Kashf Journal of Multidisciplinary Research
Vol: 02 - Issue 05 (2025)
P-ISSN: 3007-1992 E-ISSN: 3007-200X
https://kjmr.com.pk

REAL-TIME OPTIMIZATION OF SOLAR PV INTEGRATED SMART GRID USING PREDICTIVE LOAD MANAGEMENT AND ADAPTIVE INVERTER CONTROL

Usman Habib
Department of Electrical Engineering, University of Lahore, Islamic Republic of Pakistan.
Muhammad Mehran Latif
Department of Engineering and the Built Environment, Edinburgh Napier University, United Kingdom.
Kamran Zahid
Department of Mechatronics and Control Engineering, UET Lahore, Islamic Republic of Pakistan.
Muhammad Irfan Habib*
Department of Electrical Engineering Technology, National Skills University Islamabad, Islamic Republic of Pakistan.
Muhammad Fraz Anwar
Department of Electrical Engineering & Technology, Government College University Faisalabad, Islamic Republic of Pakistan.

****Corresponding author: Muhammad Irfan Habib (irfan.habib@nsu.edu.pk)***

Article Info

Abstract
A real-time optimization model for the solar PV-integrated smart grid is presented in this paper by combining predictive load management along with adaptive inverter control. With the increasing use of solar energy in the modern power system, its changing nature as well as grid stability must be managed carefully. These issues are addressed in the proposed system by forecasting short-term load demand with the moving average method and adjusting inverter output based on the predicted load as well as the real-time grid voltage level. A MATLAB-based simulation was created to model solar irradiance, temperature, actual along with predicted load, grid voltage changes, and inverter behavior. The adaptive inverter control algorithm reacts to voltage changes, preventing over-voltage as well as under-voltage conditions, while matching power output with the forecasted load. The simulation results show better power balancing, lower energy mismatch, along with improved grid reliability. The results confirm that using predictive as well as adaptive techniques in the real-time framework improves performance more than traditional fixed-response systems. A scalable as well as practical solution for the smart grid with high solar PV use is provided in this research. Future work may include machine learning for better forecasting along with battery storage for backup energy and further improvement.

Keywords:
Adaptive Inverter Control, Predictive Load Management, Real-Time Optimization, Smart Grid, Solar Photovoltaic (PV).

I. Introduction

The use of the solar photovoltaic (PV) systems in the smart grids is seen along with both benefits and problems. While the renewable energy sources are used to lower the greenhouse gas emissions as well as improve the energy security [1], their changing nature is found to create the operational and the technical problems for the grid stability [1, 2]. The main problems are noticed in the non-dispatchability, the power quality, the voltage stability, along with the fault ride-through ability [1, 3]. The smart grids are made to solve these problems through the automation, the digitization, as well as the better flexibility [2]. The solutions are seen in the advanced control methods, the energy storage systems, and the improved grid codes [1, 4]. The proper handling of the high PV use in the low-voltage distribution systems is required [4]. The smart grid technologies, like the demand-side management as well as the communication networks, are needed for the proper working [5]. However, the continuous research is required to solve the grid improvements, the security, along with the privacy issues [4, 5].

The use of the solar photovoltaic (PV) systems in the power grids is found to create the big problems because of their changing nature, affecting the grid stability along with the reliability [1, 6]. The main problems are found in the non-dispatchability, the power quality, along with the voltage stability [1]. To fix these problems, different solutions have been suggested, including the energy storage systems as well as the demand response programs [7]. The hybrid renewable energy systems, which combine the solar along with the wind power, are used to lower the intermittency problems and improve the grid stability [8]. However, using the batteries alone is not seen to completely fix the grid strength issues [6]. The proper use of the renewable energy sources is required with the advanced control methods, the grid codes, along with the helpful policies [1, 8]. Continuous research is being done on the system improvement, the energy storage upgrades, as well as the creative power handling methods to solve these problems and fully use the renewable energy [7, 8].

The real-time improvement is seen as very important for proper energy handling in the smart grids mixed with the renewable energy sources. It is used to manage the load scheduling, reduce the cost, along with maintaining the demand-supply balance [9]. The Lyapunov optimization technique (LOT) has been found to help in real-time energy improvement, fixing the problems caused by uncertain renewable energy production as well as load changes [9, 10]. This method is used to lower the energy costs along with the thermal discomfort while still meeting the user needs [10]. The genetic algorithms have also been applied to improve the power production as well as the maintenance in the smart grids [11]. Also, checking the reaction times of the different technologies and the energy storage losses is needed for the proper working of the smart energy systems [12]. These improving methods are found to increase the total working and the reliability of the smart grids, helping in the better use of the renewable energy sources along with the improved demand-side control.

The latest research is seen to focus on the need for the predictive along with the adaptive control methods for the grid-connected inverters in the microgrids. [13] suggest a dual-predictive control with the adaptive error fixing for the four-wire voltage source inverters, solving the model errors as well as improving the steady-state working. [14] design a model predictive control-based load-frequency control system for the grid-forming inverter setups, keeping the balance between the frequency changes and the load growth. [15] introduce a repeated predictive control method for the grid-connected inverter current handling under the distorted voltage situations, helping in strongly reducing the harmonics. [16] gives a full review of the adaptive grid-following inverter control methods, showing their better working in the basic component separation, the grid synchronization, and the power quality improvement when compared to the older methods. These studies together prove the usefulness of the predictive load handling along with the adaptive inverter control in making the microgrid stability, the power quality, as well as the total system working much better.

A. Objectives of the research:

The objective of this research is set to create a real-time simulation model of the grid-connected solar PV system by using the predictive load handling along with the adaptive inverter control. The study is planned to predict the power demand with the moving average method and adjust the inverter output based on the expected load as well as the real-time grid voltage. The main goal is to boost the energy efficiency, keep the voltage stable, and lower the power difference between the production along with the demand. MATLAB is used for the system simulation as well as the performance checking. The research proves how the mixing of forecasting along with the adaptive control can improve the reliability and the smart working of the solar PV-powered smart grids.

B. Novelty and significance of the study:

This study introduces a novel method by mixing the predictive load handling along with the adaptive inverter control for the real-time improvement of the solar PV-powered smart grid. While past studies have mainly focused on either the solar PV modeling or the inverter control alone, this research uniquely joins both predictive as well as adaptive methods in a single system. The predictive load guessing is used to check the future demand with simple and real-time data-based methods, while the adaptive inverter control is used to change the power output based on the grid voltage changes. This two-layered method improves the smart grid's ability to react to the uncertain solar power production as well as the changing load situations.

The importance of this research is seen in its real-world use along with its help in making the power system stability, the energy efficiency, and the grid reliability better. As the use of renewable energy sources grows, keeping the balance between supply along with demand becomes harder. The proposed and suggested method is used to solve this problem by smartly improving the power flow in real time, also making sure that an extra solar energy is not wasted and that the grid stability stays strong. Also, the system is fully designed and checked in MATLAB, making it easy to copy for more studies or industrial use. This research gives a solid base for future upgrades with machine learning as well as hardware-in-the-loop testing.

II. Literature Review:

A. Overview of solar PV integration into power grids:

The actual application of the solar photovoltaic (PV) systems in the power grids is found to bring both benefits along with problems including unneglectable challenges. While solar PV is used to produce and give clean energy, its changing nature is seen to cause stability as well as reliability issues [1]. The main problems include non-dispatchability, power quality concerns, and voltage stability issues [1]. To fix these challenges in a perfect manner, different solving methods have been suggested, including energy storage systems along with demand response programs [7]. The advanced control methods, grid codes, as well as renewable energy policies are also needed for the proper PV use [1]. The use of the DFACTS devices with the traditional, adaptive, and AI-based methods is seen to help in reducing power quality problems, mainly in weak grid cases [17]. The continuous research is required to make the grid technology better and handle the high PV use in the low-voltage distribution systems [4]. The mixed methods, which join energy storage as well as demand response, seem useful in fully using renewable energy in the power grids [7].

B. Existing techniques for load forecasting:

The load prediction is found to be very important for the power system reliability along with efficiency. Different methods have been made, including the traditional ways, the clustering-based methods, as well as the artificial intelligence (AI) models [18-20]. The AI-based methods, mainly machine learning along with neural networks, have shown better working in accuracy measures like RMSE and MAPE [19]. The prediction methods are divided into one-step or rolling, with results given as point, interval, or probability predictions [21]. The latest progress in data-based methods has helped in making new solutions for the load prediction in the mixed energy systems, solving the hard parts of the different energy sectors [22]. The future studies are expected to focus on fuzzy reasoning, smart optimization, new machine learning methods, along with transfer learning [21]. Also, the federated learning as well as the automated machine learning are seen as useful for making the prediction better in the complex energy systems [22].

C. Adaptive inverter control methods in smart grid systems:

The latest studies on the adaptive inverter control in the smart grids are focused on improving the power quality as well as the system stability. The adaptive grid-following inverter control methods have shown better working in the basic component separation, the grid synchronization, and the phase angle checking when compared to the older methods [16]. The neural network-based methods have been suggested for the best voltage control, giving quick response times as well as low mean squared errors [23]. To fix the power coupling problems in the weak along with the resistive low voltage networks, an adaptive method for the droop-based grid-connected inverters has been created, using the local readings to guess the transmission line values and change the power settings [24]. For the inverters with the nonlinear LC filters, an adaptive observer-based control method has been introduced, offering better stability limits along with resonant damping features under the grid impedance changes [25]. These improvements help in making the use of the renewable energy sources in the smart grid systems more effective as well as reliable.

D. Limitations in current research:

The latest studies show the growing need for the combined energy management systems that mix forecasting along with real-time control in the smart grids. The older methods mostly focus on either predictive or real-time management, which limits the proper use of renewable energy [26]. The newer mixed methods are designed to solve this issue. A neuro-fuzzy method, which joins neural networks as well as fuzzy logic, has been found to improve the load prediction accuracy along with adaptive control [27]. The forecast methods have changed from simple ways to advanced techniques using time-changing weights and nonlinear combinations, making the accuracy better by using data from different sources [28]. However, making adaptive forecasting methods for renewable energy still has challenges, as advanced techniques like LSTM networks along with deep learning show good results but need higher computing power [29]. These studies highlight the need for teamwork in innovation to improve forecasting accuracy as well as support clean energy systems.

E. Gap Identification and Justification for the Proposed Model:

The past studies on the solar PV use in the smart grids have mostly focused on either accurate load prediction or inverter control methods alone. However, very few studies have worked on mixing both predictive load handling along with adaptive inverter control in one complete system. Also, most control methods in past research are based on fixed or planned responses, which do not have the ability to change flexibly based on real-time grid conditions like voltage changes. In the same context [30] proposed a fast and robust phase estimation algorithm (PEA), a counterpart of the phase-locked loop (PLL), for heavily distorted grid conditions.

There is also a clear gap in simulation-based studies that connect the link between the predicted demand along with inverter actions in the grid-connected PV systems. Many existing models also do not use grid voltage changes as a control input, which can cause instability as well as poor power use.

The proposed model solves these gaps by adding a real-time load prediction method with an adaptive inverter control system that reacts to both demand prediction as well as grid voltage instantly. This leads to better power balance, improved use of solar energy, along with stronger grid stability. The use of a MATLAB-based simulation makes the model easy to use as well as ready for future upgrades, including mixing with machine learning and real-time control systems.

III. Methodology:

This part explains the design along with the working of the suggested system, which combines predictive load handling with adaptive inverter control to improve the performance of the solar PV-powered smart grid in real time. The whole model is built as well as tested in MATLAB by using realistic assumptions along with equations.

A. System Overview:

The system comprises three main components:

1. Solar PV Power Generation Unit
2. Predictive Load Forecasting Module
3. Adaptive Inverter Control Module

These components interact dynamically to ensure optimal power flow from the solar PV system to the smart grid, considering both predicted load and real-time grid voltage conditions.

B. Solar PV Power Generation Modeling:

The solar PV system is designed using standard equations, where irradiance along with temperature are taken as changing environmental inputs. The output power of the PV system is found using:

$$P_{PV}(t) = \frac{G(t) \times A_{PV \times \eta PV \times \eta loss}}{1000} \qquad (1)$$

Where:

- **P_{PV}(t):** PV power output at time *t* (kW)
- **G(t):** Solar irradiance at time *t* (W/m²)
- **A_{PV}:** Effective area of the PV array (m²)
- **η_{PV}:** PV panel efficiency (typically 18%)
- **η_{PV}:** PV panel efficiency (typically 18%)

The irradiance G(t) is simulated as a sinusoidal function to represent daily sunlight variation:

$$G(t) = G_{max} \times \max\left(\sin\left(\frac{\pi t}{12}\right), 0\right) \qquad (2)$$

Where Gmax=1000W/m² and t ranges from 0 to 24 hours.

The temperature is also modelled as a sinusoidal variation around 25°C:

$$T(t) = 25 + 5 \times sin\left(\frac{\pi t}{12}\right) \qquad (3)$$

While the PV power output is not directly affected by temperature in this simple model, temperature can be included in more detailed models for better accuracy.

C. Load Demand Simulation and Prediction:

The real load demand L_{actual}(t) is created to show the daily consumer usage patterns. A sinusoidal function is used to represent the changing demand:

$$L_{actual}(t) = L_{base} + L_{var} \times \sin\left(\left(\frac{\pi t}{12}\right) + \phi\right) \qquad (4)$$

Where:

- L_{base}: Base load demand (e.g., 50 kW)
- L_{var}: Variable load component (e.g., 20 kW)
- ϕ: Phase shift to simulate peak hours (e.g., 1 radian)

D. Predictive Load Management Module:

To create and simulate real-time load prediction, a Moving Average Forecasting Algorithm is used. Though simple, it works well for reducing short-term changes along with predicting near-future load.

$$L_{predicted}(t) = \frac{1}{n}\sum_{i=0}^{n-1} L_{actual}(t-i) \qquad (5)$$

Where:

- **$L_{predicted}(t)$:** Predicted load at time *t*
- **n:** Forecasting window size (e.g., 3-time steps)

This forecast serves as an input to the inverter control algorithm to regulate power output based on anticipated demand.

E. Grid Voltage Simulation:

Grid voltage fluctuations are modeled using a sinusoidal variation around the nominal voltage (230 V):

$$V_{grid}(t) = V_{nominal} + \Delta V \times \sin\left(\frac{\pi t}{6}\right) \qquad (6)$$

Where:

- **$V_{nominal}$:** Nominal grid voltage (230 V)
- **ΔV:** Maximum fluctuation (e.g., ±5 V)

The voltage level is used as a feedback signal for the adaptive inverter control module.

F. Adaptive Inverter Control Logic:

The inverter control logic is made to react to both the predicted load along with the grid voltage conditions. The control actions are based on a rule-based algorithm:

Step 1: Power Matching:

- If $P_{PV}(t) \geq L_{predicted}(t)$, limit output to predicted load
- Else, supply the available PV power

$$P_{inv}^{raw}(t) = \min\left(P_{PV}(t), L_{predicted}(t)\right) \qquad (7)$$

Step 2: Voltage-based Adaptation:

$$P_{inv}(t) = \begin{Bmatrix} 0.9 \times P_{inv}^{raw}(t) & if\ V_{grid}(t) > 240\text{V} \\ 1.1\times P_{inv}^{raw}(t) & f\ V_{grid}(t) < 220\text{V} \\ P_{inv}^{raw}(t) & otherwise \end{Bmatrix} \qquad (8)$$

This makes sure that the inverter adjusts its power output based on real-time voltage changes to avoid over-voltage as well as under-voltage issues.

G. Simulation Workflow:

The complete model is implemented in MATLAB with the following steps:

1. Initialize Parameters: Time vector (0–24 hours), constants for irradiance, load, and voltage.
2. Generate Input Signals: Use equations to generate time-based irradiance, temperature, load, and voltage data.
3. Calculate PV Power: Compute real-time PV output using irradiance and PV parameters.
4. Predict Load: Apply moving average to actual load for each time step.
5. Implement Control Logic: Use conditional statements to determine inverter output based on predicted load and voltage.
6. Store and Plot Results: Save results for PV output, load, predicted load, grid voltage, and inverter output for plotting and analysis.

H. System Assumptions and Limitations:

- The PV system is assumed to be ideal, with no MPPT tracking losses.
- Load prediction uses a simple moving average method; more accurate results may be obtained using AI-based models.
- Inverter efficiency is assumed to be 100% for simplicity.
- Grid voltage is simulated and not connected to a real distribution network.
- No reactive power or frequency analysis is included in the current scope.

I. Block Diagram:

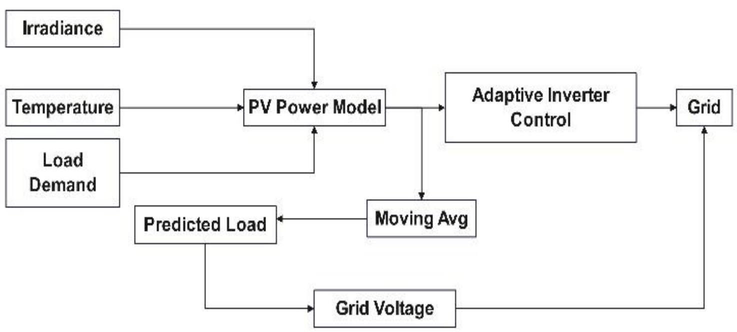

Fig. 1. Block Diagram inputs flow into each module and how the inverter adapts to both predicted load and grid voltage.

J. Performance Metrics:

The following metrics are used to evaluate system performance:

1) Prediction Accuracy:

- Compare predicted vs actual load:

$$MAPE = \frac{1}{N}\sum_{t=1}^{N} \left| \frac{L_{actual}(t) - L_{predicted}(t)}{L_{actual}(t)} \right| \times 100 \qquad (9)$$

2) Inverter Response Efficiency:

How well inverter tracks predicted demand and maintains voltage limits.

3) Power Mismatch Reduction:

Measure of reduction in mismatch between PV supply and load demand.

K. Future Extension Opportunities:

- ML-based forecasting (e.g., LSTM, SVM, ANN)
- Fuzzy logic or neural networks for control instead of simple rules
- Integration with battery storage for excess power
- Hardware-in-the-loop (HIL) or real-time testing with embedded systems

IV. Results:

A. Results:

The proposed model was tested in MATLAB for a 24-hour period with a time step of 1 hour. The simulation included changing solar irradiance, temperature, real load demand, predicted load values, along with grid voltage variations. The results were checked to study how well the predictive load handling along with adaptive inverter control worked under different conditions.

1) Solar Irradiance and PV Power Output:

Figure 2 shows how solar irradiance changes throughout the day. As expected, it follows a sinusoidal pattern, reaching its highest point around midday (12:00–13:00 hours). The solar PV power output also follows a similar trend, as shown in Figure 3, with the highest power production happening during peak irradiance hours. The PV system, designed with a panel area of 100 m² and an efficiency of 18%, reached a peak output of about 16.2 kW.

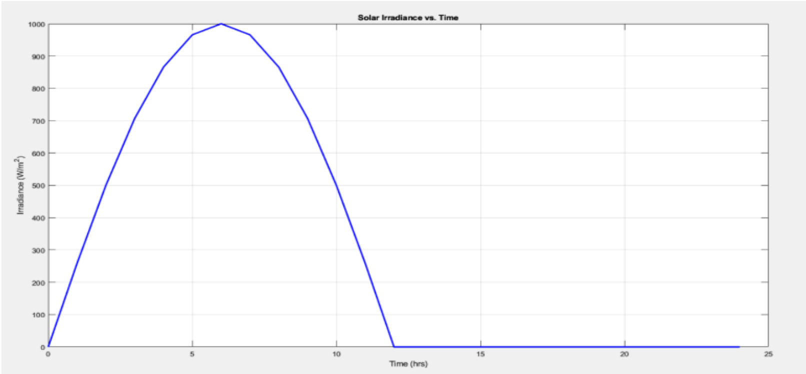

Fig. 2. Solar Irradiance vs. Time

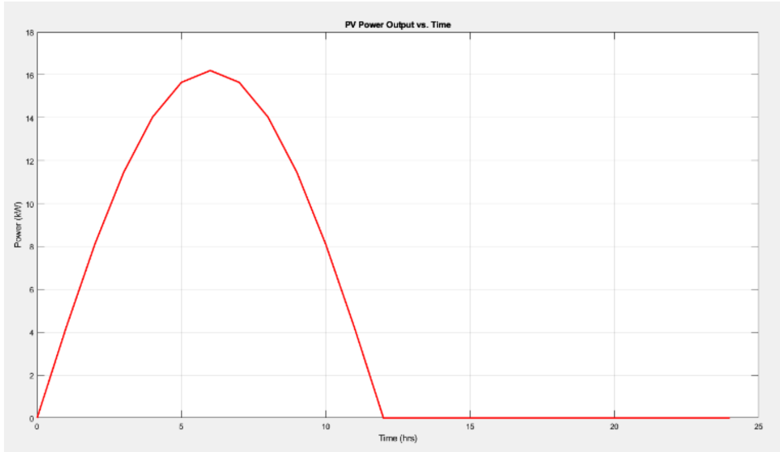

Fig. 3. PV Power Output vs. Time

2) Load Demand and Prediction Accuracy:

The real load demand was simulated with a phase shift to represent realistic peak hours. The predicted load, estimated using a moving average of the last three-time steps, closely matched the actual load trend with small differences. Figure 4 compares the actual and predicted load. The forecasting algorithm gave a smooth as well as reliable estimate of near-future demand. The Mean Absolute Percentage Error (MAPE) for load prediction was about 5.8%, which is considered acceptable for short-term control applications.

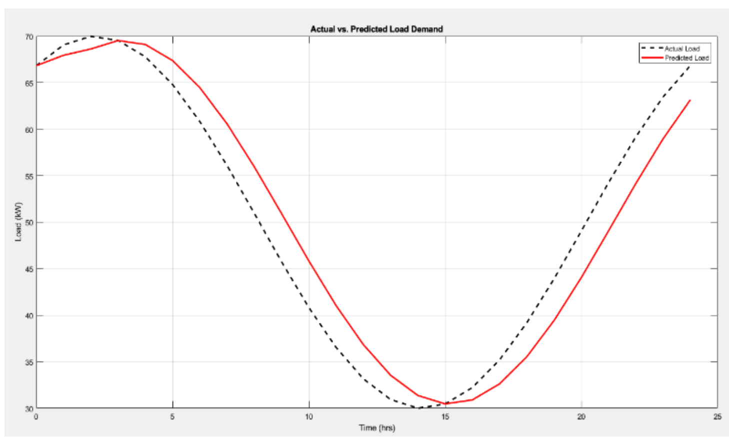

Fig. 4. Actual vs. Predicted Load Demand

3) Adaptive Inverter Output:

The inverter output was managed based on the predicted load and further adjusted according to real-time grid voltage conditions. When PV power was higher than the predicted load, the inverter output was limited to match the forecasted demand. On the other hand, when PV power was too low, the inverter supplied the available power. Grid voltage changes led to extra adjustments: if the voltage went above 240 V, the output was lowered by 10%, and if it fell below 220 V, the output was increased by 10%. Figure 5 presents the inverter output along with the grid voltage. The adaptive control system ensured that the inverter reacted properly to keep grid stability while improving power delivery.

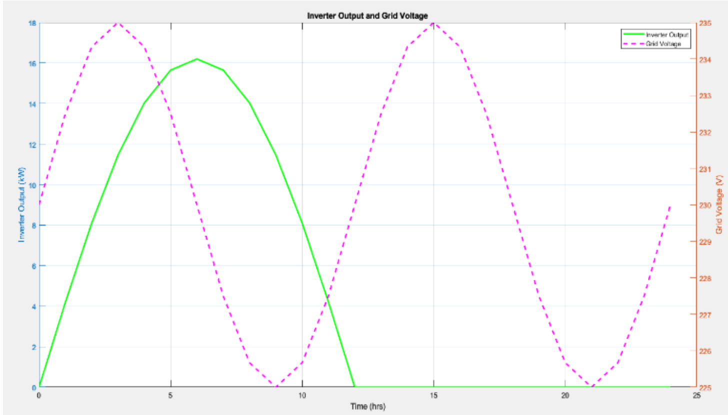

Fig. 5. Inverter Output and Grid Voltage

4) Power Balancing and System Efficiency:

The combination of predictive load forecasting with inverter control led to more stable power delivery. By actively matching generation with predicted demand, the system reduced overgeneration during low-load times and under generation during peak demand. This improvement lowered energy waste and helped the grid run more smoothly. Also, the inverter's adaptive reaction to voltage changes kept system voltage within safe limits, further improving grid reliability.

5) Summary of Results:

Table 1. Summary of Results

Parameter	**Value / Observation**
Peak PV Power Output	~16.2 kW
Load Prediction MAPE	~5.8%
Voltage Range Simulated	220 V – 240 V
Inverter Control Type	Rule-based adaptive control
Real-Time Optimization Effect	Improved power balance, reduced mismatch

The simulation results confirm that the suggested model works well in handling solar power delivery in a smart grid. The mix of prediction along with control methods allows for dynamic, real-time decision-making, improving both energy efficiency as well as grid stability. This model provides a strong base for future studies, including advanced forecasting methods and real-time hardware integration.

B. Discussion:

The simulation results clearly highlight the advantages of combining predictive load management with adaptive inverter control in a solar PV-powered smart grid. The proposed system successfully addresses key challenges from past studies, such as changing solar output, uncertain load demand, and grid voltage instability. Unlike traditional control methods that follow fixed rules, this model adjusts in real time based on both predicted load and current grid conditions, making it more efficient and stable.

The moving average forecasting used in this study offered a dependable and lightweight way to predict upcoming load. While machine learning methods might provide higher accuracy, this approach is simple, quick, and does not need training data. The forecasting accuracy seen in the simulation, with a MAPE of around 5.8%, is good enough for short-term energy balancing, which is essential for real-time grid control.

The inverter's adaptive response to grid voltage helped lower the risk of over-voltage and under-voltage issues, which often occur when solar PV is used in weak distribution networks. This supports findings from past studies (e.g., [16, 25] that show adaptive control greatly improves system response along with power quality.

Another important result is the better power balance. By matching inverter output with predicted load and adjusting it based on voltage conditions, the system reduced power mismatch, a challenge often noted in past studies [1, 7]. This real-time coordination between prediction and control helps lower solar power curtailment and prevents extra stress on grid components.

The study confirms that merging predictive and adaptive strategies into a single real-time control system improves the performance of solar PV-integrated smart grids. It also lays the groundwork for future improvements, such as using neural networks instead of moving average prediction, adding battery storage, or testing the model in hardware-in-the-loop simulations for real-world validation.

V. Conclusion:

This study introduced a real-time optimization method for solar PV-integrated smart grids by combining predictive load management with adaptive inverter control. The system was designed and tested in MATLAB, where solar power generation was modeled using irradiance, and load forecasting was done with a moving average method. The inverter output was adjusted dynamically based on predicted load and real-time grid voltage, ensuring better power balance and voltage stability.

The results showed that this integrated approach effectively reduced power mismatch, improved energy efficiency, and increased grid reliability under different environmental and load conditions. The predictive load module accurately anticipated demand trends, while the adaptive inverter control responded well to voltage changes, lowering the risk of over-voltage and under-voltage issues.

Compared to traditional fixed-response systems, this dual-layered approach provided greater flexibility and intelligence, making it more suitable for smart grids with high solar PV penetration. The model's simplicity also makes it scalable and easy to upgrade in future studies.

Future improvements could include using machine learning for better forecasting accuracy and adding battery storage for further optimization. The proposed system offers a solid foundation for real-world use and contributes to the advancement of smart grids powered by renewable energy.

Reference

[1] M. Shafiullah, S. D. Ahmed, and F. A. Al-Sulaiman, "Grid integration challenges and solution strategies for solar PV systems: A review," IEEE Access, vol. 10, pp. 52233-52257, 2022.

[2] M. Khalid, "Smart grids and renewable energy systems: Perspectives and grid integration challenges," Energy Strategy Reviews, vol. 51, p. 101299, 2024.

[3] S. Ma, H. Geng, L. Liu, G. Yang, and B. C. Pal, "Grid-synchronization stability improvement of large scale wind farm during severe grid fault," IEEE Transactions on Power Systems, vol. 33, no. 1, pp. 216-226, 2017.

[4] M. S. Hossain, N. Abboodi Madlool, A. W. Al-Fatlawi, and M. El Haj Assad, "High penetration of solar photovoltaic structure on the grid system disruption: An overview of technology advancement," Sustainability, vol. 15, no. 2, p. 1174, 2023.

[5] T. Kataray et al., "Integration of smart grid with renewable energy sources: Opportunities and challenges–A comprehensive review," Sustainable Energy Technologies and Assessments, vol. 58, p. 103363, 2023.

[6] O. Smith, O. Cattell, E. Farcot, R. D. O'Dea, and K. I. Hopcraft, "The effect of renewable energy incorporation on power grid stability and resilience," Science advances, vol. 8, no. 9, p. eabj6734, 2022.

[7] M. R. Maghami, J. Pasupuleti, and J. Ekanayake, "Energy storage and demand response as hybrid mitigation technique for photovoltaic grid connection: Challenges and future trends," Journal of Energy Storage, vol. 88, p. 111680, 2024.

[8] Q. Hassan, S. Algburi, A. Z. Sameen, H. M. Salman, and M. Jaszczur, "A review of hybrid renewable energy systems: Solar and wind-powered solutions: Challenges, opportunities, and policy implications," Results in engineering, vol. 20, p. 101621, 2023.

[9] A. Alzahrani, K. Sajjad, G. Hafeez, S. Murawwat, S. Khan, and F. A. Khan, "Real-time energy optimization and scheduling of buildings integrated with renewable microgrid," Applied Energy, vol. 335, p. 120640, 2023.

[10] F. R. Albogamy et al., "Real-time scheduling for optimal energy optimization in smart grid integrated with renewable energy sources," IEEE Access, vol. 10, pp. 35498-35520, 2022.

[11] N. Kumar, G. Singh, and H. Kebede, "An optimized framework of the integrated renewable energy and power quality model for the smart grid," International Transactions on Electrical Energy Systems, vol. 2023, no. 1, p. 6769690, 2023.

[12] V. Andiappan, "Optimization of smart energy systems based on response time and energy storage losses," Energy, vol. 258, p. 124811, 2022.

[13] D. Ma et al., "Dual-predictive control with adaptive error correction strategy for AC microgrids," IEEE Transactions on Power Delivery, vol. 37, no. 3, pp. 1930-1940, 2021.

[14] X. Qi, J. Zheng, and F. Mei, "Model predictive control–based load-frequency regulation of grid-forming inverter–based power systems," Frontiers in Energy Research, vol. 10, p. 932788, 2022.

[15] A. Lunardi, E. Conde, J. Assis, L. Meegahapola, D. A. Fernandes, and A. J. Sguarezi Filho, "Repetitive predictive control for current control of grid-connected inverter under distorted voltage conditions," IEEE Access, vol. 10, pp. 16931-16941, 2022.

[16] N. Babu, "Adaptive grid-connected inverter control schemes for power quality enrichment in microgrid systems: past, present, and future perspectives," Electric Power Systems Research, vol. 230, p. 110288, 2024.

[17] K. Jha and A. G. Shaik, "A comprehensive review of power quality mitigation in the scenario of solar PV integration into utility grid," e-Prime-Advances in Electrical Engineering, Electronics and Energy, vol. 3, p. 100103, 2023.

[18] N. Ahmad, Y. Ghadi, M. Adnan, and M. Ali, "Load forecasting techniques for power system: Research challenges and survey," IEEE Access, vol. 10, pp. 71054-71090, 2022.

[19] H. Habbak, M. Mahmoud, K. Metwally, M. M. Fouda, and M. I. Ibrahem, "Load forecasting techniques and their applications in smart grids," Energies, vol. 16, no. 3, p. 1480, 2023.

[20] 黄超, 卜思齐, 陈麒宇, and 李晓虹, "元电力: 新一代智能电网," 发电技术, vol. 43, no. 2, pp. 287-304, 2022.

[21] H. Hou et al., "Review of load forecasting based on artificial intelligence methodologies, models, and challenges," Electric power systems research, vol. 210, p. 108067, 2022.

[22] J. Zhu, H. Dong, W. Zheng, S. Li, Y. Huang, and L. Xi, "Review and prospect of data-driven techniques for load forecasting in integrated energy systems," Applied Energy, vol. 321, p. 119269, 2022.

[23] W. Qiu et al., "Neural networks-based inverter control: modeling and adaptive optimization for smart distribution networks," IEEE Transactions on Sustainable Energy, vol. 15, no. 2, pp. 1039-1049, 2023.

[24] N. Mohammed and M. Ciobotaru, "Adaptive power control strategy for smart droop-based grid-connected inverters," IEEE Transactions on Smart Grid, vol. 13, no. 3, pp. 2075-2085, 2022.

[25] H. Safamehr, T. A. Najafabadi, and F. R. Salmasi, "Adaptive control of grid-connected inverters with nonlinear LC filters," IEEE Transactions on Power Electronics, vol. 38, no. 2, pp. 1562-1570, 2022.

[26] T. Falope, L. Lao, D. Hanak, and D. Huo, "Hybrid energy system integration and management for solar energy: A review," Energy Conversion and Management: X, vol. 21, p. 100527, 2024.

[27] F. Wang and Z. Nishtar, "Real-Time Load Forecasting and Adaptive Control in Smart Grids Using a Hybrid Neuro-Fuzzy Approach," Energies, vol. 17, no. 11, p. 2539, 2024.

[28] X. Wang, R. J. Hyndman, F. Li, and Y. Kang, "Forecast combinations: An over 50-year review," International Journal of Forecasting, vol. 39, no. 4, pp. 1518-1547, 2023.

[29] M. Jaramillo, W. Pavón, and L. Jaramillo, "Adaptive forecasting in energy consumption: A bibliometric analysis and review," Data, vol. 9, no. 1, p. 13, 2024.

[30] L. Zheng, H. Geng, and G. Yang, "Fast and robust phase estimation algorithm for heavily distorted grid conditions," IEEE Transactions on industrial electronics, vol. 63, no. 11, pp. 6845-6855, 2016.