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Robust Multi-Objective Model Predictive Control for Optimal PV–BESS Energy Scheduling Under Forecast Variations

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Abstract- The increasing penetration of renewable energy sources, particularly photovoltaic (PV) systems, introduces operational challenges in modern power grids, including energy imbalance, grid congestion, and battery degradation. Energy Storage Systems (ESS), especially Battery Energy Storage Systems (BESS), play a crucial role in mitigating these issues when supported by an effective energy management strategy. This paper proposes a Model Predictive Control (MPC)-based energy management system for a PV–BESS microgrid to enhance system performance compared to conventional control methods.

A one-year dataset from a real microgrid in Lindenberg, Germany, with a residential load profile equivalent to a four-person household (4.5 MWh annual consumption), is used for simulation. The system is modeled with a 6 kW PV array and a 9.375 kWh BESS, where battery sizing considers both investment cost and degradation. A sampling interval of 5 minutes is adopted, and a 24-hour control horizon is implemented in the MPC framework to capture the daily cyclic behavior of the system. A linear Coulomb counting model is used for the BESS to ensure computational tractability of the quadratic optimization problem.

Simulation results demonstrate that the proposed MPC approach significantly improves system performance. Compared to conventional methods, MPC increases the self-consumption ratio (SCR) from 60% to 74.9%, while also achieving a balanced trade-off between battery degradation and grid feed-in. Although higher battery utilization leads to increased degradation relative to conventional methods, it remains substantially lower than idealized scenarios without practical constraints. Additionally, MPC effectively manages grid interaction, reducing excessive feed-in and improving overall grid stability. Furthermore, the impact of prediction uncertainties inherent in forecasting PV generation and load demand is analyzed, and a constraint-tightening strategy is proposed to enhance robustness. The results confirm that MPC provides a flexible and efficient framework for optimizing PV–BESS operation under realistic conditions, outperforming traditional energy management techniques across multiple performance metrics.

Keywords- Model Predictive Control (MPC), Energy Storage Systems (ESS), Photovoltaic (PV) Systems, Prediction Uncertainty, Energy Management Systems.

I. INTRODUCTION

Over the past ten years, the numbers of household PV installations has increased, particularly in European grids, adding to the steadily expanding pool of cleaner energy sources.

Considering their environmental friendliness, they could not be grid-friendly. The cause is their sporadic production and unregulated power input into the main grid, which results in grid congestion, issues with voltage regulation, and instability [1-2]. ESS can be used to address the aforementioned PV integration problems, but they must be properly handled [3]. PV energy has achieved grid parity as a result of the growing integration of PV sources [4]. This indicates that using the produced PV energy on-site (self-consumption) as opposed to transferring it to the grid provides the owner (user) with the greatest financial gain [4]. In order to maximize the financial benefit, home PV installation with battery energy storage systems (BESS) use the maximizing self-consumption management technique. This is where the main issue resides. As a result, BESS is completely charged in the morning.

As a result, excess electricity is sent into the grid during periods of peak PV output. This consumer power injection is normally not under control of the grid operator [2]. Regardless of grid design, the grid may get crowded if several PV units operate in unison without a high enough demand for load. Numerous instances of the same congestion occurrences in European grids [2] have confirmed this. In order to address this, PV systems are now subject to feed-in power constraints [2, 4], which come at the expense of PV power consumption.

The BESS degradation is another drawback of the traditional maximization of self-consumption approach. Cyclic and calendar ageing are the two main aging mechanisms in BESS (Li-ion based) [6]. These are the outcomes of degradation imposed on by prolonged dwell times at high SOC levels and significant BESS cycling. According to the typical design, early BESS charging causes higher BESS deterioration [5-6] and long SOC dwell times (Fig.1). By gradually adding electricity to the grid instead of emphasizing at peak output, household PV sources can help reduce grid congestion. This may be accomplished and has been demonstrated to reduce these problems while maintaining sufficient self-consumption through the use of forecast data in individual BESS management [7]. Energy management (EM) systems might prevent early BESS full charging (addressing calendar aging) and ensure BESS capacity availability during peak PV generation by using this knowledge of future power production and consumption patterns. This reduces grid congestion and feed-in electricity. Using this kind of prediction information for EM of BESS, prior studies have concentrated on offline methods [8-9]. But they lead to less-than-ideal system behavior.

Online techniques that are well suited for these issues include Model Predictive Control (MPC), which can offer better performance.

From the view point of the grid operator, the use of MPC for energy management in electric systems has been investigated in order to increase operational efficiency [10-11], operating costs [12-13], and energy arbitrage [14-15].

In addition to economic reasons, MPC has been used to enhance electric characteristics in grids with a large concentration of renewable sources, such as voltage regulation [16]. The use of MPC has also concentrated on distributed control [16-17] and centralized control [12], [15] approaches.

However, there hasn't been any discussion of using MPC to reduce the real-world problem of grid congestion caused on by peak PV power input from consumer-side installations in several European grids. The impact of forecast uncertainty on MPC performance is an additional important aspect that hasn't been covered in earlier studies [18]. Although there are stochastic MPC strategies [19], no examples of how to use them to solve real-world issues have been provided. This is important because taking into consideration stochastic behavior causes the MPC to make conservative decisions, which have an important effect on the financial gain of doing so. There is currently no comprehensive, quantitative study on this, decrease in MPC performance under forecast errors, or the addition of actual data from prediction systems to stochastic MPC algorithms in the literature. There is currently no comprehensive, quantitative study on this, decrease in MPC performance under forecast errors, or the addition of actual data from prediction systems to stochastic MPC algorithms in the literature. Last but not least, the earlier studies lack a comprehensive MPC architecture that combines the prediction and decision-making phases to show how MPC is used in practice. In light of the aforementioned, the primary contributions of the study might be summed up as follows:

- Residential installations of PVBESS systems use MPC for energy management in order to achieve goals including maximizing self-consumption, reducing grid congestion, and preventing BESS deterioration.
- Introducing the complete MPC structure that incorporates the stages of prediction and decision-making.
- Using real data from the forecast stage and a straightforward, realistically achievable constraint tightening technique, MPC decision making may address forecast uncertainty without becoming overly cautious.
- Evaluation of MPC's performance quantitatively in comparison to the traditional energy management approach (maximizing self-consumption) and the effect of forecast uncertainty on MPC

The aim will simulate and examine long-term system behavior for a year in order to fully offer the quantitative analysis of MPC performance. The paper's remaining sections are arranged as follows. In Section II literature review of previous studies is discussed. With its forecasting phase and MPC-based scheduling, Section III presents the analysis of predictive energy management scheme (PEMS). PV-BESS scheduling results with the PEMS are shown in Section IV, which also quantifies the enhancements made possible by the same. Finally, Section V concludes the work and Section VI presents acknowledgement of the work.

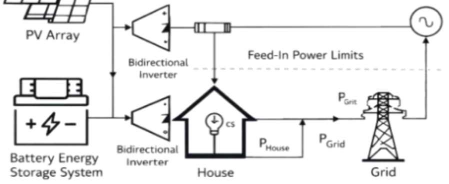

Figure 1. Micro-grid Test Case Schematic

II. LITERATURE REVIEW

The problem of Enhancing Photovoltaic (PV) power forecasting to improve the performance of battery energy storage systems (BESS) linked with PV production facilities is addressed by the model presented by Nuttapat [20]. They suggest a hybrid forecasting model that optimizes gated recurrent units (GRU) through the use of genetic algorithms (GA), allowing for more precise inter-day hourly forecasts. While comparing to traditional approaches, their proposed methodology minimized forecasting mistakes, enabled improved energy management tactics that maximized revenue and minimized PV energy curtailment. Verified using actual data from a photovoltaic facility in Taiwan, the technique shows enhanced forecasting accuracy, resulting in better BESS operation, lower energy losses, and higher financial returns in every weather scenario.

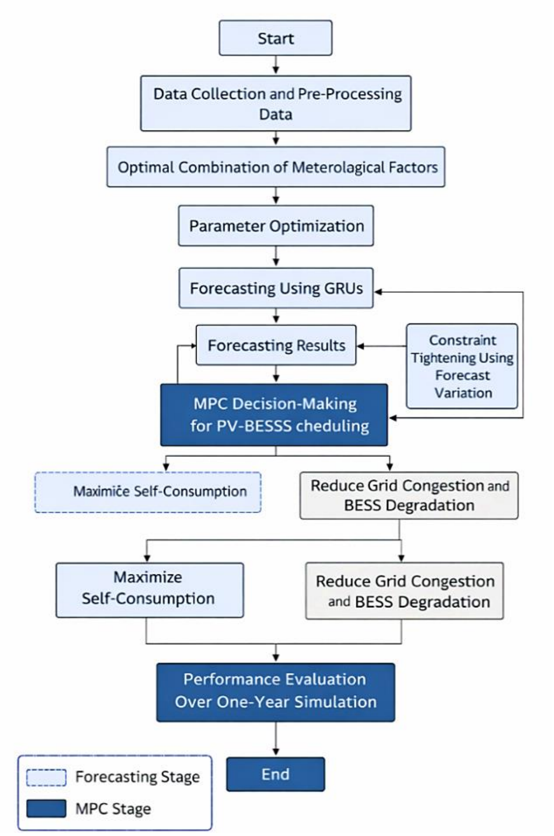

Figure 2. Flowchart of Strategy Used by Nuttapat

Fig. 2 Illustrate the methodology of their proposed model. The model was configured to operate at a matching 60-minute time resolution to align with the time resolution of the PV power data, which had been converted from its original 5-minute interval to 60 minutes. Any outliers within the data were identified through an examination of both the PV power and irradiance curve. The missing data and erroneous entries were rectified through the application of linear interpolation.

A solar PV power facility in Zhi Guang, Tainan, Taiwan, provided the PV power data was utilized in their model. An 85 MW peak power solar photovoltaic plant was erected with the goal of increasing the installation's overall flexibility in order to get closer to becoming carbon neutral and boost involvement in energy markets. The PV power data was gathered at 5-minute intervals over the course of a year. Furthermore, the WRF stations are crucial elements for obtaining weather forecast data. The model looked at how PV energy is integrated into the grid, highlighting how crucial BESS is to improving viability and stability of system. Furthermore 85 MW PV installation capacity was utilized to a 50 MW wholesale feeder capacity, to generate renewable energy and distribute it efficiently throughout the grid. A BESS with a 93.6 MWh battery energy and a 23.3 MW power capacity was added to this PV arrangement to complement it. By operating between the lower and upper SOC limits of 100% and 10%, respectively, the BESS maintains grid stability by extending battery life. They claimed 92% efficiency in cycles of charging and discharging through BESS.

Mostafa [21]. proposed a model that focuses on the optimization of PV-battery and BESS. They tried to overcome the difficulties of PV generation issues. They applied a FFNN (feed-forward neural network) integrated with a two stage SO (Stochastic Optimization) model. To modify the probabilistic scenarios of PV output a backward scenario reduction approach was used. To reduce battery deterioration and daily grid use the optimization algorithm was applied on real-world data from smart meters. Energy management seen improved by taking in consideration of operational limits of BESS and uncertainties of PV output.

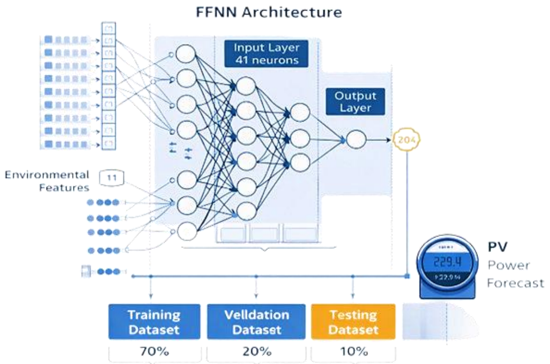

Figure 3. Proposed FFNN Model for PV Forecasting

As shown in Fig.3 a FFNN model and propagation techniques is used for PV forecasting problem. The architecture consists of 41 neurons as input layer, so the value of m=41, also consisting of 36 date and time features and 5 environmental features including sun height, air temperature, the inclined plane's reflected irradiance, light diffusion on the plane that is inclined, and beam irradiance on the plane that is inclined. The twelve months of the year and the hourly figures are part of the Date Time feature set. It is important to remember that before the feature set is sent into the input layer, it is normalized between [0,1]. The one-hot encoding technique, is used to normalize the Date Time elements, which transforms categorical variables into binary vectors. A total of 15 months of actual data (Dec 2018–Feb 2020) were used to train the FFNN. 70% of this dataset is used for training, 20% is used for validation, and 10% is used for testing. Upon network training, a proposed two-stage optimization model was assessed using actual data gathered from installed smart meters on April 20, 2020. Fig. 4 displays a schematic illustration of the system being used.

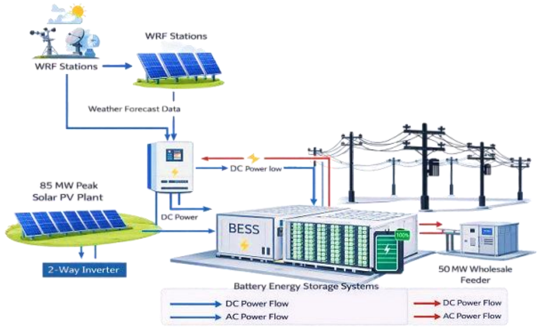

Figure 4. System Used in Proposed Model

Proposed system was consisting of a PV panel array with eight panels and a 2-kW nominal output. Also installed was a stationary battery energy storage system with a 6-kWh total capacity. A 7th generation Intel Core i7-1058 H 2.7Ghz Windows-based Dell Precision 3551 with 32 GB RAM specs was used to execute simulations in MATLAB R2023a. They claimed that when compared to the on-site rule-based paradigm, the suggested method reduces bill expenses by 76%.

III. ANALYSIS OF SCHEME

The proposed Predictive Energy Management Scheme (PEMS) is structured into two main stages: a forecasting unit and an MPC-based scheduling unit. Initially, the forecasting stage processes historical and real-time data to predict PV generation and load demand using advanced learning techniques. These predictions are then utilized by the MPC-based scheduling stage to optimally manage the PV–BESS system, ensuring efficient energy utilization. The overall framework is designed to enhance self-consumption, mitigate grid congestion, and reduce battery degradation through intelligent and coordinated decision-making.

A. Forecasting Unit

In this work, the PEMS under consideration will be forecasted using a neural network (NN) [22]. It should be mentioned that this study does not contribute to the development of innovative forecasting models as per; instead, NNs are taken into consideration. Even though NNs aren't the most accurate forecast models [23], their predictions have been proved to give a decent picture of the behavior of the actual system [22], therefore this study uses them to explain how to integrate the forecast model with MPC. Fig. 6 displays the standard NN structure that was employed in this study. An input layer, two hidden layers, and an output layer make up this structure.

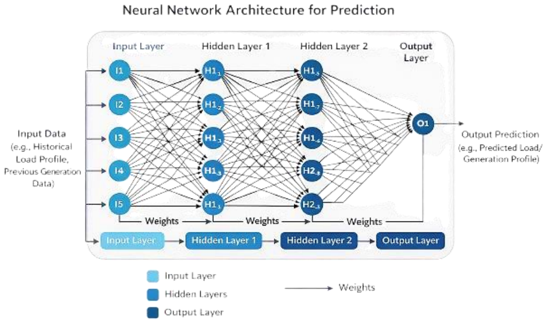

Figure 5. Architecture of a Neural Network Displaying Input, Hidden, and Output Layers

The NN system must be trained using previous data in order to produce extremely precise predictions on generation or load profiles. The training step may be considered as the NN's learning phase, during which it examines the underlying behavioral pattern using load data and prior generation data. This work does not include the mathematical formulations used in the training process or the associated algorithms [24]. For the same, interested readers are referred to [25].

B. Scheduling Unit Based on MPC

MPC is a novel optimum control technique that makes it possible to effectively manage constraints and non-linearities [19]. Economic MPC is usually taken into account in EM situations [19]. The MPC predicts the development of system states into a future predetermined time period known as the control horizon using expected generation values, load profiles, and a suitable system model. To make it possible for the system states to follow an ideal trajectory inside this horizon, MPC will adjust the manipulated inputs through online optimization. This will consequently guarantee that the system's behavior is optimized in relation to a few predetermined performance metrics. Eq(i) show the function used by MPC for balanced grid feed-in and batter wear.

$$min \sum_{t=1}^{T}(\lambda_g P_{grid,t} + \lambda_g(SOC_t - SOC_{opt})^2 + \lambda_d Cycle) \qquad (1)$$

C. Grid Feed in Limitation

Utility operators implement restrictions in order to reduce grid congestion caused by large excess PV power feed-in. As an illustration, consider Germany, where PV systems with power ratings under 30 kW are required to restrict their input to 70% of their stated value [26]. With MPC, this condition is easily implemented through constraints P_{grid}. The optimization problem's penalized weights must be ideally established before more choice variables may be added. A less-than-ideal outcome may arise from failing to define the same.

In addition, the power curtailment decision variable will raise MPC's processing requirements. Fig. 7 displays the complete PEMS for the PV-BESS with real-time control unit, managing power curtailment. This displays a control system that is hierarchical.

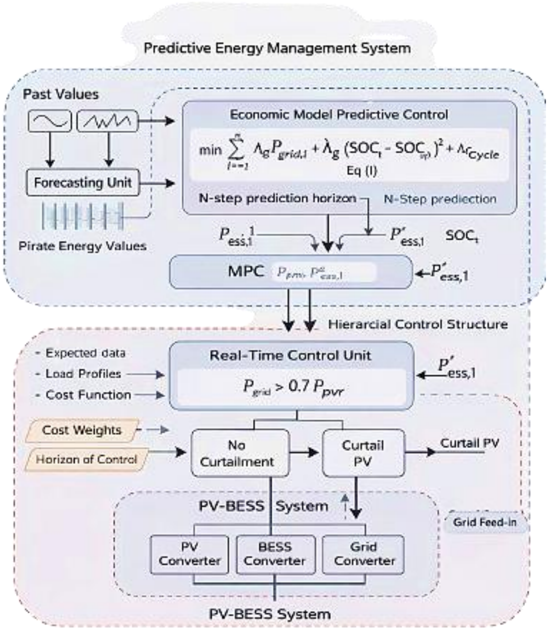

Figure 6. Flowchart for PV-BESS System's Energy Management Decision-Making Process with Predictive Control

IV. CONTRIBUTIONS OF THE STUDY

This study presents a comprehensive framework for optimal energy management in PV–BESS systems by integrating forecasting and control within a unified architecture. A Predictive Energy Management Scheme (PEMS) is developed, which combines a machine learning-based forecasting unit and a Model Predictive Control (MPC)-based scheduling unit to enhance system performance under realistic operating conditions. In the forecasting stage, an Artificial Neural Network (ANN) is utilized to predict photovoltaic (PV) generation and load demand using historical time-series data. Prior to model training, the dataset undergoes preprocessing, including handling missing values through forward and backward filling methods and normalization using Min-Max scaling to ensure balanced feature contribution.

In the control stage, an MPC algorithm is employed to optimize energy scheduling over a finite prediction horizon, considering system constraints and multiple performance objectives. The MPC framework solves a quadratic optimization problem based on predicted states to determine optimal control actions. The objective of the MPC can be mathematically expressed as:

$$\min_u \sum_{k=0}^{N}\left(\lambda_1 P_{grid}(k)^2 + \lambda_2 \Delta SOC(k)^2\right) \qquad (2)$$

where $P_{grid}(k)$ represents grid power exchange, $\Delta SOC(k)$ denotes the change in battery state of charge, λ_1 and λ_2 are weighting factors, and N is the prediction horizon. This formulation enables a balanced trade-off between minimizing grid feed-in and reducing battery degradation. Furthermore, a linear Coulomb counting model is adopted to represent battery dynamics, ensuring computational efficiency of the optimization process. To address uncertainties in PV generation and load forecasting, a constraint-tightening technique is incorporated into the MPC framework, improving system robustness without introducing excessive conservatism. The proposed model is validated using a real-world one-year microgrid dataset, demonstrating significant improvements over conventional methods. Specifically, the system achieves higher self-consumption, better grid interaction management, and an optimized balance between battery usage and degradation. Overall, this study contributes an efficient, robust, and practical solution for intelligent energy management in modern PV–BESS systems.

V. RESULTS AND DISCUSSION

Data from a working micro-grid in Lindenberg, Germany, lasting a year, is used to simulate PV generation and load demand. The load is equivalent to a four-person family with a 4.5 MWh yearly consumption. A sampling time of five minutes was used to collect the data, yielding 288 samples daily. The findings of the studies [27], which suggest 1–1.55 kWh of BESS capacity per 1 kW of installed PV capacity, are used to determine the BESS's size. For this experiment, an ideal battery size of 9.375 kWh for 6 kW of PV array output was selected. The BESS sizing shown above takes investment cost and BESS deterioration into account. The references listed above provide a thorough overview of the subject. The control horizon in MPC (N) was selected as 24 hours in this study because to

the PV-BESS system's daily cyclic behavior. Thus, the forecasting unit's goal at any given time will be to provide predictions for the upcoming 24 hours.
It should be stated that the coulomb counting model was used to describe the BESS model as a linear approximation. This was carried out with the intention of maintaining the quadratic optimization issue. The optimization problem has about 600 choice variables, taking into account the 24-hour prediction horizon and the 5-minute sampling time. In this situation, the convergence of the optimization problem to solution may not be guaranteed by employing a more intricate non-linear formulation of BESS. Aside from this, the linear representation of provides a rather realistic depiction of BESS behavior given the shorter sample interval of five minutes.

D. Handle Missing Values

The dataset used in this study is obtained from a working microgrid located in Lindenberg, Germany, covering a one-year period and is utilized to simulate photovoltaic (PV) generation and load demand. The dataset is first loaded into a panda DataFrame for preprocessing and exploratory analysis, during which the dataset structure, including column names and data types, is carefully examined. Identifying missing and duplicate values is a crucial step in data preprocessing, as their presence can significantly affect the performance and reliability of machine learning models. Missing values may lead to biased results, reduced accuracy, and instability in model predictions if not properly handled. In this dataset, missing values are observed across several features, including PCS Active Power (73), PCS Reactive Power (72), Campus Net Load (72), Campus Load (73), PCS Vab (72), PCS Vbc (72), PCS Vca (72), PCS Ia (72), PCS Ib (72), PCS Ic (72), Battery Power (2402), Battery Voltage (1046), Battery Current (2567), and Battery State of Charge (183), while the Sample Time feature contains no missing values. The relatively high number of missing values in battery-related parameters suggests possible issues related to sensor readings or data acquisition inconsistencies. Therefore, appropriate data cleaning and imputation techniques must be applied to handle these missing values before proceeding with further analysis and model development.
Data is cleaned and normalized to make it ready for training In Eq (II) normalization function is explained that is used for the normalization of data. To ensure dataset is fully prepared for further analysis missing values are filled by using backward and forward filling methods.

$$X' = \frac{X - Xmin}{X_{max} - X_{min}} \quad (3)$$

E. Splitting Features and Data Scaling

Dataset is spited into Input(x) and output (y) features. In this dataset 'Campus Net Load (kW)' feature is used and input also as output feature to predict the future values by using past values. Furthermore, all the values are normalized by using 0-1 scaling so each feature contributes equally in the modeling process. After applying all the pre-processing techniques, the size of dataset reduced to 1.07 MB which reflects the changes made due to pre-processing.

F. Neural Network (NN) Forecasting Model

At this stage, NN model is applied on pre-processed dataset to predict PV generation and load demand. Initially data of first 72 hours is used to predict the next 24 hours. 'Campus Net Load' and 'Battery Power' features are selected for input and prediction. The dataset is structured as time series format. The dataset is spited into train and test sets. Model is trained on the train split and the tested on the test split to determine the accuracy. Fig. 7 and fig. 8 illustrate result of one day's PV generation forecast and result of load demand forecast using NN.

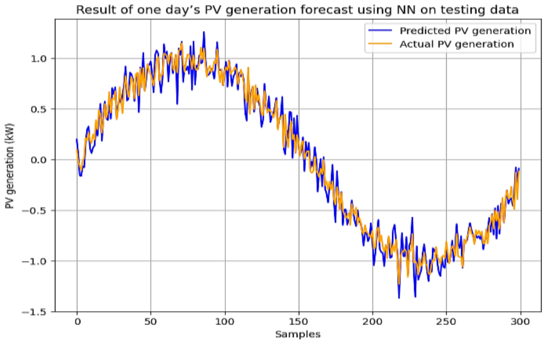

Figure 7. PV Generation Forecast

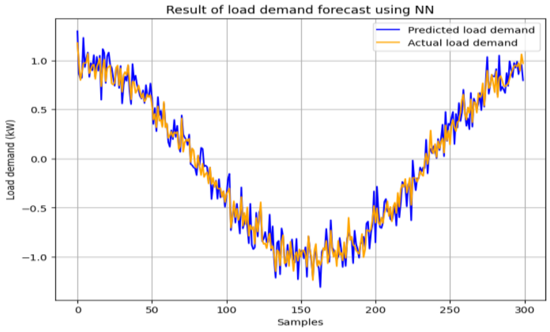

Figure 8. Load Demand Forecast

G. MPC Setup for Energy Scheduling

At this stage, NN model is applied on pre-processed dataset to predict PV generation and load demand. Initially data of first 72 hours is used to predict the next 24 hours. 'Campus Net Load' and 'Battery Power' features are selected for input an prediction. The dataset is structured as time series format. The dataset is spited into train and test sets. Model is trained on the train split and the tested on the test split to determine the accuracy. Eq (III) is used for accurate model prediction for scheduling.

$$MSE = \frac{1}{N} \sum (yi - y^{\wedge} i)^2 \quad (4)$$

H. Performance Evaluation

To evaluate the system's performance firstly Self-Consumption Ratio is calculated which is directly proportional to PV energy generated in kWh consumed directly by loads or stored in BESS. Unlike classification-based studies [27-50] that use accuracy, precision, recall, and F1-score, this work focuses on an energy scheduling problem. Therefore, performance is evaluated using domain-specific metrics, including Self-Consumption Ratio (SCR), battery degradation, and grid feed-in.

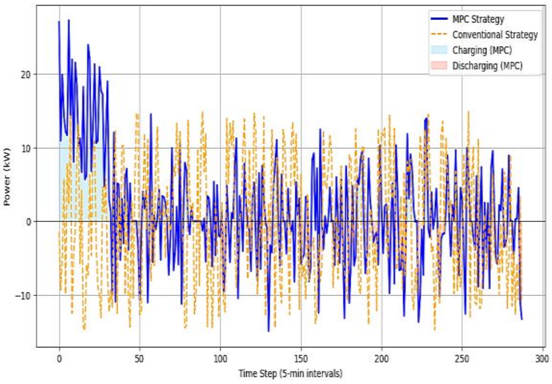

Figure 9. Daily BESS Profile Comparison Between Conventional and MPC Strategies

Fig 9. Illustrate the comparison of charging and discharging pattern by conventional and MPC strategy. It can be seen that how MPC manages these key factors more efficiently and also minimizing the unnecessary cycles to optimize the energy use as compared to conventional method.

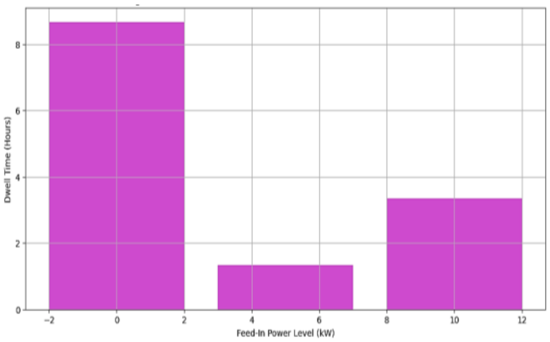

Figure 10. Grid Power Feed-In Dwell Times at Different Power Levels

In Fig 10. a comparison of feed-in power level with dwell time is shown. In this comparison power is represented in kW and time in hours. This comparison explains the system's behavior of peak feed-in period that is very important to understand the patterns of energy export and to optimize grid capacity with tariff requirements.

Fig.11 Illustrate the state of charge (SOC) of battery in kWh over time. Data shown in the intervals of 5 minutes, that highlights charging and discharging cycles to insight battery's usage patterns and energy flow.

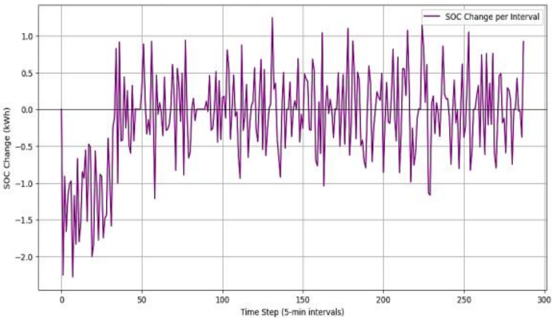

Figure 11. BESS Cycling Profile (Charge and Discharge Events)

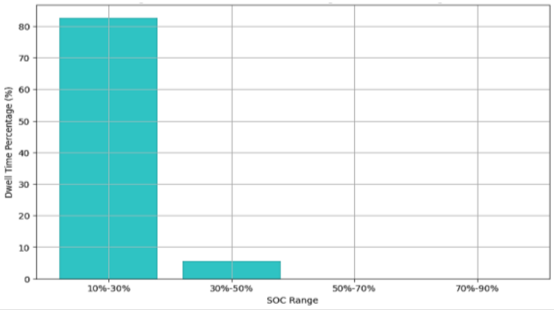

Figure 12. SOC Dwell Time Percentages in Different Ranges

Fig.12 represents the percentage of time that the battery spend in SOC rages.

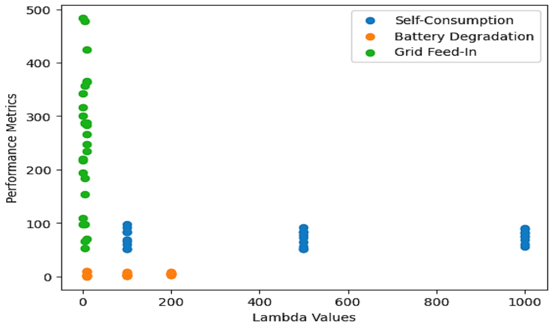

Figure 13. Performance Metrics

Self-Consumption, Battery Degradation and Grid-In features are used in Fig.13 to illustrate the performance metrics over Lambda values.

Table 1. Comparison of Scheduling Methods

Scheduling Method	**SCR**	**Battery Degradation**	**Grid Feed-In**
MPC	74.900379	58.12	8881.579431
Conventional	60.000000	8.00	1000.000000
Ideal	98.000000	2.00	200.000000

Table.1 compares the performance of scheduling methods over SCR, Battery Degradation and Grid Feed-In metrics. Conventional method gives lower SCR 60% and 8% battery degradation by giving 1000kWh grid feed-in. While MPC performs balanced by giving 74% SCR, 58.12% batter degradation, and 8881.58 kWh grid feed-in.

VI. CONCLUSION

In this study, a Model Predictive Control (MPC)-based energy management scheme is presented, demonstrating significant advantages over conventional methods used in PV–BESS systems. By leveraging predictive information and optimal decision-making, MPC enhances overall system performance through improved self-consumption and more efficient battery utilization. Although increased battery usage may lead to higher degradation compared to conventional strategies, MPC achieves a balanced trade-off between performance improvement and battery lifespan under realistic operating conditions. Furthermore, the analysis of prediction uncertainty emphasizes the importance of constraint-tightening techniques to maintain system reliability under uncertain PV generation and load demand.

The results of this study confirm that MPC is an effective solution for addressing challenges associated with the integration of renewable energy sources into conventional power grids. It not only improves operational efficiency but also contributes to better management of energy storage systems. Future work may focus on the real-world implementation of MPC using advanced algorithms, such as robust and adaptive control techniques, to further enhance system reliability and performance. Overall, this study highlights the potential of MPC to improve the sustainability, resilience, and intelligent operation of modern power systems.

VII. ACKNOWLEDGEMENT

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