and $P(X)$ and $P(Y)$ represent their marginal probability distributions (Zhou et al., 2022). Normalized mutual information (NMI) is used to standardize evaluations across feature scales. A high NMI score indicates strong dependence between the target feature and the input feature. NMI scores range from 0 to 1, with 1 representing perfect correlation (0 = no mutual information). Figure 3 shows NMI scores between all the features and battery SoC. Battery voltage, solar voltage, load voltage, and battery current have the highest NMI scores, all with NMI score above 0.2. Therefore, based on both analyses, the following features can be considered as features for improving the SoC forecasting model: battery voltage, load voltage, solar voltage, load current, and battery current.

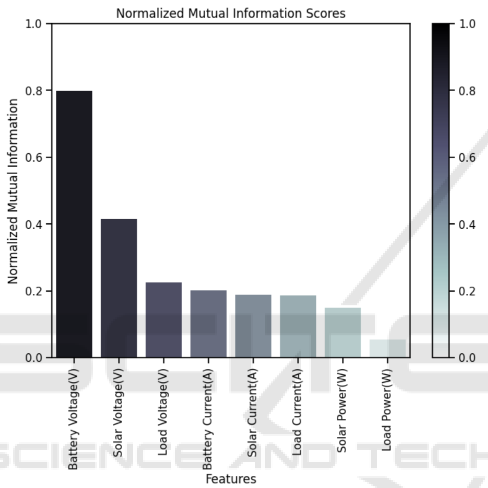

Figure 3: Normalized mutual information score between SoC and the features.

In the experiment, the Date and Time were set as the time series index. The SoC percentage and the features selected based on the Pearson correlation and NMI score were used as input data.

4.2 Forecasting Models

Various multi-step and multivariate time series forecasting models were applied to the resampled datasets with different time intervals to forecast the SoC of the battery. Both machine learning and deep learning modeling approaches were used in this study. Initial benchmarks were established using machine learning models such as DT and RF. The data was then modeled using deep learning models including CNN, LSTM, GRU, Bi-LSTM, and Bi-GRU, in order to capture complex temporal patterns. Forecast horizons of 2 hours, 5 hours, and 10 hours were used to evaluate the effectiveness of these models. Training and testing of the models were conducted on resampled subsets of data for each forecast horizon. Using this approach, we were able to evaluate model performance over various time intervals and forecast horizons. The look-back window determines the amount of historical data used for forecasting future time steps. In this study, the look-back windows are set to the same duration as the forecast horizons in each model. Adam optimizer is used for tuning the developed deep learning models, and the dropout regularization to avoid overfitting. The forecasting models were implemented using Keras 2.6.0 API with Tensorflow 2.12.0 as the backend, within the Python 3.11.4 environment. Table 2 presents the parameters used for training and evaluating the forecasting models,

Table 2: Parameters Set for the Models.

Parameter	Value
Training and Testing portion	85% and 15% of total data
Validation portion	30% of training data
Normalization	MinMax normalization (range 0 to 1)
Regularization	Dropout = 0.2 in each layer
Early stop to avoid overfitting	Patience = 30
Look-back window size range	2-40 data points
Optimization algorithm	Adam
Maximum number of epochs	150

4.3 Evaluation

The forecasting models were assessed using mean absolute error (MAE) and root mean squared error (RMSE) to evaluate the accuracy of SoC forecasts. MAE measures the average magnitude of prediction errors. It is calculated as the mean of the absolute differences between the predicted values ($\hat{y}_i$) and the actual values (y_i) for each observation in the dataset, as shown in Equation 4. In this equation, n is the number of observations.

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{4}$$

RMSE is the square root of the average of the squared differences between the predicted values ($\hat{y}_i$) and the actual values (y_i) for each observation in the dataset, represented by Equation 5.

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{5}$$

Both MAE and RMSE express average model prediction error in units of the variable of interest, which, in this study, is the SoC of the battery. The SoC is expressed as percentage with 100% representing a fully charged battery and 0% indicating an empty battery.

Figure 4 provides a detailed comparison of the forecasting models used in this study, based on the MAE and RMSE performance metrics. Three resampled datasets with 15-minute, 30-minute, and 1-hour scales are used to evaluate the forecasting models, covering forecast horizons of 2 hours, 5 hours, and 10 hours. The figure displays the errors for each model's last time step forecast, providing insights into the effectiveness of the models for long-term forecasting. It is observed that RMSE errors are generally higher than MAE errors, indicating RMSE's sensitivity to large errors. Additionally, and as expected, errors for all models tend to increase with increasing forecast horizons, reflecting the complexity and uncertainty of long-term forecasts. The Bi-GRU model outperforms other models across various forecast horizons and dataset scales, making it a good choice for more accurate predictions.

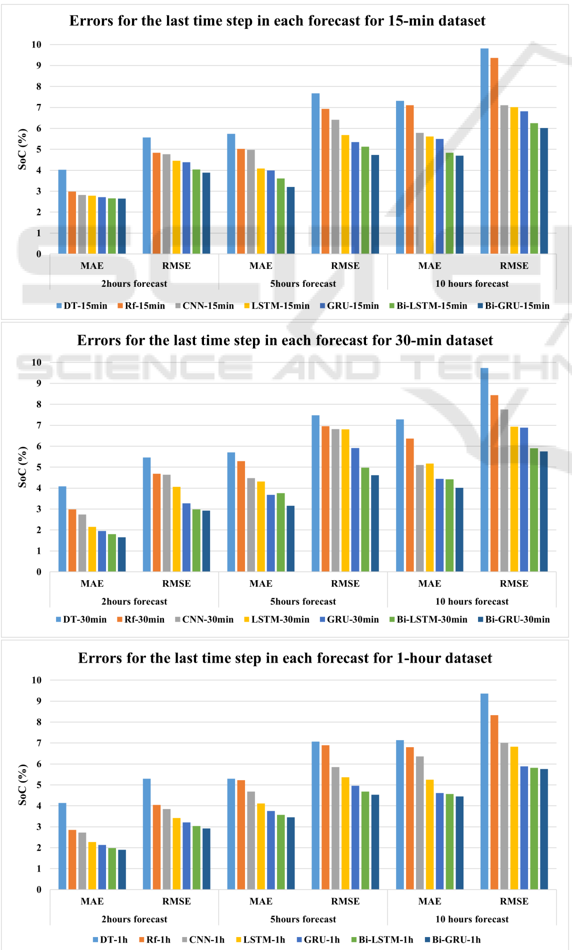

Figure 4: Comparison of forecasting models for the last time step on each dataset.

Further quantative evaluation of forecasting models was conducted in addition to visual analysis from the figure. While the figure enabled comparison of forecasts for the last time step, Table 3 provided an assessment of the models' overall performance. This evaluation involved comparing the average errors for all time steps across the longest forecast horizon of 10 hours. In this way, the assessment allowed for evaluating the model's accuracy and reliability across the entire forecast period, gaining a better understanding of their overall performance and forecasting capabilities. Bi-GRU model has the lowest MAE and RMSE, indicating the highest accuracy among all models.

Table 3: Overall Forecast Performance on Test Data for the Horizon of 10 Hours.

Models	15 min dataset		30 min dataset		1 hour dataset	
	MAE	RMSE	MAE	RMSE	MAE	RMSE
DT	6.02	7.33	4.76	6.91	6.20	7.46
RF	4.49	5.71	3.56	5.36	4.70	5.84
CNN	4.45	5.60	3.91	4.92	4.39	5.59
LSTM	4.63	5.34	3.88	4.69	4.24	5.46
GRU	4.46	5.30	3.71	4.55	3.39	4.34
Bi-LSTM	3.88	4.69	3.70	3.42	2.93	3.72
Bi-GRU	**3.61**	**4.57**	**2.55**	**3.26**	**2.79**	**3.66**

Considering both visual and quantitative assessments, the Bi-GRU model consistently outperforms other models, highlighting the effectiveness of its bidirectional architecture and gated recurrent units for Battery SoC forecasting.

5 CONCLUSION

The integration of AI and IoT in AIoT-driven solutions presents innovation, but also energy challenges. To tackle these challenges while adhering to the principles of responsible AI, it is crucial to prioritize the sustainability of these solutions through the promising adoption of renewable energy sources. Despite the benefits of renewable energy, challenges such as its intermittent nature necessitate the implementation of an effective power management system. This study focused on developing an effective power management system, serving as a decision-making framework for AIoT solutions. It was exemplified by the development of a battery-powered AIoT device charged through a solar panel named "SCiNe", with a specific emphasis on accurate battery State of Charge (SoC) forecasting. To understand the behavior of system, an experiment was designed and a custom data logging system was developed to gather relevant data, enabling accurate analysis and model development. The study explored the multivariate and multi-step time series forecasting domain, using a variety of models, including DT and RF, to deep learning models of CNN, LSTM, GRU, Bi-LSTM, and Bi-GRU. The models were evaluated using both last time step forecasts for a comparative view and average errors over the entire forecast period for a comprehensive evaluation. The Bi-GRU model outperformed other models across datasets with varying time intervals and forecast horizons. These findings highlight the potential of the Bi-GRU model for real-world applications in similar systems. Incorporating additional input features, such as weather and solar data, exploring alternative time series forecasting models, and integrating the SoC forecasting solution into the decision-making system, offer promising avenues for future enhancements in the study. This study has primarily addressed the first phase of the decision-making system for managing AIoT device power – accurate battery SoC forecasting. The next step is to design and implement control strategies that enable dynamic adjustments to service levels of the device. These service levels define specific operating modes for the device, with each level corresponding to different functionalities and power consumption limits, ensuring both system stability and power efficiency. These enhancements lead to the development of a sustainable power management system for AIoT applications.

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