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Research Article

Deep Learning Model on Energy Management in Grid-Connected Solar Systems

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Because of increased electricity consumption and the inherent limitations of fossil fuel ability to replenish themselves in the future, a shift to renewable energy sources is unavoidable. Although renewable energy sources are afflicted by intermittency, this problem can be alleviated by combining them with other sources of electricity. As a result of the above situation, the secondary source will take over if the primary source is unable to match the load demand. In this paper, we develop a hybrid renewable source that is connected with grids in an optimal way for the prediction of energy using an energy management system (EMS). The study is aimed at optimal handling of energy production, grid interaction, and the storage system, all of which must be accomplished simultaneously. The current state information from the battery, as well as control objectives, is used in this study to design control actions that maximise the amount of electricity injected into the grid. During the prediction window, it is assumed that the control inputs received at the start of the window will remain consistent throughout the duration of the window. The results of RMSE show errors lesser than 0.3% that shows improved rate of accuracy using EMS.

1. Introduction

The imported energy source is a major cause of contention for their governments and citizens. A key present challenge [1] is the reliance on imported fossil fuel energy, as well as the availability of freshwater and waste management. As a result of this trend, the share of renewable energy resources in the generation of island-generated electricity has increased dramatically in recent years.

Wind energy is considered as a popular renewable energy sources. As a result of the fluctuating nature and instability of wind energy, it poses substantial operational challenges, particularly for weak or isolated transmission networks. In order to comply with the grid code obligation to assure a controlled power output as well as the provision of additional ancillary services, wind generating installations must meet certain criteria. Because of the unpredictable behaviour of the wind, scheduling becomes more complex, and the cost of operating the system increases, which necessitates a reduction in frequency [2, 3].

As a result, the number of wind turbines (WTs) being constructed on a global scale is continuously increasing over the years. In wind-powered systems, the output is intermittent due to the variable speed of the wind, which results in lower efficiency [4]. As a result, penalties for failing to comply with day-ahead bids are now unavoidable. While these issues are exacerbated in island networks such as Guadeloupe, it is critical to maintain control over them in order to improve grid efficiency without compromising power quality and reliability [5].

As a means of overcoming these challenges, wind turbines can be integrated with production or storage technology to form hybrid power plants (HPPs). Using a combination of conventional and renewable energy sources [6, 7], wind-thermal hybrid systems [8, 9], wind-hydro hybrid systems [10, 11], and wind-solar hybrid systems [12–15] to manage energy and reduce the variability of wind-generated electricity, HPPs can reduce the cost of energy and the environmental impact of their operation [16]. Additionally, wind energy can be used with energy storage technologies, fuel cells, and hydrogen storage to provide even more renewable energy. Power injection into the grid on-demand and support for traditional power-generating systems are both made possible in this way, and they are both beneficial [17]. Not only are hybrid power plants capable of accepting a wide range of production and storage resources, but their integration into traditional power grids may also improve the efficiency and reliability of the hybrid system, allowing it to fulfil demand more reliably [18–20].

Optimizing control operations is critical for ensuring that high-pressure water-pumped wind-storage activities run smoothly. It is possible to have energy storage units that service the entire wind farm, or they can be distributed such that each wind turbine has its own storage unit in a hybrid wind power system. These configurations can be controlled by an energy management system (EMS). An EMS must find a balance between the multiple objectives of a power plant operation in order to get the most out of its output. When determining the most effective management plan, a variety of considerations must be taken into consideration. Design and operational requirements, as well as control and optimization methodologies, are all included in this category of requirements.

Recent research has focused on the development of EMS for grid-connected microgrid power dispatch, with particular attention paid to HPPs in rural areas and island territories that integrate wind turbines and energy storage systems [17–19]. The purpose of storing extra electricity and releasing it when there is an energy crisis is to deal with periods of high availability of electrical power.

Due to the fact that it is based on assumptions about the future, the wind/storage HPP power dispatch is inherently problematic. Every optimization computation makes use of the hybrid plant real-time WT production and other measures, which are used as input data for each computation. As a result, in order of resolving the entire problem, a reactive optimization is required. In the energy management microgrid community, there has been a substantial surge in interest in model predictive control (MPC). Using forecasts and newly updated information, this control strategy can determine the future trajectories of the system, and it is capable of handling a wide range of constraints successfully.

Although much has been accomplished, there are still a plethora of challenges linked to criteria, such as integrating production sources and storing them in numerous storage technologies, effective load management, and profitability operations, which must be addressed. Optimizing resource utilisation while simultaneously reducing operational expenses, while taking into consideration the global market, applications, and many technical factors, can increase a system performance and efficiency. The main novelty of the article includes the development of a hybrid renewable source that is connected with grids in an optimal way for the prediction of energy using an EMS.

2. Related works

More than one study has looked at energy management [21–23], and they have discovered that different storage systems, energy sources, and whether or not they are connected to the grid all make a difference in how efficiently energy is managed.

The authors of [24] compared an intuitive solution to an optimal solution is worth mentioning. According to the results, the ideal system is more cost-effective than the predictive system when it comes to lowering electricity expenses. The adoption of intuitive approach fails to consider cost constraints or the price per time slot available. The system does not consider the possibility of employing PV energy of an excess of solar energy. Batteries are further restricted by the fact that they can only be in one of two states at any given time: charging or discharging mode.

The authors of [25] developed a hybrid architecture that incorporates solar, wind, and battery technology. It was decided to use parallel resource solutions to manage energy consumption, which may result in losses if the energy can be supplied by renewable sources.

The authors in [26] are concerned about how long the battery will last in their system. The study focuses on countries where power providers distribute their available energy on a predetermined schedule, resulting in intentional blackouts. There is no doubt about it. In order to tackle this, mixed-integer nonlinear programming was applied, and the outcome was a predictive switching, as shown in Figure 1. However, due to the system construction, the electrical current is only permitted to flow in one direction through the system. Because of this, as well as the fact that the grid is still considered a key source of energy, there are limits to how much excess PV can be managed.

In contrast, the authors of [27] conducted a comparative analysis of two distinct energy control systems that included hybrid energy storage. Initially, a rule-based technique is employed, and secondly, a model predictive control strategy is employed. When it comes to the DC bus voltage, the inverter input voltage threshold is not honored, regardless of whether the load is being injected or supplied with alternating current. To make matters worse, the intuitive

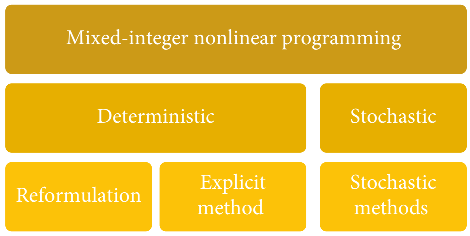

Figure 1: Mixed-integer nonlinear programming.

technique makes use of a decision variable that has no influence on the state of the battery charge, such as voltage, which makes the situation even worse. Although the prior work used dynamic and linear programming, the research presented below used a technique called reduced state number programming.

According to the authors of [28], that authors considered solar system sizing to provide enough electricity for the load while also charging their battery. This technique can be used to track the amount of demand on the power system. Because of the oversizing of the installation, the panels generated an excessive amount of electricity, and the limited mode was employed to reduce the amount of electricity created. Indeed, when sizing, the writers must take into consideration the maximum amount of electricity that may be pumped into the grid. However, on the other hand, the usage of 85% capacity by the EMS is detrimental to the battery general health. As a consequence of this outcome, we investigated how a PV-battery system could share its energy in order to meet the demand in our situation: As a matter of fact, our energy management system mandates that the grid be handled as an emergency line after mathematical modelling is completed for the various components of our hybrid system. At the beginning of each time slot, the output of the PV plant is evaluated; if it is unable to fulfill the load, a battery is used to supplement the PV plant production. In the event of an emergency, the energy that has been sold to the grid will be refunded.

3. Proposed Method

A family of control methods known as model predictive control (MPC) employs the controlled system model as the control signal in order to minimise the user-defined objective function. MPC is a technique for minimising the objective function of a controlled system. Due to the fact that MPC permits constraints to be incorporated into the control design criteria, it is possible to deal with them methodically. MPC capacity to run systems at their constraint boundaries distinguishes it from more classic linear unconstrained approaches such as PID, which operate systems farther away from their constraints. In simple terms, MPC is a method for forecasting future control actions that will result in the intended outcome within a limited time period that is easy to understand. For the purpose of calculating the control signals, a cost function is used as a criterion. The signals are then evaluated in terms of how close they are to the reference trajectory. The current state information from the Li-ION BESS, as well as future control objectives, is used in this study to design control actions that maximise the amount of electricity injected into the grid. During the prediction window, it is assumed that the control inputs received at the start of the window will remain consistent throughout the duration of the window.

Several key performance indicators (KPIs) have been devised to evaluate the EMS predicted wind-storage high-performance power generation performance. While the key performance indicators (KPIs) chosen for this study evaluate performance, they also highlight margins that can be used to optimise the efficient and smart operation of a grid in a way that is both cost-effective and energy-efficient. The objectives and limits of the wind-storage HPP were critical in the development of the key performance indicators in this example.

3.1. Commitment Failure (CF%). Because the output of the wind turbines changes instantly, it is necessary to determine how the storage system should be used (i.e.,which portion of production should be used to charge the BESS and how much power should be discharged) to inject power into the electric grid in accordance with a committed generation schedule (i.e.,how much power should be discharged) (CF%). The commitment profile is then generated based on the data from the day-ahead prediction. It is possible to suffer economic penalties as a result of a violation of the accepted injection area above and below the commitment. The %age of time that the penalty condition was in force is then used to calculate the number of commitment failures, which is expressed as follows:

$$\mathrm{CF\%} = 100 * \frac{\text{penalty triggered time}}{\text{test time}}. \quad (1)$$

3.2. Curtailment Power. It is possible that losses will be incurred as a result of excessive wind turbine production when the BESS is completely charged. These losses can be monitored and measured in order to test a suggested energy management system (EMS) that regulates how battery cycles adhere to the day-ahead commitment while also minimising these losses. This key performance indicator (KPI) is calculated using the following formula:

$$(\mathrm{ifPWECS} > \mathrm{bandceiling}):\ \mathrm{Pcurt} = \mathrm{PWECS} - (\mathrm{PSCHED} + \mathrm{tol}). \quad (2)$$

3.3. Not Supplied Power. It is as follows that in the event of a commitment failure, the complete remuneration injection is made:

$$\mathrm{PINJ} = \mathrm{PWECS} + \mathrm{PBESS} - \mathrm{Pcurt} - \mathrm{Pnotbilled}. \quad (3)$$

3.4. Counting Battery Cycles. Several factors influence the longevity of a battery, and one of these factors is the total charge-discharge cycles each battery undergoes. The most effective strategy to maximise the lifespan and return on investment of your battery is to make an accurate prediction

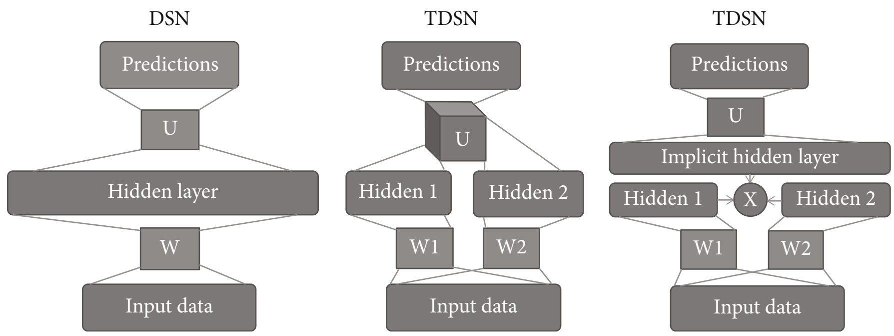

Figure 2: Single module DSN, TDSN, and equivalent TDSN forms.

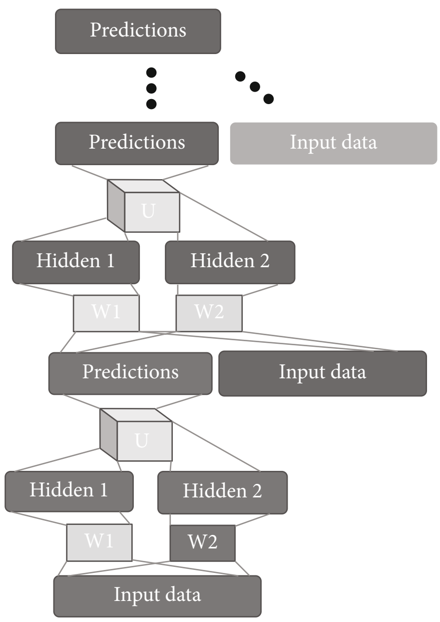

Figure 3: TDSN modules with prediction vector concatenating with input vector.

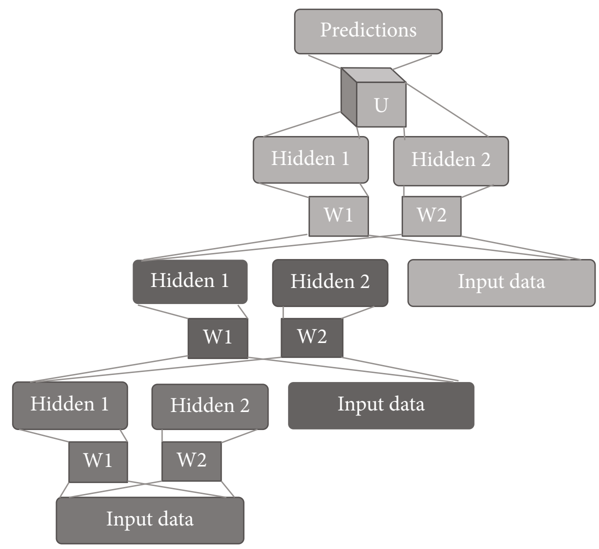

Figure 4: TDSN modules stacking by two hidden-layer concatenating with input vector.

of how quickly it will degrade over time. Here are some things to keep in mind while calculating the storage system utilisation during partial charging and discharging cycles:

$$\text{BESScycles} = \text{BESScycles}+. \tag{4}$$

3.5. Deep Stacking Network for Prediction. Recently, a tensorized variant of the Deep Stacking Network (DSN) architecture, named Tensor DSN (TDSN), was generalized and made available to the public. Although it is not as parallelizable as DSN in learning, it does give higher-order feature interactions that are missing from DSN parallelizability [29].

There are significant similarities between the TDSN and DSN architectures when it comes to stacking operations. A deep architecture may be formed by putting TDSN modules together in the same way that Lego pieces are stacked. TDN and DSN are distinguished by the modules that make up their respective systems. When using DSN, a hidden layer is generated by a single set of hidden units, as can be seen in Figure 2(a). Instead, Figures 2(b) and 2(c) depict two different hidden layers, one labelled hidden 1 and the other hidden 2, for each TDSN module, with the first labelled hidden 1 and the second labelled hidden 2. Consider that the weights of the upper layer, denoted by the letter U in Figure 2 shift from two-dimensional arrays (matrices) in DSN to three-dimensional arrays (tetrahedrons) in TDSN when this difference is taken into consideration.

Figure 2 depicts a comparison between a DSN module (Figure 2(a)) and a tensorized-DSN module (Figure 2(b)) (TDSN). Figure 2(c) displays the TDSN module, which is shown in two different variations. The optimal solutions are attained with the help of DSN, TDSN, and equivalent TDSN forms, where the errors passing through the layers are mitigated.

There are three places where the tensor U is linked: to the prediction layer, to the hidden layers, and output layer. Figure 3 shows how a similar TDSN module can be produced by expanding the two independent concealed layers into their outer products, as seen in the right panel of the figure. All possible pair-wise products of the two hidden layer vector sets contained within the enormous vector are represented by this vector. To put it another way, the size of the prediction layer, as well as the product of the sizes of the two hidden layers, is used to recreate the matrix. Because

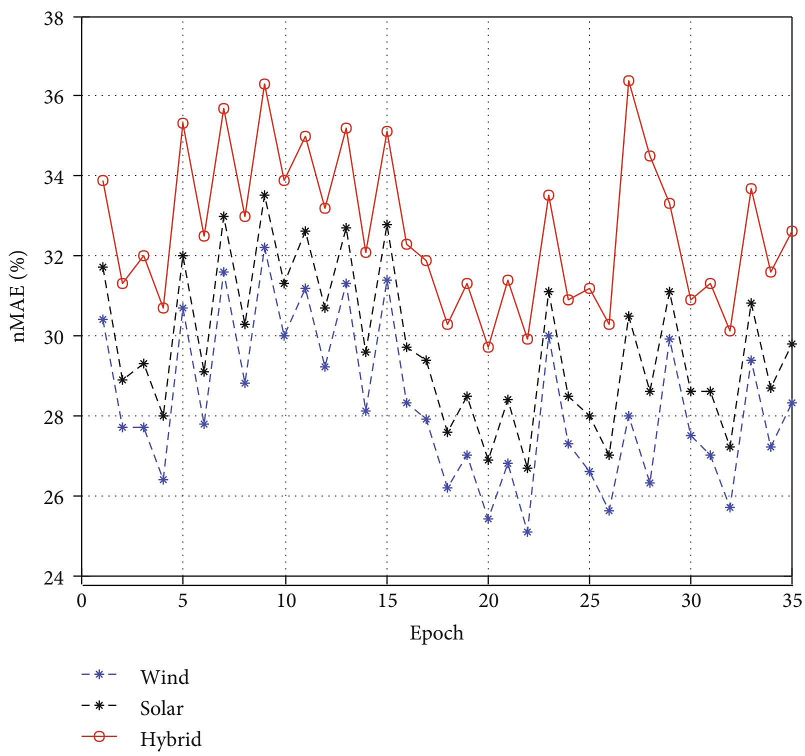

Figure 5: nMAE of all models.

of this equivalence, a convex optimization for learning U can be used to learn tensor U with the same results. Furthermore, the outer product design of TDSN big, implicit hidden layer allows for higher-order hidden feature interactions due to the big, implicit hidden layer implicit hidden layer.

The process of concatenating many vectors in TDSN modules in order to form a deep architecture is similar to that of DSN construction. There are two possible scenarios, as represented in the accompanying pictures. Because of the huge hidden layer in DSN, note stacking by concatenating hidden layers with input (as depicted in Figure 4) is not possible.

4. Results and Discussions

In this section, the validation considered 30 PV plants for one year. There is a plethora of ways available for analysing the success of a single or numerous forecasts. However, in the domain of PV forecasting, there has been no prior study comparing this prediction outcomes. It is also being investigated how wind speed data influences the optimum model selection, as well as the procedures and benefits associated with it.

Because we assume that the fluctuation in power demand is dependent on time slots, this method is logically predictive. Furthermore, it is realistic to anticipate that solar irradiation will vary substantially from one hour to the next. Figure 5 shows nMAE of all models.

Solar energy generation, battery storage, and grid intervention are all given the highest priority possible in this plan. As a result, the usage of switches ensures that this is the outcome. It is noteworthy that when one of the sources intervenes, the switch on the unit alters the unit state, allowing it to participate in the DC bus. During the MATLAB modelling and simulation process, the efficiency of the conversion systems was taken into consideration, which explains the gap between the required power and the actual power used in the experiment. When solar energy is adequate to satisfy the load, excess electricity is delivered back into the grid unless the battery maximum charge level is reached. However, if the power requirements of the load exceed the capacity of the solar system, the battery will step in to make up the difference. Even if the solar panels are unable to keep a minimal charge on the battery, the grid will step in to cover the void left by the solar panels.

Clearly, the separation and transposition models have the greatest impact on prediction accuracy because their average metric differences are so large; this suggests that model selection has the greatest impact on accuracy during the two computation phases of separation and transposition models, respectively. Despite the fact that there is a little difference between the three models of inverters, this difference is insignificant due to the fact that it is so minor. Even after accounting for a large number of unplanned losses in solar power facilities, a 0.3% underestimation of power generation is discovered. Models that are simpler in nature tend to have a lower variance than models that are more complex in nature. In the absence of irradiance measurements, it is hard to determine whether the underdispersion is caused by NWP forecasting or by physical power simulation.

In contrast to their substantial negative correlations with the transposition and cell temperature models, their relationships with the other performance measures are a little more ambiguous. In addition, they have a high correlation

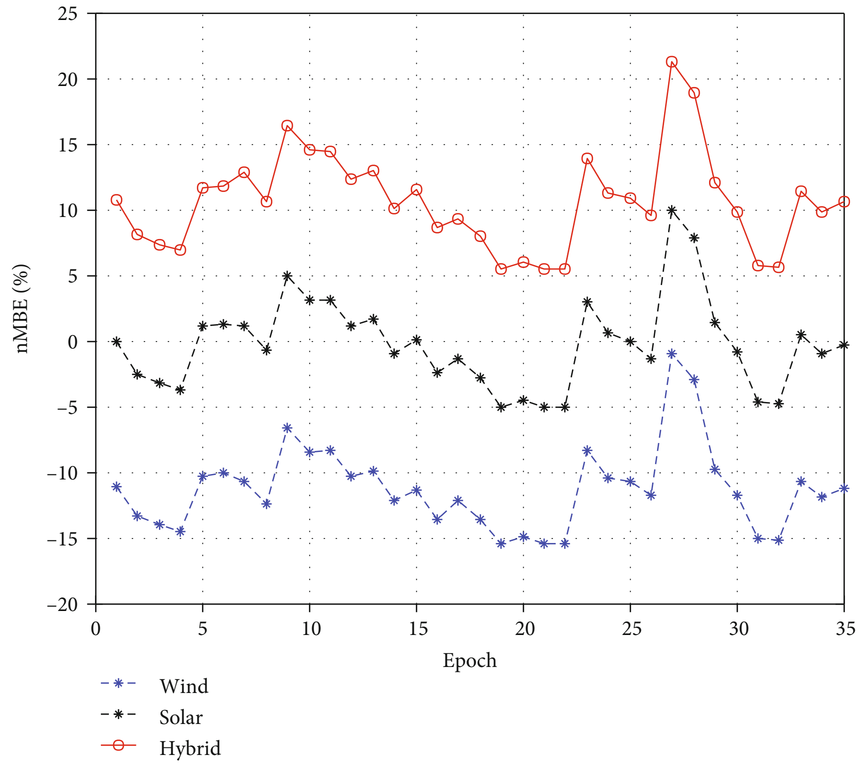

Figure 6: nMBE of all models.

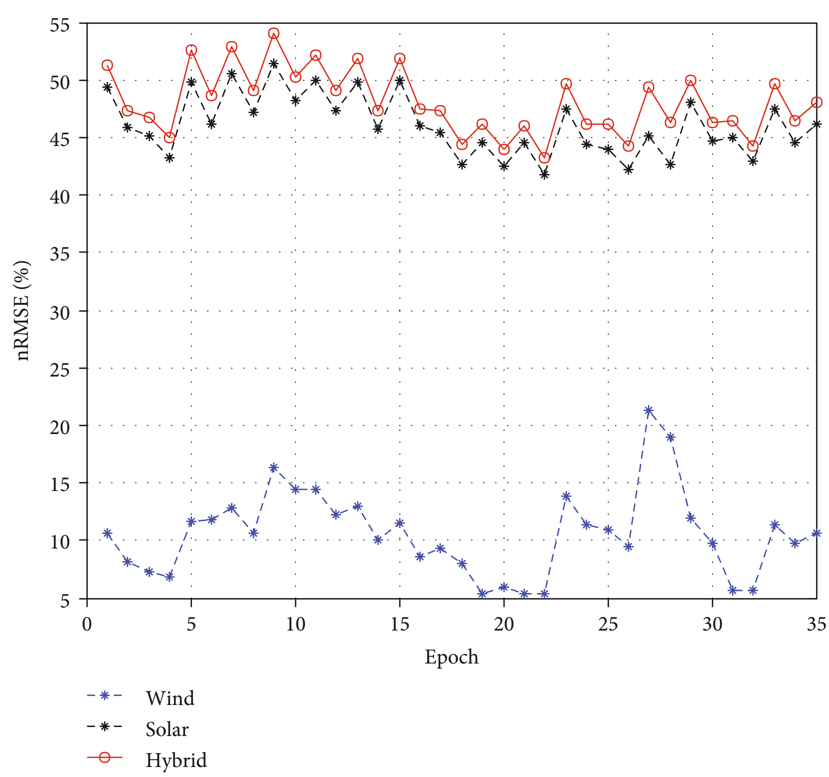

Figure 7: nRMSE of all models.

with the separation, reflection, and shading models. Average errors are reduced in MAE and RMSE directions by utilising the BRL separation model, which includes reflection and shading losses. In contrast, the RMSE and MAE are both at their lowest levels in the Liu-Jordan transposition model. To build skill ratings, the RMSE is used. As a result, these values provide no further information about the relative performance. As a result, there is a strong relationship between variance and root mean square error, which suggests that forecasts that are less scattered are more accurate. In prior research, it was found that regional averaging can improve the accuracy of forecasts.

When compared to their combined performance, it is only slightly more accurate than the individual best model. As a result, the selection of the physical model may be based on data from other power plants in the same geographical area depicted in Figure 6. Despite having a slightly higher RMSE than the best models, the basic model has an MAE that is 8% higher than the best models.

With respect to a comparison with the best model found in the literature, just 2.8% of the MAE is higher, while the residual mean square error is higher by 6.2%. A basic PV model may outperform a complete one if the RMSE is considered to be the most significant error measure. Furthermore, there is a significant difference in bias and variance between the two groups of participants. The low-MAE model chains, which have a lower nMBE and a higher variance ratios, are related to a higher variance ratio. Even a minor bias can have a considerable impact on the mean absolute error since the absolute error is sensitive to small and large errors of the same magnitude. When comparing high-RMSE model chains to low-RMSE model chains, the variance ratios are both lower than when comparing low-RMSE model chains as in Figure 7.

5. Conclusions

The solar panel, the grid, and battery storage are all components of the energy management algorithm that we have proposed in this paper. In order to function properly, system configuration must be considered at both the scale and management levels. The proposed energy management system, if it does not include a battery storage system, prioritizes the national electrical grid when it comes to solar energy output. In addition, even in the event of an overflow, the solar system energy output is controlled and monitored. Because of resistance losses, our mathematical model of the solar system has been shown to be accurate to within a few watts of the actual system in several experiments. To be certain, a one-day simulation was conducted, and the results revealed that the system fits completely with all of the modelling requirements and adheres to the prioritization orders specified in the preceding section. In future, the RMSE can further be reduced using effective optimistic technique that should constantly work on improving the rate of optimization of target solution.

Data Availability

The data used to support the findings of this study are included within the article. Further data or information is available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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