

MEASURING ENERGY AND POWER EXCHANGE FOR PV-ESBS SYSTEM USING MATLAB/SIMULINK

Gurpinder Singh

ECE Department, BGIET, Sangrur

Sushil Kakkar

ECE Department, BGIET, Sangrur

Shweta Rani

ECE Department, GZSCCET, MRSPTU, Bathinda

ABSTRACT:

The transition to renewable energy, particularly solar photovoltaic (PV) systems, necessitates robust energy storage solutions. To facilitate this shift, accessible models of PV systems integrated with battery storage (ESBS) are crucial for engineers. These models enable the evaluation of technical and economic advantages during system design. This work introduces a comprehensive model that accurately represents power flows and energy exchanges within a PV-ESBS system. It offers two PV generation approaches: a Gaussian model and a meteorological data-based (MDB) model. The MDB model is shown to be more effective for short-term analysis, while the Gaussian model aligns better with long-term measured data. The model is versatile, capable of simulating various energy management strategies, including peak-shaving and maximizing self-consumption, applicable across different PV-ESBS scales. Validation is achieved by comparing simulation results with data from a real-world grid-tied PV-ESBS, demonstrating the model's accuracy and reliability.

1. INTRODUCTION

The urgency of climate change mitigation is undeniable. Extreme weather events are stark reminders of its growing impact on humanity. Swift and decisive action is crucial to minimize these detrimental consequences. Delaying mitigation efforts will only exacerbate the challenges, leading to more severe and irreversible damage. Therefore, immediate implementation of effective strategies is paramount to safeguarding our future and mitigating the escalating risks posed by climate change.

Industrialized nations' unsustainable energy consumption necessitates immediate action to combat climate change. Reducing global energy use and rapidly expanding renewable energy production are vital. Electrification of transportation and heating, while crucial for transition, demands a significant increase in renewable energy capacity and storage.

However, dispersed renewable energy sources can cause overvoltages in low-voltage networks, and increased power demand from electric vehicles and heating can lead to grid congestion. Energy storage systems offer a solution by stabilizing the distribution network, mitigating these potential issues and ensuring a smoother transition to a sustainable energy future. The integration of energy storage with renewable energy is poised for substantial growth. This surge is driven by the necessity to address unsustainable energy consumption and climate change. Among renewable technologies, photovoltaic (PV) energy stands out due to its cost-effectiveness and widespread availability. Consequently, the deployment of PV systems coupled with energy storage is expected to escalate significantly in the coming years. This combination offers a promising pathway towards a more sustainable and resilient energy future, leveraging the abundance of solar resources and the flexibility of storage solutions.

The anticipated dramatic expansion of global photovoltaic (PV) system installations underscores the urgent need for robust design models. These models are essential tools for engineers and practitioners, enabling accurate profitability analyses and energy yield simulations, both crucial for effective system design.

To achieve this accuracy, the models must meticulously simulate the power flow between all PV system components: PV modules, the electrical grid, and the battery pack. Furthermore, these simulations must adhere to the established standards of Energy Management Systems.

By accurately representing the energy exchange within the system, these models facilitate informed decision-making during the design process, optimizing performance and ensuring compliance with industry standards. This ensures that the projected growth in PV installations translates into efficient, reliable, and economically viable renewable energy solutions.

ASSOCIATED ARTICLES

Various mathematical models have been developed to predict photovoltaic (PV) generation across different time scales, from short-term to long-term forecasts. These models are crucial for optimizing PV system performance and ensuring grid stability.

For instance, one approach employs a higher-order Markov chain, as demonstrated in [9], to predict PV generation 15 minutes ahead. This method calculates the probability distribution function, incorporating temperature and irradiance data to estimate the PV system's operational points. This provides a granular, short-term forecast, essential for real-time grid management.

Another technique, detailed in [10], utilizes satellite imagery and on-site observations to forecast PV power over periods ranging from 5 minutes to 36 hours. This broader range allows for both short-term adjustments and medium-term planning.

As highlighted in [11], these forecasting methods are particularly valuable in smart grid environments. Accurate PV power predictions are vital for maintaining electrical grid stability, especially with the increasing integration of renewable energy sources. Precise forecasts enable grid operators to anticipate and manage fluctuations in PV generation, ensuring a reliable and efficient power supply. These models are essential tools for a reliable energy transition.

While renewable energy sources, like solar PV, are vital, their dependence on weather patterns presents a challenge to grid stability. Therefore, integrating energy storage systems is essential. Effective PV system design requires optimizing PV peak power and battery capacity, alongside quantifying economic benefits.

Numerous models have been developed to simulate the interaction between renewable energy sources and battery energy storage systems (ESBS). However, these models heavily rely on historical data for validation, highlighting the critical role of accurate data.

Most models necessitate temperature and irradiance observations to produce accurate outputs. These data can be sourced from various platforms, including ERA-Interim, regional meteorological institutes, global programs, and software like Meteonorm© and SolarGIS©.

Despite the availability of data sources, forecasting remains crucial for precise system behavior prediction. Accurate forecasts allow for proactive management of energy fluctuations, ensuring grid stability and optimizing the performance of PV-ESBS systems. This combination of reliable data and accurate forecasting is fundamental to building robust renewable energy grids.

This paper offers a comprehensive PV-ESBS model, supporting both peak-shaving and self-consumption optimization strategies. It details two open-access PV system models, outlining their integration within a general PV-ESBS framework. Furthermore, it provides clear recommendations for each PV model's application, based on their strengths, limitations, and data requirements. Specifically, it distinguishes between models suited for short-term analysis and those better for long-term investigations, enabling informed selection for diverse research and practical applications. This approach facilitates a more nuanced and effective implementation of PV-ESBS systems.

2. PV-ESBS Model

Figure 2.1 presents the open-access system, broken down into key elements. The PV modeling component calculates the generated solar power. This output is then managed by the Energy Management System (EMS), which directs energy flow between all system components based on operational settings.

Battery modeling plays a vital role, continuously monitoring the battery's state-of-charge (SoC). This data informs the EMS, determining whether the battery should charge, discharge, or remain inactive.

Additionally, the PV model incorporates an optimization feature, determining the ideal tilt and azimuth of the PV array. This ensures maximum annual energy yield, enhancing the overall efficiency of the system. This modular approach allows for transparent analysis and control of PV-ESBS systems.

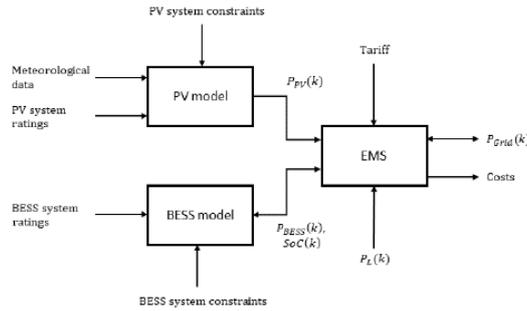


Fig.2.1 the open-access system

2.1. Modelling of PV

This section presents two PV power estimation methods: the Gaussian model and a meteorological data-based model. Each has unique advantages and disadvantages, requiring distinct input data. This allows for selecting the most appropriate model based on available data and project requirements. The Gaussian model and the meteorological model provide flexibility, enabling accurate PV power estimation for diverse applications.

2.1.1. Model Based on Meteorological Data

This model for PV system power estimation comprises three main parts: a solar calculator, an optimization block for PV array orientation, and a thermal model. The solar calculator, as illustrated in Figure 2.1, utilizes the PV system's latitude and longitude, along with the analysis date, as inputs.

It then calculates the sun's position, expressed as azimuth (As) and altitude (as), through a series of steps. These coordinates, determined at each time step (k), are then fed into the optimal orientation block.

This block optimizes the PV array's tilt and azimuth for specific goals, such as maximizing annual yield, winter yield, or peak demand production. By dynamically adjusting the orientation based on the sun's position, the model ensures efficient energy capture.

To calculate the total irradiance (Gm) on a PV module, the model utilizes the module's azimuth (Am) and inclination (am), alongside annual irradiance data. The optimization block adjusts Am and am to find the combination yielding maximum annual energy (kWh/m²). This allows for analysis of modules with non-ideal orientations due to installation constraints, like roof alignment. By simulating various orientations, the model assesses energy production under real-world limitations, ensuring accurate performance predictions even when ideal placement isn't feasible..

While the impact of PV array tilting is often overlooked, this meteorological data-based model addresses it by offering flexibility in tilt angle calculations. It can determine the optimal tilt for maximum energy yield or evaluate output at any given tilt, accommodating real-world installation limitations where ideal angles aren't always achievable. This feature is crucial for designers adapting to diverse site conditions.

The model's input requirements align with advanced techniques, utilizing essential meteorological data—temperature, irradiance, longitude, and latitude—along with PV and ESBS ratings. Its non-iterative nature ensures low computational costs, making it efficient for various applications.

However, the model's reliance on historical data can lead to inaccuracies in real-time applications. To mitigate this, using current measurements as input significantly enhances output precision. Similarly, for forecasting purposes, the accuracy of temperature and irradiance predictions directly impacts the model's reliability. Therefore, careful consideration of data quality and source is essential for achieving accurate and dependable results.

In essence, this model offers a valuable tool for PV system design, balancing flexibility, efficiency, and data-driven accuracy. Its ability to handle varying tilt angles and its compatibility with standard meteorological data make it a practical asset for engineers and practitioners.

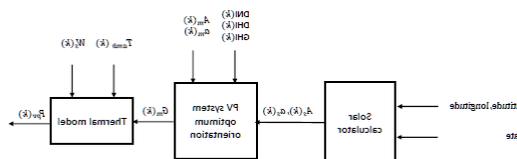


Fig.2.2 Block diagram of the meteorological data-based model

2.1.3. Battery Modeling

A major challenge in integrating PV systems into distribution networks is their unpredictable energy output, causing sudden fluctuations that can lead to overvoltage's or grid congestion. Battery energy storage systems (ESBS) provide a solution by acting as buffers, absorbing excess energy and compensating for shortages. This enhances grid stability and flexibility.

Beyond benefiting distribution system operators (DSOs), PV-equipped ESBS offer financial advantages to system owners. By smoothing energy flow and optimizing self-consumption, these systems can reduce reliance on the grid and lower electricity costs, making them a valuable investment.

Energy storage systems (ESBS) offer significant economic advantages in fluctuating energy markets. They can strategically purchase energy from the grid during off-peak, low-cost periods, reducing or eliminating the need for expensive on-peak purchases.

This paper models the ESBS using an energy-balance method, a common approach in existing research. The energy stored within the ESBS at any given time is determined by the power exchanged between sampling intervals and the system's previous state. Crucially, many variables influencing this energy balance are dependent on external factors.

Battery capacity and charge/discharge efficiency are affected by temperature and the depth of charge or discharge. These parameters also degrade over time due to battery aging. Furthermore, the state-of-charge (SoC), a critical metric, must be estimated rather than directly calculated. The estimation method varies depending on the ESBS technology, but often relies on battery voltage measurements.

Two distinct energy management strategies, peak shaving and maximizing self-consumption, were evaluated. In the peak-shaving application, the EMS prioritizes meeting demand with PV generation. If PV power is insufficient, the ESBS supplies the remaining energy. Any remaining demand unmet by the combined PV and ESBS output is then fulfilled by grid purchases.

Conversely, the self-consumption maximization strategy focuses on utilizing PV energy directly. Batteries are charged solely with excess PV generation and discharge only when PV output is insufficient to meet demand. Both applications are constrained by the ESBS inverter's capacity, which limits the maximum charge and discharge power.

In essence, these models demonstrate the versatility of ESBS in managing energy flow and optimizing economic benefits. By strategically utilizing storage capacity and adapting to fluctuating energy prices, ESBS can enhance grid stability, reduce reliance on grid purchases, and maximize the utilization of renewable energy resources. The chosen energy management strategy directly impacts the system operation and economic outcome.

3. INPUTS TO THE MODELS

Figures 2.2 and 3.1 illustrate the algorithms for the Gaussian and meteorological data-based models, with source code available in [25]. The meteorological model, as defined by Equations (2), (3), (5), (6), and (8), requires ambient temperature, wind speed, and solar irradiance components (DNI, DHI, GHI) as inputs.

For this study, an annual hourly dataset from Meteonorm was utilized. It's crucial to acknowledge that Meteonorm datasets are generated using meteorological station data as a reference, with location adjustments. Consequently, while these datasets provide a general representation of local meteorological conditions, they may not perfectly align with specific on-site measurements. This highlights the importance of considering potential discrepancies when using such datasets for precise PV system modeling

3.1. Installing the PV System

To validate the model's accuracy, data from an operational photovoltaic system was employed. This system featured 17 Canadian Solar modules, each rated at 265 Wp, configured in a single string. These modules were connected to a 7.6 kW SolarEdge SE7600A-US inverter via SolarEdge P400 power optimizers.

3.2. Press Start.

The electrical load profile, based on Costa Rica's average weekly electricity consumption from [3], was used for model validation.

This load profile serves as a flexible reference, allowing for easy adjustment and scaling to explore various operational scenarios. Its adaptability is crucial for simulating different demand patterns and analyzing the PV-ESBS system's performance under diverse conditions.

4. RESULTS AND DISCUSSION

This section presents the simulation results obtained from the Simulink model of the integrated PV-ESBS system. MATLAB Simulink was chosen for its suitability in modeling and simulating complex engineering systems like PV-ESBS.

The analysis focuses on the PV-ESBS system's performance, summarizing key findings through tables and graphs. These visual representations provide a clear overview of the system's behavior. The significant conclusions derived from these results are discussed in detail within the subsequent sections, offering insights into the system's operational characteristics and performance under various conditions..

4.1 PV module and array performance

First, the PV array's overall and each PV module's specific simulation test results have been given. A total of 100.7 kW is produced by 330 solar modules under standard test and conditions (STC). Five SunPower modules (with specification SPR-305E-WHT-D according to Table 4-1) are connected in series within each of the 66 parallel strings that make up the PV array. The PV array's maximum capacity at 25 °C or STC is $66 \times 5 \times 305.2 \text{ W} = 100.7 \text{ kW}$, as shown in Table 4.2.

Table 4-1. Technical data of a PV module (SPR-305E-WHT-D) at STC

Short Circuit Current I_{sc}	5.96 A
Current at maximum power point I_{mpp}	5.58 A
Voltage at maximum power point V_{mpp}	54.7 V
Open circuit voltage V_{oc}	64.2 V
Number of cells in Series n_s	96

Table 4-2. Technical data of the PV array (capacity 100 kW at STC).

Number of modules in string series N_{ss}	5
Number of modules in string parallel N_{pp}	66
Output Voltage rating	273.5 V
Output Current rating	368.3 A
Maximum Power Output	100.7 KW

4.2 Simulation results for PV-ESBS

To thoroughly analyze the PV-ESBS system, the simulation explored three operational scenarios: continuous PV power generation, ESBS discharge when PV output is insufficient, and ESBS charging when PV output exceeds demand. These scenarios, reflecting real-world system behavior, are implemented according to the flowchart detailed in Figure 4.1.

This approach provides a comprehensive understanding of how the PV-ESBS system responds to varying power availability, showcasing its ability to balance energy supply and demand through the dynamic interaction between PV generation and battery storage.

4.3 Case 2: PV supplies constant power, ESBS has no impact

In this simulation, the utility grid, the electrical load, and the PV-ESBS system are connected in a parallel configuration. The photovoltaic array operates at its maximum capacity, generating 100 kW of power. Under these conditions, the battery energy storage system (ESBS) plays a minimal role in the overall energy flow.

The ESBS primarily intervenes during transient periods, specifically when the PV system is stabilizing its output. This limited activity signifies that the PV array effectively meets the load demand.

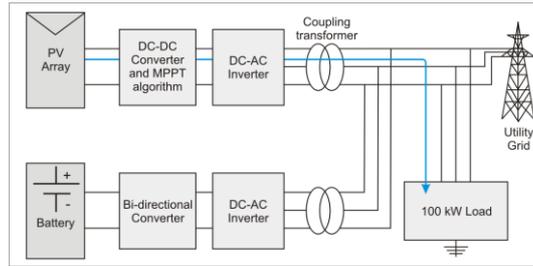


Figure 4-1. Energy flow for PV-ESBS System

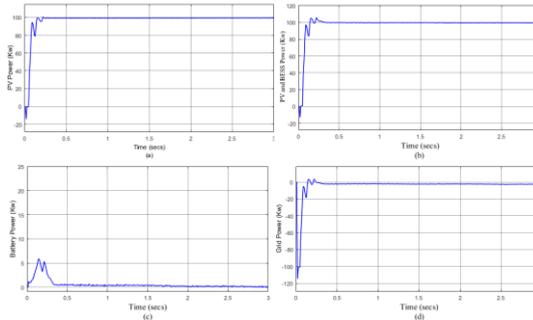


Figure 4-2. Power (a) PV (b) Battery (c) PV and Battery (d) Grid

4.4 Case 3: ESBS discharging due to change in PV

This simulation explores the PV-ESBS system's response to fluctuating solar irradiation. The PV output power is modeled to vary significantly, decreasing from 1000 W/m² to 150 W/m² at defined intervals. This variation simulates real-world conditions where cloud cover or other factors can impact solar energy generation.

To ensure a consistent power supply to the load, the ESBS, assumed to be pre-charged, discharges its stored energy. This compensatory action bridges the gap between the reduced PV output and the load's demand.

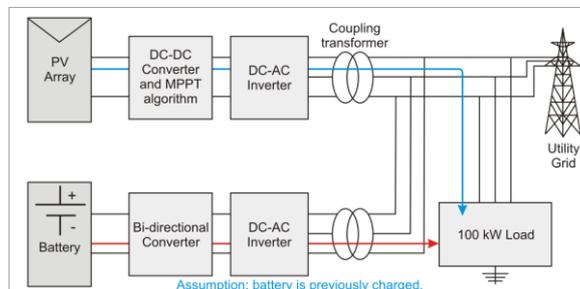


Figure 4-3. Energy flow for the PV-ESBS System

Case 3 examines the system's response when PV generation falls short of the load demand. To compensate, the battery discharges, ensuring the load's power requirements are met.

Figure 4-5 illustrates the fluctuating PV power output, ranging from 100 kW to 15 kW, reflecting changes in irradiance between 0 and 8 seconds. Figure 4.2 shows the corresponding power discharged from the battery, demonstrating its role in supplementing the PV output.

Figure 4.3 presents the combined power delivered to the load by both the PV array and the ESBS, highlighting the seamless integration of these energy sources. Figure 4.4 shows that the grid supplies zero power in this scenario. Finally, Figure 4.5 provides a consolidated view of the combined power flow, showcasing the dynamic interplay between PV generation and battery discharge in maintaining a stable power supply.

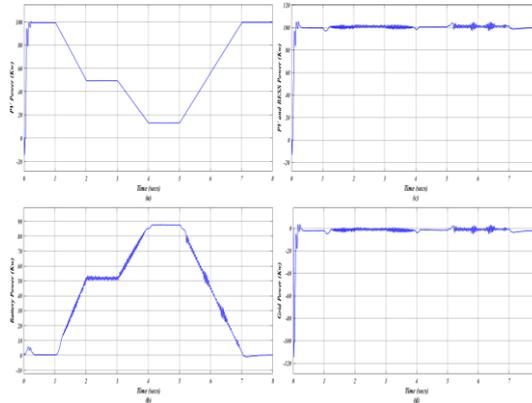


Figure 4-4. Power generated from (a) PV (b) Battery (c) PV and Battery (d) Grid.

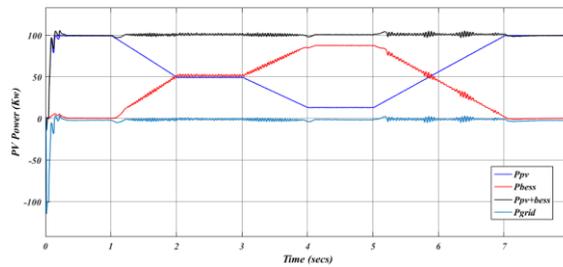


Figure 4.5 Power generation of the whole system in one diagram

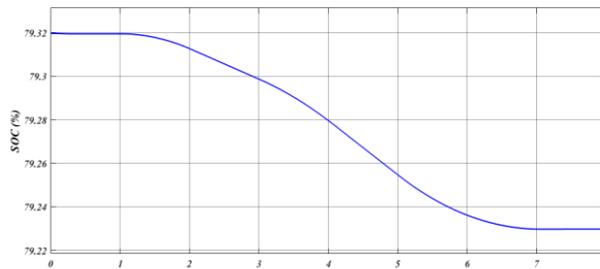


Figure 4.6. State of Charge (in %) of battery bank

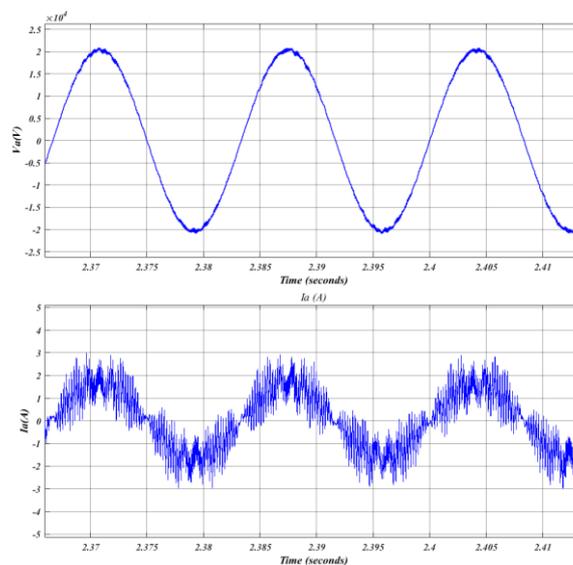


Figure 4.7. Voltage and current waveform at the point of PCC for Case 3.

6.5 Case 4: Battery charging from access PV power

This scenario investigates the battery's charging behavior when the PV array generates excess power. To facilitate this analysis, the electrical load is set to a constant 50 kW. This allows for a clear observation of how the system manages surplus PV generation.

When the PV output surpasses the 50 kW load demand, the excess energy is directed towards charging the battery energy storage system (ESBS). This process stores the surplus energy for later use, optimizing the utilization of the generated solar power.

Figure 4-8 visually represents the overall power flow within the system during this charging phase. It illustrates how the excess PV energy is diverted to the battery, demonstrating the system's ability to efficiently manage and store surplus renewable energy. This scenario emphasizes the ESBS's role in balancing energy supply and demand, maximizing the use of PV generation.

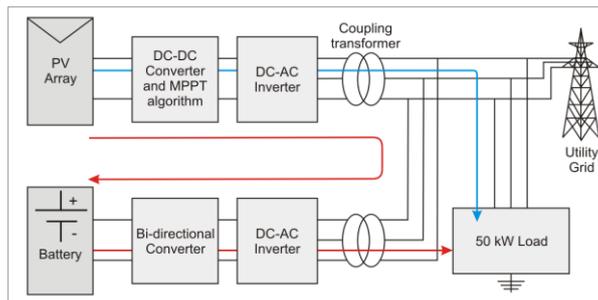


Figure 4.9. Energy flow showing battery charging and discharge to the load

Figure 4.9 depicts the charging process when PV generation exceeds load demand. Initially, the PV array produces 100 kW, while the load consumes 50 kW, directing the surplus to charge the batteries.

Battery charging commences between 0 and 3 seconds, during which PV output remains constant. While steady-state charging can occur in under a second with optimized ESBS control, the model avoids complex control strategies. This simplification reflects the complexity of precise control implementations.

However, enhancing the controller could improve the overall power quality of the PV-ESBS system.

At 6 seconds, PV generation diminishes to near zero, and the ESBS assumes full responsibility for powering the 50 kW load, demonstrating its ability to maintain continuity during periods of low solar irradiance.

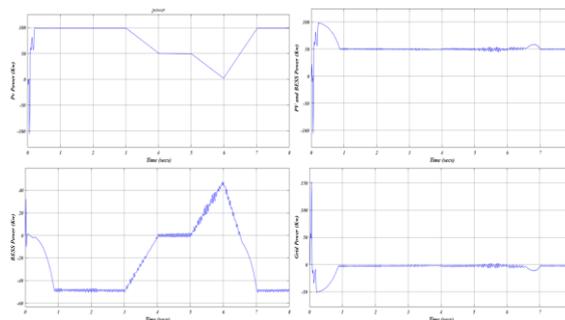


Figure 4.10. Power delivery to the load from the PV array, battery system and the AC grid

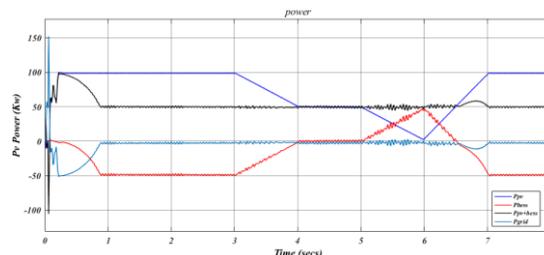


Figure 4.11 Power generation of the whole system in one diagram

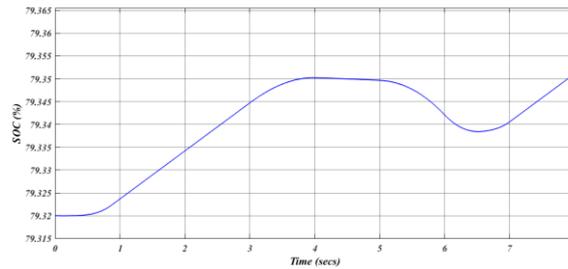


Figure 4.12. State of charge (%) of the battery

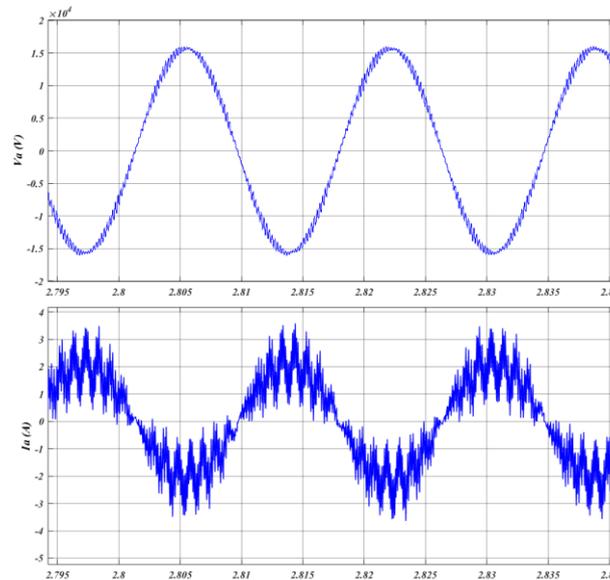


Figure 4.13. Voltage and current waveform at the point of PCC for Case 4

4.4 Summary

This section details the simulation results of the proposed PV-ESBS system, conducted using MATLAB/Simulink. The simulations demonstrate the system's effectiveness in providing a stable power supply to a load under varying irradiance conditions.

The results confirm that integrating battery energy storage (ESBS) significantly enhances performance compared to a standalone PV system. The PV-ESBS system effectively mitigates the inherent variability of solar energy, ensuring a more consistent and reliable power delivery.

Furthermore, the study suggests that refining the ESBS controller could further optimize the system's performance, leading to improved overall power quality. This highlights the potential for further advancements in PV-ESBS technology through targeted controller enhancements.

Due to MATLAB's computational demands, the simulations presented here cover a limited time frame. However, they effectively illustrate the system's response to initial environmental changes. Specifically, the simulated variations in irradiance, resembling shifting cloud cover affecting the PV panel's temperature, provide a realistic representation of real-world atmospheric conditions. This approach offers a valuable analogy for understanding the PV-ESBS system's dynamic behavior under transient conditions.

5. CONCLUSIONS AND FUTURE PROSPECTS

This paper extensively simulated a combined PV-ESBS system using MATLAB/Simulink. The PV system model encompassed several key components: a PV array, a boost-type DC/DC converter implementing an incremental conductance MPPT algorithm with integral regulation, a three-phase VSC-type DC/AC inverter, and a coupling transformer connecting to both the load and the point of common coupling with an equivalent power grid.

The ESBS model was similarly detailed, comprising a battery pack, a VSC-type DC/AC inverter, a Cuk-type bi-directional DC/DC converter, and a coupling transformer, also linked to the common coupling point. This comprehensive modeling approach allowed for in-depth analysis of the integrated system's performance.

The central objective of this paper was to evaluate the performance of an integrated PV-ESBS system under dynamic temperature and irradiance conditions, while maintaining a consistent power supply to an AC load. During the modeling process, it was found that connecting the ESBS in parallel with the PV system, rather than linking both DC/DC converters to a shared DC/AC inverter's DC bus, significantly simplified the model's complexity. This design choice streamlined the simulation and analysis, facilitating a more efficient investigation of the system's performance.

5.1 Future work recommendations

This paper primarily focused on active power regulation in response to fluctuating PV output. Future research should expand this scope to include scenarios involving variations in both active and reactive power demand at the load point.

Furthermore, future studies should incorporate more realistic environmental conditions. Specifically, they should utilize recorded daily demand curves and simulate more accurate solar radiation and temperature patterns on PV panels. The environmental variations used in this paper were deliberately simplified, and more realistic simulations would provide a more comprehensive understanding of the PV-ESBS system's performance.

REFERENCES

1. H. Ritchie and M. Roser, "Energy Production & Changing Energy Sources," OurWorldInData.org, 2022. [Online]. Available: <https://ourworldindata.org/energy-production-and-changing-energy-sources/>. [Accessed November 2022].
2. S. Hegedus and A. Luque, "Achievements and challenges of solar electricity from photovoltaics," in Handbook of Photovoltaic Science and Engineering, John Wiley & Sons, Ltd, 2021, pp. 2-38.
3. I. E. AGENCY, "World Energy Outlook 2020.," 2021. [Online]. Available: <https://www.iea.org/publications/freepublications/publication/WEO2013.pdf>. [Accessed November 2017].
4. I. E. Agency, "Snapshot Of Global Photovoltaic Markets," 2020. [Online]. Available: http://www.iea-pvps.org/fileadmin/dam/public/report/statistics/IEA-PVPS_-_A_Snapshot_of_Global_PV_-_1992-2016__1_.pdf. [Accessed October 2019].
5. REN21, "Renewables 2017 Global Status Report "Market And Industry Trends"," 2017. [Online]. Available: http://www.ren21.net/wp-content/uploads/2017/06/17-8399_GSR_2017_Full_Report_0621_Opt.pdf. [Accessed December 2017].
6. J. V. Appen, M. Braun, T. Stetz, K. Diwold and D. Geibel, "Time in the Sun: The Challenge of High PV Penetration in the German Electric Grid," IEEE Power and Energy Magazine, vol. 11, no. 2, pp. 55-64, March-April, 2018.
7. D. Spiers, "Batteries in PV Systems," in Practical Handbook of Photovoltaics, Elsevier, December 2020, pp. 721-776.
8. R. Corkish, M. A. Green, M. E. Watt and S. R. Wenham, Applied Photovoltaics, 2nd ed., Earthscan, 2021.
9. G. Dzimano, Modeling Of Photovoltaic Systems, Doctoral Paper, The Ohio State University, 2008.
10. M. R. SUNNY, "Sizing An Energy Storage To Be Used In Parallel With PV Inverter To Balance The Fluctuations In Output Power From PV Generator Msc, Paper," Tampere University of Technology, 2021.
11. R. Messenger and A. Abtahi, Photovoltaic Systems Engineering, Fourth ed., CRC Press, 2017.
12. A. Luque and S. Hegedus, Handbook of Photovoltaic Science and Engineering, second ed., John Wiley & Sons, 2022.
13. M. R. Patel, Spacecraft Power Systems, CRC Press, 2004.
14. A. MÄKI, "Topology Of A Silicon-Based Grid-Connected, Photovoltaic Generator, MscPaper," Tampere University of Technology, 2020.
15. S. Kjaer, J. Pedersen and F. Blaabjerg, "A review of single-phase grid-connected inverters for photovoltaic modules," IEEE Transactions on Industry Applications, vol. 41, no. 5, pp. 1292-1306, Sept.-Oct. 2005..
16. D. T. Lobera, Measuring actual operating conditions of a photovoltaic power generator, MscPaper, Tampere University of Technology, 2010.

17. B. Sørensen, "Chapter 33: Battery storage," in Renewable Energy Conversion, Transmission and Storage, 2007.
18. D. Linden and T. B. Reddy, Handbook of Batteries, 3rd ed., McGraw-Hill, 2002, p. 1.8.
19. D. Berndt, "Electrochemical Energy Storage," in Battery Technology Handbook, CRC press, 2003.
20. P. J. Grbovic, "Ultra-capacitors in Power Conversion Systems Applications," in Analysis And Design From Theory To Practice, John Wiley & Sons, 2012, p. 17.
21. Ralph J. Brodd, "Synopsis of the Lithium-Ion Battery Markets", " in Lithium-Ion Batteries, Science and Technologies, Springer, 2009, p. 2.
22. G. Blomgren, R. Powers and D. MacArthur, "Lithium and Lithium Ion Batteries," 2002.
23. S. Piller, M. Perrin and A. Jossen, "Methods for state-of-charge determination and their applications," Journal of Power Sources, pp. 113-120, 2001.
24. X. Hu, S. Li, H. Peng and F. Sun, "Robustness analysis of State-of-Charge estimation methods for two types of Li-ion batteries,," Journal of Power Sources, vol. 217, pp. 209-219, November 2012.
25. R. Huggins, Advanced Batteries Materials Science Aspects, 2010.