Design of an integrated forecasting and scheduling model for power plants to balance solar and wind energy variability using real-time weather data

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ABSTRACT

The integration of variable renewable energy sources such as solar and wind creates challenges for power system stability and operational scheduling due to their intermittent characteristics. This study proposes an integrated forecasting and scheduling framework using real-time weather data for a hybrid renewable power system consisting of photovoltaic, wind, geothermal, and hydropower plants. Solar irradiance and wind speed data were collected using pyranometer and anemometer sensors and modeled using ARIMA for 24-hour-ahead forecasting. Based on AIC and BIC evaluation, ARIMA (2, 1, 2) and ARIMA (1, 1, 1) were selected for solar irradiance and wind speed forecasting, respectively. The forecasting results achieved MAPE values of 18.43% for solar irradiance and 14.12% for wind speed. The forecasted renewable outputs were integrated into a generation scheduling model, where geothermal power operated as a base-load unit and hydropower acted as a balancing source. The proposed scheduling strategy was evaluated through a 24-hour Newton-Raphson load flow simulation. Results showed that system power losses remained below 2% and bus voltage levels were maintained within acceptable limits, demonstrating reliable operation under fluctuating weather conditions.

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1. INTRODUCTION

Electricity has become a fundamental component of modern life, supporting residential, industrial, and economic activities. However, continued dependence on fossil fuel-based generation contributes significantly to greenhouse gas emissions and climate change [1]. Consequently, many countries, including Indonesia through its Net Zero Emission (NZE) 2060 target, are accelerating the integration of renewable energy sources such as solar and wind power [2]–[4]. Although renewable energy reduces carbon emissions, its weather-dependent nature introduces operational challenges for maintaining reliable and stable power system operation [5]. Solar and wind power generation is highly influenced by atmospheric conditions, creating uncertainty in maintaining the balance between power generation and demand. In systems with high renewable penetration, this intermittency may lead to voltage deviations, frequency instability, and inefficient generator dispatch. Therefore, renewable forecasting and its integration into operational scheduling are essential to maintain grid stability and energy security [6], [7]. Hydropower plants are well suited for load-following applications due to their fast-ramping capability, enabling compensation for sudden fluctuations in solar and wind generation [8]. Meanwhile, geothermal plants provide stable base-load generation that complements intermittent renewable sources [9]. Together, these plants play an important role in maintaining grid stability in hybrid renewable power systems. The geographic dispersion of generation and load centers may increase transmission losses and complicate power system operation, particularly in archipelagic countries such as Indonesia [10]. Therefore, renewable integration must be supported by effective scheduling strategies and coordinated load flow analysis to ensure operational efficiency and system reliability [11], [12].

Recent studies on renewable-integrated power systems have shown significant progress in the development of forecasting and scheduling methodologies. Various renewable energy forecasting approaches have been widely explored, including statistical time-series models such as ARIMA [13]. In parallel, research on power system scheduling has focused on optimizing generator dispatch in systems with high penetration of intermittent energy sources using approaches such as economic dispatch, unit commitment, and heuristic optimization methods [14]. Several scheduling studies also continue to rely on deterministic or predefined renewable generation data for operational analysis [15]. Furthermore, machine learning techniques [16] and hybrid forecasting models that combine multiple predictive algorithms [17] have demonstrated strong capability in capturing temporal patterns of solar irradiance and wind speed, making them valuable tools for predicting renewable power output. However, despite these advancements, several critical gaps remain in the existing literature. First, most studies still treat renewable energy forecasting and power system scheduling as separate problems, resulting in a lack of integrated frameworks that can directly translate forecast outputs into practical dispatch decisions for balancing power plants [13], [14]. Second, many scheduling approaches continue to rely on deterministic or predefined input data, which do not adequately capture the real-time variability and uncertainty inherent in solar and wind generation [15]. Third, only a limited number of studies have investigated the combined impact of forecast-based scheduling on overall power system performance, particularly in terms of voltage stability and transmission losses under dynamic operating conditions[18]–[20]. These limitations indicate that existing methodologies are not yet fully capable of supporting real-time, data-driven decision-making in renewable-integrated power systems. Therefore, further research is required to develop a comprehensive approach that integrates forecasting, scheduling, and system-level analysis within a unified operational framework. This is particularly important in modern power systems where renewable sources are predominantly interfaced through power electronic converters, which require coordinated operational scheduling and system-level evaluation.

Despite these advancements, several critical research gaps remain. First, most studies still treat renewable energy forecasting and power system scheduling as separate problems, resulting in a lack of integrated frameworks that directly translate forecast outputs into dispatch decisions. Second, many scheduling approaches continue to rely on deterministic renewable generation data that do not adequately represent real-time variability. Third, only limited studies have evaluated the system-level impacts of forecast-based scheduling, particularly in terms of voltage stability and transmission losses. These gaps motivate the development of the integrated forecasting, scheduling, and load flow framework proposed in this work. Specifically, this work addresses these gaps by integrating ARIMA-based renewable energy forecasting with hydro-geothermal generation scheduling and validating the resulting dispatch strategy through 24-hour Newton–Raphson load flow analysis within a unified operational framework.

In light of these needs, this research aims to design a practical model that supports the scheduling of balancing power plants in response to real-time variability in solar and wind energy generation. The model employs the ARIMA method to predict hourly solar irradiance and wind speed using three days of historical weather data, which are then converted into power output forecasts for photovoltaic (PV) and wind power plants. These forecasts form the basis for constructing a generator dispatch schedule, where hydropower plants act as load-followers and geothermal plants serve as stable base-load units operating at 40% capacity. This configuration is particularly relevant to the Indonesian power system, where abundant hydropower and geothermal resources provide significant flexibility and stable generation to complement the increasing penetration of intermittent solar and wind energy. Subsequently, a 24-hour load flow simulation is conducted using software to assess the effects of this scheduling strategy on voltage levels and power losses across the system. Through this integration of forecasting, scheduling, and simulation, the work establishes a closed-loop operational framework for renewable-integrated power system analysis, particularly relevant for power electronic-based renewable generation systems.

The main contribution of this work is the development of an integrated operational framework that combines ARIMA-based renewable forecasting, balancing power plant scheduling, and 24-hour load flow validation within a single workflow. Unlike recent integrated frameworks that commonly employ advanced machine learning or optimization techniques, the proposed framework emphasizes a simple, computationally efficient, and reproducible approach that directly translates renewable forecasts into dispatch decisions and evaluates their impacts through system-level load flow analysis. Rather than proposing a new forecasting algorithm, this work demonstrates how short-term renewable forecasting can be effectively integrated with operational scheduling and power system evaluation for renewable-integrated power systems.

2. METHOD

This work adopts an integrated experimental and simulation-based approach to develop a forecasting-based generation scheduling framework for renewable-integrated power systems. The experimental component involves real-time acquisition of solar irradiance and wind speed data using a SEM228A pyranometer and a VMS-3000-FSJT-N01 anemometer connected to a Raspberry Pi 3 Model B+ system, with measurements recorded at hourly intervals over 72 hours and stored in CSV format. The dataset, characterized by short-term temporal variability, is preprocessed through timestamp alignment and consistency checks before being used for forecasting. In addition to the measured data, standard technical parameters of photovoltaic and wind turbine systems, as well as a representative 24-hour load profile derived from typical distribution demand patterns, are incorporated. The implementation utilizes Python for data processing and ARIMA modeling, Microsoft Excel for generation scheduling, and power system simulation software based on the Newton–Raphson method for load flow analysis. This integrated design is specifically intended to address the gap in existing studies that treat forecasting and operational scheduling separately by combining both within a unified, reproducible, and computationally lightweight framework. The use of low-cost sensing hardware, statistical forecasting, and widely available software tools makes the proposed workflow accessible for practical implementation, particularly in resource-constrained and developing-country environments.

The overall procedure is structured as a sequential workflow consisting of data acquisition, forecasting, power conversion, scheduling, and system evaluation. Time-series forecasting is performed using the ARIMA model, with parameters determined through stationarity testing (ADF) and ACF/PACF analysis, to generate 24-hour-ahead predictions of solar irradiance and wind speed. The predicted variables are then converted into electrical power outputs using standard photovoltaic and wind turbine models incorporating operational constraints such as rated capacity and cut-in/cut-out conditions. A rule-based scheduling algorithm is subsequently applied to satisfy the power balance constraint, where geothermal generation operates as a base-load unit, and hydropower dynamically compensates for residual demand. The resulting dispatch is evaluated using load flow analysis on a 14-bus system employing the Newton–Raphson method to assess voltage profiles and transmission losses. Validation is conducted through both statistical and technical evaluation, including AIC and BIC for model adequacy, while system performance is assessed based on voltage limits (typically within ±5% of nominal values), transmission losses, and the ability of the system to maintain supply–demand balance. This integrated forecasting–scheduling–evaluation framework provides a clear and reproducible methodology that directly links data-driven prediction with operational decision-making and system-level validation.

2.1. Forecasting of renewable energy output

The first stage in the proposed methodology involves forecasting the output power from solar and wind power plants based on real-time weather parameters. Two primary environmental variables, solar irradiance and wind speed, are utilized due to their direct influence on photovoltaic (PV) and wind turbine generation performance. Solar irradiance (measured in W/m²) determines the energy received per unit area on a solar panel, while wind speed (measured in m/s) governs the kinetic energy available to drive wind turbine blades [21], [22]. These parameters are measured using a pyranometer and an anemometer, respectively, installed in the field for continuous data acquisition. The real-time data collection system is designed to record readings at regular intervals, enabling accurate short-term forecasting through time series modeling.

The hardware implementation of the data acquisition system is based on a Raspberry Pi 3 Model B+, a compact and energy-efficient single-board computer well-suited for environmental monitoring applications. This device is responsible for interfacing with the pyranometer and anemometer via GPIO and serial communication protocols. The pyranometer model used in this work is the SEM228A, which offers high sensitivity and reliable performance under varying solar conditions. For wind measurement, the VMS-3000-FSJT-N01 anemometer is employed, capable of capturing a broad range of wind speeds with good accuracy and response time. The complete sensor network is integrated through the Raspberry Pi, powered by a regulated supply and housed in a weather-protected enclosure. A schematic diagram of the full measurement system, including sensor placement and wiring configuration, is illustrated in Figure 1.

To support autonomous operation and data logging, a custom Python-based script was developed and executed within the Raspberry Pi operating environment. The program is responsible for reading sensor values, converting analog signals to digital format if necessary, and saving the results into a structured CSV file. The script also includes timestamp generation to enable consistent and chronological alignment of readings, which is crucial for time series analysis. While the software implementation is relatively lightweight, it supports robust data handling for subsequent processing stages. The simplicity and portability of the setup ensure that the system can be deployed in remote areas with minimal maintenance requirements.

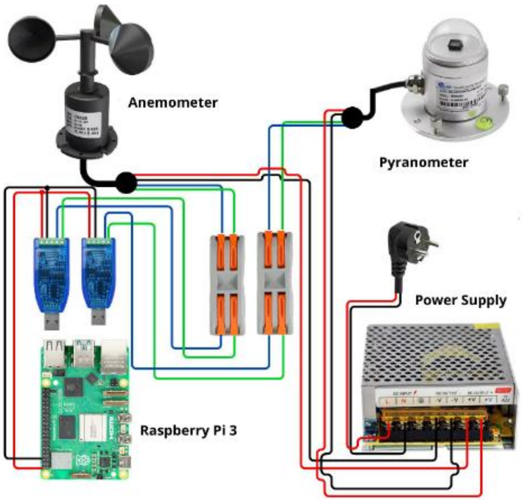


Figure 1. Schematic diagram of the measurement system

After gathering three days (72 hours) of historical solar irradiance and wind speed data, the next step involves forecasting the expected values for the subsequent 24 hours on an hourly basis. The three-day (72-hour) dataset was selected to support short-term operational forecasting, where the objective is to capture recent weather patterns for the subsequent 24-hour scheduling horizon rather than to develop a generalized long-term forecasting model. The autoregressive integrated moving average (ARIMA) model is selected due to its effectiveness in modeling and predicting time series with short-term trends and stationary behavior. The ARIMA model is formulated as a combination of autoregressive and moving average components applied to differenced time-series data. The general expression is given in (1) [23].

$$y_t = \alpha_1 y_{t-1} + \dots + \alpha_p y_{t-p} + e_t - \theta_1 e_{t-1} - \dots - \theta_q e_{t-q} \tag{1}$$

To apply the ARIMA model, the historical data must first be tested for stationarity using the Augmented Dickey-Fuller (ADF) test. If the data is found to be non-stationary, differencing is applied until the time series becomes stationary, thus determining the parameter d in ARIMA (p, d, q). The autocorrelation function (ACF) and partial autocorrelation function (PACF) plots are then analyzed to identify suitable values of p and q. Once the model parameters are selected, the ARIMA model is trained and used to forecast future values of solar irradiance and wind speed. The accuracy of the forecasts is evaluated using standard statistical indicators such as the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), which guide model selection by penalizing overfitting.

In this work, ARIMA is selected as a baseline statistical forecasting model due to its simplicity, interpretability, and low computational cost. Although more advanced approaches such as machine learning and hybrid forecasting models have been reported in the literature, this work focuses on a lightweight and reproducible method suitable for real-time operational scheduling with limited data availability. A comparative implementation of alternative models is identified as a direction for future work to further evaluate forecasting robustness and computational efficiency.

The photovoltaic power output is estimated based on a linear irradiance-to-power relationship under standard test conditions. The simplified conversion model assumes constant temperature and efficiency conditions, making it suitable for hourly-scale forecasting, as expressed in (2) [24].

$$P_{out} = \begin{cases} P_{max}\ x\ \frac{G}{G_{STC}}, & \text{if } G < G_{STC} \\ P_{max}, & \text{if } G \geq G_{STC} \end{cases} \tag{2}$$

In this work, the PV conversion assumes standard test conditions (STC) with a rated capacity of 2 MW, constant module efficiency, and constant operating temperature. Temperature-dependent derating and efficiency variations are intentionally neglected to maintain a simplified power conversion model that is suitable for evaluating the proposed forecasting–scheduling framework rather than detailed PV performance.

Wind turbine output is modeled using a piecewise function based on cut-in, rated, and cut-out wind speeds, as defined in (3) [25].

$$P_{out} = \begin{cases} 0, & \text{if } V < V_{cut-in} \\ P_{rated}\ x \left(\dfrac{V^3 - V_{cut-in}^3}{V_{rated}^3 - V_{cut-in}^3}\right), & \text{if } V_{cut-in} \leq V < V_{rated} \\ P_{rated}, & \text{if } V_{rated} \leq V \leq V_{cut-out} \\ 0, & \text{if } V > V_{cut-out} \end{cases} \quad (3)$$

The wind turbine model assumes a rated capacity of 5 MW, a cut-in wind speed of 3 m/s, a rated wind speed of 12 m/s, and a cut-out wind speed of 25 m/s. These parameters are adopted as fixed operational characteristics throughout the simulation to provide a consistent basis for renewable power conversion.

The combination of real-time environmental monitoring, statistical forecasting using ARIMA, and deterministic conversion to electrical power forms the foundation for the next step in this research: generation scheduling of balancing power plants. The predicted power profiles of PV and wind generators serve as primary input for dispatch planning, where hydropower and geothermal units are allocated accordingly to maintain power balance across the system.

2.2. Generation scheduling based on forecasted output

Once the hourly forecasts for solar and wind power output are obtained, the next stage in the methodology involves determining the operational schedule of the balancing power plants, namely the hydropower plant and the geothermal power plant. The main objective of this scheduling process is to ensure that electricity generation meets the hourly system demand reliably and efficiently. The forecasted power outputs from the photovoltaic (PV) and wind power plants are considered as variable, non-dispatchable sources due to their dependence on weather conditions. On the other hand, the hydropower plant is used as a flexible, dispatchable unit capable of adapting to fluctuations in real time, while the geothermal power plant is scheduled as a base-load generator operating steadily at 40% of its maximum capacity. This approach ensures that the balancing generation can respond appropriately to the residual demand that cannot be met by renewable sources. Accordingly, the proposed scheduling procedure is intended as a proof-of-concept to demonstrate the integration of renewable forecasting, operational scheduling, and power system evaluation, rather than to replace optimization-based scheduling methods.

To carry out this scheduling task, Microsoft Excel is used as a practical computational tool. Rather than serving as an optimization platform, Excel was selected to provide a transparent, low-complexity, and easily reproducible implementation of the proposed scheduling procedure. Its tabular format and ease of calculation make it suitable for operational planning in early-stage studies. The Excel sheet is organized with 24 columns representing each hour of the day, and rows allocated for each generation unit: photovoltaic, wind, geothermal, and hydropower plants. The first step involves entering the hourly forecasted power outputs from PV and wind plants obtained from the ARIMA-based forecasting model. The geothermal plant is assigned a constant output of 40% of its rated capacity, representing base-load operation. A standard daily load profile derived from historical system data is then introduced. The next step involves calculating the remaining load that must be covered by the hydropower plant. This is done by subtracting the total output of the photovoltaic, wind, and geothermal plants from the load demand at each hour. The generation scheduling is formulated based on the power balance constraint, which ensures that total generation meets system demand at every time step. The scheduling relationship is defined in (4):

$$\text{Load Demand} = \text{PV Output} + \text{Wind Output} + \text{Geothermal Output} + \text{Hydropower Output} \quad (4)$$

The resulting values determine the exact amount of power that the hydropower plant must supply in order to maintain a balanced system. This equation represents the core scheduling formulation used in this work, where hydropower output is adjusted to compensate for the residual demand. The resulting generation schedule provides a complete 24-hour operational plan that aligns generation with demand on an hourly basis. The use of Excel allows for rapid iteration, easy updates, and transparent inspection of scheduling behavior, particularly the ramping of the hydropower plant to respond to renewable intermittency. The schedule clearly highlights hours of surplus or deficit in renewable generation and shows how dispatchable resources compensate accordingly. While this scheduling approach is straightforward, it establishes a systematic foundation that can be further enhanced with optimization techniques in future work. Moreover, the outputs from this stage, specifically the dispatch levels of each generator, are used in the subsequent phase, where a power flow simulation is conducted to validate the operational feasibility of the schedule and assess technical performance indicators such as voltage levels and transmission losses.

2.3. Power system evaluation using load flow analysis

The final stage of this work’s methodology involves the evaluation of the electrical power system's performance through load flow analysis, aimed at testing the operational feasibility of the forecast-based scheduling strategy. Load flow analysis is essential for determining steady-state operating conditions, such as bus voltages, power flows, and system losses, under given generation and load scenarios. The simulation is structured around a 14-bus system network that incorporates all relevant system components, including generation units, transmission lines, transformers, and load centers. This network serves as a representative model to assess whether the hourly scheduled power injections from different generation sources can be technically accommodated within the constraints of voltage and current limits.

The system model is constructed by defining the topology and parameters of each electrical component. The buses are configured to represent different load and generation nodes, while transmission lines are modeled based on assumed or typical impedances suitable for medium-voltage distribution systems. Transformers are included to simulate voltage level transitions, particularly for integrating renewable energy sources which may be connected at lower voltage levels. Each generator is assigned to a specific bus based on practical connection points, with their hourly power outputs defined by the results from the forecasting and scheduling stages. The photovoltaic and wind power plants are modeled with time-varying power injection, while the geothermal power plant is set to provide constant output. The hydropower plant's generation is adjusted hourly to balance the net load, acting as a dispatchable unit. An overview of the modeled system architecture is illustrated in Figure 2, which presents the single-line diagram (SLD) of the 14-bus system network.

The 14-bus network represents a simplified transmission–distribution power system designed to capture the essential characteristics of renewable-integrated operation. The transmission level accommodates the wind power plant, geothermal plant, hydropower plant, and a representative transmission load, while the distribution level includes the photovoltaic power plant and several distributed load buses. This simplified configuration enables the coordinated evaluation of power transfer between transmission and distribution networks while maintaining a computationally efficient test system suitable for validating the proposed forecasting-based scheduling framework. The adopted electrical parameters, including representative line impedances, transformer ratings, and bus voltage bases, were kept constant throughout all simulation scenarios to ensure a consistent evaluation of the proposed scheduling framework.

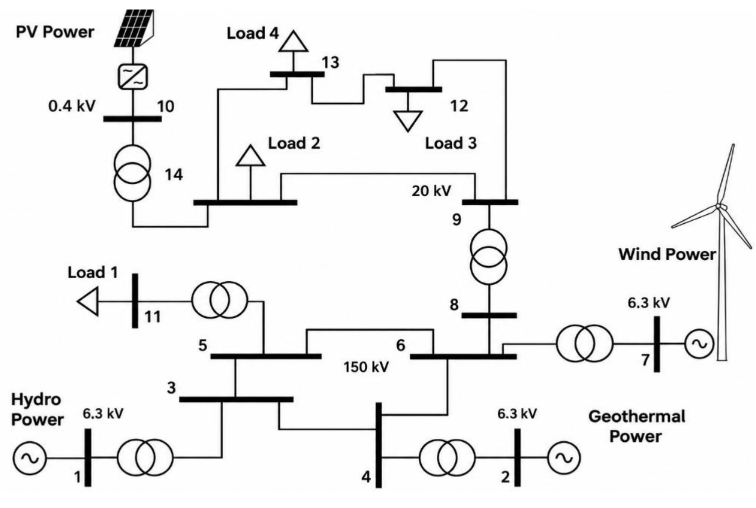


Figure 2. Single-line diagram of the 14-bus system

The simulation process involves running 24 separate load flow analyses, one for each hour of the day, corresponding to the hourly forecast and dispatch schedule. For every simulation, bus voltages, line currents, active and reactive power flows, and real power losses are calculated. The analysis is conducted using the Newton-Raphson method, which offers high accuracy and convergence speed for power flow problems. The setup also includes system-wide constraints such as voltage limits (typically ±5% from nominal voltage), thermal limits of transmission lines, and generator operating boundaries. These constraints are embedded within the simulation to ensure that each hour’s operating point remains within safe and feasible limits. By automating the simulations for all 24 hours, a full-day operational profile is constructed for the modeled system, enabling further evaluation in later stages.

Throughout the simulation setup, attention is given to maintaining consistency between the forecast-schedule data and the model inputs. All generator capacities, time-series outputs, and load values are preprocessed in Excel and as input data of program simulation for accuracy and traceability. Furthermore, all buses are labeled and organized systematically to track their behavior across different time intervals. Although the simulation results themselves are not interpreted in this section, the methodology ensures that sufficient data is generated for analyzing key performance metrics in the next phase of the research. The structured approach taken in this modeling and simulation stage ensures that technical validation of the forecast-driven schedule is grounded in standard power system practices and reflects realistic operating conditions.

3. RESULTS AND DISCUSSION

3.1. Results of renewable energy forecasting and conversion to power output

The forecasting process in this work begins with the real-time acquisition of environmental parameters, specifically solar irradiance and wind speed, using a custom-built measurement system. Real-time solar irradiance and wind speed data were collected using pyranometer and anemometer sensors integrated with a Raspberry Pi-based monitoring system. Hourly data were recorded continuously for three days and used for short-term forecasting analysis. The entire setup is enclosed in a protective, weather-resistant box to withstand field conditions. The forecasting system configuration is shown in Figure 3, where the Raspberry Pi-based monitoring unit and power supply were installed in a shaded and protected location, while the environmental sensors were placed outdoors to directly measure solar irradiance and wind speed. Figure 3(a) shows the Raspberry Pi-based monitoring unit and power supply system configured for continuous data acquisition and processing. Figure 3(b) presents the outdoor solar irradiance and wind speed sensors connected to the Raspberry Pi through cables for continuous data transmission and real-time environmental data collection. This configuration enables the system to continuously acquire and process environmental measurements under actual outdoor conditions.

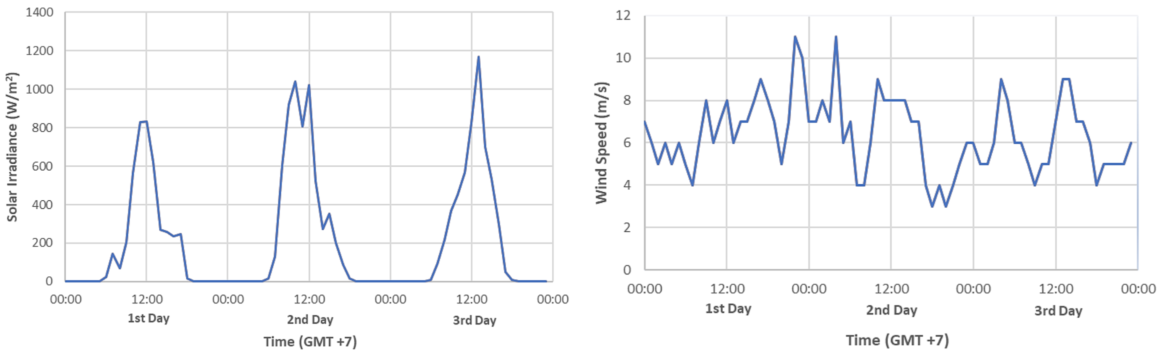
(a) (b)

Figure 3. Forecasting system: (a) the Raspberry Pi-based monitoring and power supply unit, and (b) the outdoor solar irradiance and wind speed sensors

Data were collected at hourly intervals for three consecutive days, forming the basis for time series forecasting. The irradiance profile exhibits a typical bell-shaped curve during daylight hours, peaking at noon and dropping to zero at night, while wind speed shows more erratic fluctuations throughout the day. These patterns are presented in Figure 4, which displays the historical data for both (a) solar irradiance and (b) wind speed. The historical data exhibit temporal variability in both solar irradiance and wind speed profiles over the observation period. Although the dataset is limited to three days of hourly measurements, it is considered sufficient for short-term forecasting aimed at operational scheduling, while longer datasets are recommended for improving generalization performance.

The ARIMA model was selected to forecast both solar irradiance and wind speed due to its ability to handle short-term, univariate time series data effectively. For each variable, several candidate models were evaluated using the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) to select the most suitable configuration. The results of the model selection process are summarized in Table 1(a) for solar irradiance and Table 1(b) for wind speed. Based on these criteria, ARIMA (2,1,2) was selected for solar irradiance, while ARIMA (1,1,1) was chosen for wind speed forecasting. The selected ARIMA configurations are consistent with the ACF/PACF diagnostic analysis and were further confirmed using the lowest AIC and BIC values among the evaluated candidate models.

Using the selected models, 24-hour forecasts were generated. These predictions were compared to the last 24 hours of observed data using quantitative error metrics, including MAE, RMSE, and MAPE, to ensure rigorous validation of forecasting performance. The comparison shows that the forecasted values generally follow the temporal trends observed in the historical data. The forecasting results show that ARIMA successfully captured the short-term variability of both renewable sources. The lower MAPE obtained for wind speed forecasting suggests that wind speed exhibited relatively smoother temporal variations during the observation period, allowing the ARIMA model to capture its trend more effectively. In contrast, solar irradiance showed a higher forecasting error because it is strongly influenced by rapidly changing cloud cover and atmospheric conditions, which may introduce abrupt fluctuations that are difficult to represent using a univariate statistical model. Since the ARIMA model relies solely on historical observations without incorporating exogenous meteorological variables, its capability to capture sudden irradiance changes is inherently limited. Nevertheless, the obtained forecasting accuracy remains adequate for the short-term operational scheduling objective considered in this study.



(a) (b)

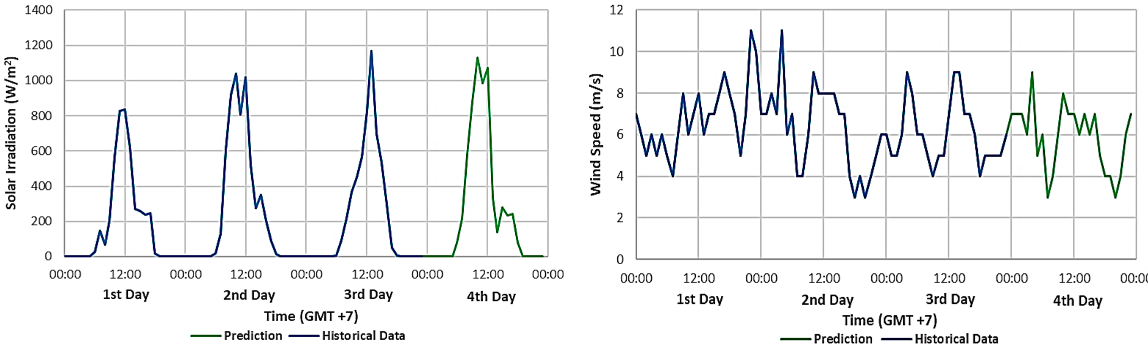
Figure 4. Historical data over three days: (a) historical solar irradiance and (b) historical wind speed

Table 1. AIC and BIC values for ARIMA models: (a) solar irradiance and (b) wind speed

	Model	AIC	BIC		Model	AIC	BIC
(a)	ARIMA (1,0,1)	531,5273	538,1816	(b)	ARIMA (1,0,1)	263,1602	272,2668
	ARIMA (1,1,1)	521,0581	525,9709		ARIMA (1,1,1)	261,6885	268,4766
	ARIMA (2,0,1)	516,7234	525,0412		ARIMA (2,0,1)	264,6240	276,0073
	ARIMA (1,0,2)	531,7503	540,0681		ARIMA (1,0,2)	264,7235	276,1068
	ARIMA (2,0,2)	518,6336	528,6150		ARIMA (2,0,2)	266,3069	279,9669
	ARIMA (2,1,1)	516,8584	523,4087		ARIMA (2,1,1)	263,1997	272,2504
	ARIMA (1,1,2)	522,9395	529,4898		ARIMA (1,1,2)	263,2997	272,3504
	ARIMA (2,1,2)	510,3167	518,5046		ARIMA (2,1,2)	264,9835	276,2969

To evaluate forecasting performance, the prediction results were validated using a historical validation approach by comparing the forecasted values with the last 24 hours of observed data. Forecasting accuracy was assessed using mean absolute error (MAE), root mean square error (RMSE), and mean absolute percentage error (MAPE). For solar irradiance forecasting, the obtained MAE and RMSE values were 112.75 W/m² and 185.65 W/m², respectively, with a MAPE value of 18.43%. Meanwhile, the wind speed forecasting produced MAE and RMSE values of 0.90 m/s and 1.03 m/s, respectively, with a MAPE value of 14.12%. These results indicate that the ARIMA models were capable of capturing the short-term temporal variability of solar irradiance and wind speed with acceptable forecasting accuracy for operational scheduling applications.

Although more advanced forecasting methods such as artificial neural networks (ANN), long short-term memory (LSTM), and hybrid models have demonstrated higher forecasting accuracy for large and highly nonlinear renewable energy datasets, the ARIMA model was intentionally adopted in this study because the available dataset consisted of only three days of hourly observations. Under such limited data conditions, ARIMA provides a simple, computationally efficient, and interpretable forecasting approach while still achieving acceptable prediction accuracy, as indicated by the obtained MAE, RMSE, and MAPE values. Since the objective of this study is to develop an integrated operational framework linking forecasting, scheduling, and power system evaluation, the forecasting accuracy achieved by ARIMA is considered sufficient to support the subsequent scheduling and load flow analyses. A comparison with simple baseline approaches, such as the persistence model, was not included in the present work because the primary objective was to demonstrate the feasibility of the integrated forecasting–scheduling framework rather than to benchmark forecasting algorithms. Such comparisons will be considered in future work. Figure 5 compares the historical observations and the corresponding ARIMA forecasting results for Figure 5(a) solar irradiance and Figure 5(b) wind speed over the 24-hour prediction horizon.

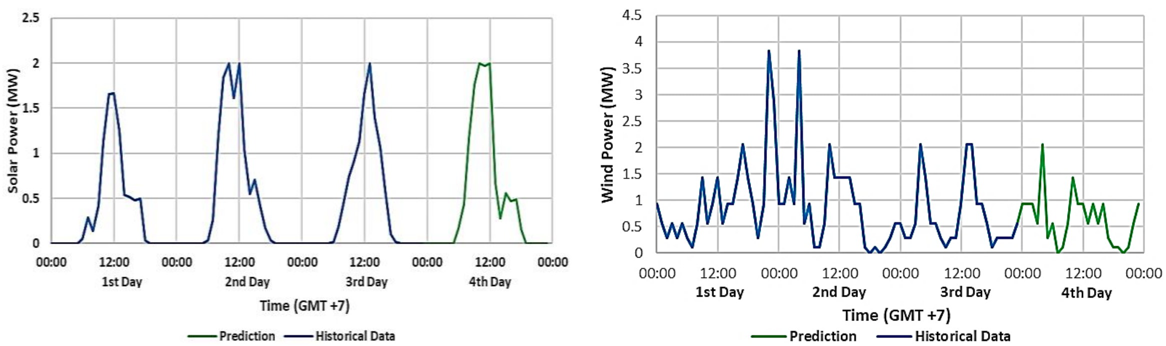


(a) (b)

Figure 5. Historical and predicted weather: (a) solar irradiation and (b) wind speed

All figures are presented with properly labeled axes and units to ensure clarity and interpretability. The historical and forecasted profiles are directly compared using time-series overlays to illustrate temporal alignment between predicted and observed values. Although normalized error plots are not explicitly included, forecasting performance is quantitatively evaluated using MAE, RMSE, and MAPE metrics, which provide standardized indicators of prediction accuracy.

The solar irradiance forecasts were then converted into electrical power output using a proportional method described in the methodology. Assuming standard test conditions (STC) with GSTC = 1000 W/m² and a photovoltaic (PV) system with Pmax = 2 MW, each hour's output was scaled linearly by the irradiance ratio. In this study, the conversion assumes constant operating conditions near STC with constant PV efficiency during the observation period. The resulting PV output forecast is shown in Figure 6(a), which indicates maximum generation near midday and near-zero output during evening and nighttime hours. For the wind power conversion, the predefined plant characteristics were used: a rated capacity of 5 MW, cut-in speed of 3 m/s, rated speed of 12 m/s, and cut-out speed of 25 m/s. Wind speeds below 3 m/s and above 25 m/s are considered non-operational, while speeds between 3 m/s and 12 m/s scale linearly to the rated capacity. The forecasted wind speeds predominantly fell within the effective generation range, allowing the wind power plant to deliver variable output throughout the 24 hours. The resulting predicted power output is presented in Figure 6(b), showing the temporal variation of wind power generation throughout the forecasting horizon.



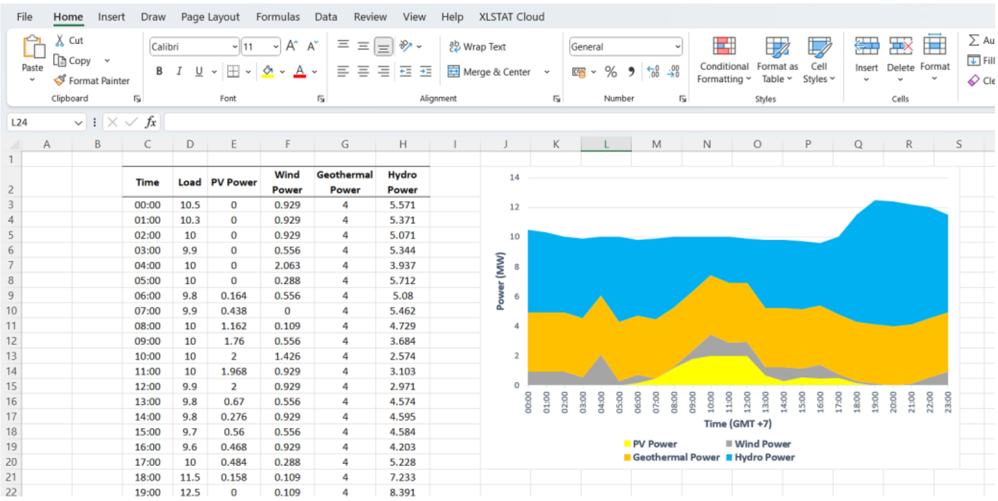
(a) (b)

Figure 6. Historical and predicted power: (a) solar power output and (b) wind power output

The forecasting results and converted renewable power outputs were subsequently used as inputs for the generation scheduling stage. The results indicate that the ARIMA-based approach was capable of capturing the short-term temporal variability of solar irradiance and wind speed, enabling more reliable estimation of renewable power availability. These forecasts formed the foundation for the subsequent scheduling and system evaluation stages, supporting proactive coordination between intermittent renewable generation and dispatchable power plants. This outcome directly addresses the research gap related to the limited integration between renewable forecasting and operational scheduling frameworks in power systems.

3.2. Generation scheduling results

Based on the forecasted power outputs from the photovoltaic and wind power plants, a 24-hour generation scheduling strategy was developed to maintain the balance between generation and load demand under varying renewable output conditions. The geothermal power plant was treated as a base-load unit, supplying a fixed output of 40% of its capacity throughout the day, while the hydropower plant was configured as a balancing generator to compensate for the mismatch between renewable supply and demand. The scheduling sheet was arranged in a tabular format, displaying hourly values for load demand, power generation from each plant, and the calculated requirement from the hydropower plant. This Excel-based approach is used as a simplified tool for modeling and does not represent a real-time implementation platform. Figure 7 presents a snapshot of the Excel-based scheduling matrix, which shows how each generator contributes to the hourly demand profile.



Time	Load	PV Power	Wind Power	Geothermal Power	Hydro Power
00:00	10.5	0	0.929	4	5.571
01:00	10.3	0	0.929	4	5.371
02:00	10	0	0.929	4	5.071
03:00	9.9	0	0.556	4	5.344
04:00	10	0	2.063	4	3.937
05:00	10	0	0.288	4	5.712
06:00	9.8	0.164	0.556	4	5.08
07:00	9.9	0.438	0	4	5.462
08:00	10	1.162	0.109	4	4.729
09:00	10	1.76	0.556	4	3.684
10:00	10	2	1.426	4	2.574
11:00	10	1.968	0.929	4	3.103
12:00	9.9	2	0.929	4	2.971
13:00	9.8	0.67	0.556	4	4.574
14:00	9.8	0.276	0.929	4	4.595
15:00	9.7	0.56	0.556	4	4.584
16:00	9.6	0.468	0.929	4	4.203
17:00	10	0.484	0.288	4	5.228
18:00	11.5	0.158	0.109	4	7.233
19:00	12.5	0	0.109	4	8.391

Figure 7. Generation scheduling developed in Excel

The load profile used in this study follows a typical daily demand curve, with moderate demand during early morning hours, a sharp increase around midday, and a gradual decline in the evening. The forecasted generation from the PV and wind plants, while substantial, is intermittent and unable to meet peak load on its own. The geothermal power plant provides consistent output, but it is not sufficient to fill the shortfall during high-demand periods. Therefore, the hydropower plant must adjust its output dynamically to ensure the demand-generation balance is maintained at each hour. The resulting scheduled hydropower output was computed by subtracting the sum of the other generators' outputs from the total hourly demand.

To visualize the overall behavior of the scheduling process, a stacked area chart was created to show the hourly contribution of each generator and the total system demand. This is shown in Figure 8, where the demand curve is overlaid with the generation curves of the PV, wind, geothermal, and hydropower plants. The chart clearly illustrates the variable nature of solar and wind generation, the steady contribution from the geothermal plant, and the compensatory role played by the hydropower plant, which ramps up and down as needed to fill the gap between demand and available renewable generation.

The scheduling results show the hourly coordination between renewable and dispatchable generation units under varying demand conditions. The balancing behavior of the hydropower plant is particularly crucial during early morning and late evening hours when solar generation is absent, demonstrating the importance of flexible generation in compensating for renewable intermittency. The results also show that accurate forecasting significantly influences the effectiveness of the scheduling strategy, since the dispatch plan depends directly on predicted renewable output. These findings indicate that the proposed integrated forecasting and scheduling framework can maintain generation-demand balance dynamically, thereby addressing the research objective of improving renewable energy integration in power system operation. The output of this scheduling step is used as an input for the subsequent power system simulation. In practical applications, this type of scheduling framework can be further developed toward real-time implementation in SCADA or EMS environments.

The scheduling results are inherently dependent on forecasting accuracy because the dispatch of the hydropower plant is directly determined by the predicted renewable generation. An overestimation of photovoltaic or wind power output would reduce the scheduled hydropower generation, potentially creating temporary supply deficits during actual operation. Conversely, underestimation of renewable generation would result in unnecessary hydropower dispatch and reduced utilization of available renewable energy. Although forecasting uncertainty was not explicitly quantified in this study, the proposed framework demonstrates how forecast information directly influences operational scheduling decisions, highlighting the importance of improving forecasting accuracy for future implementations.

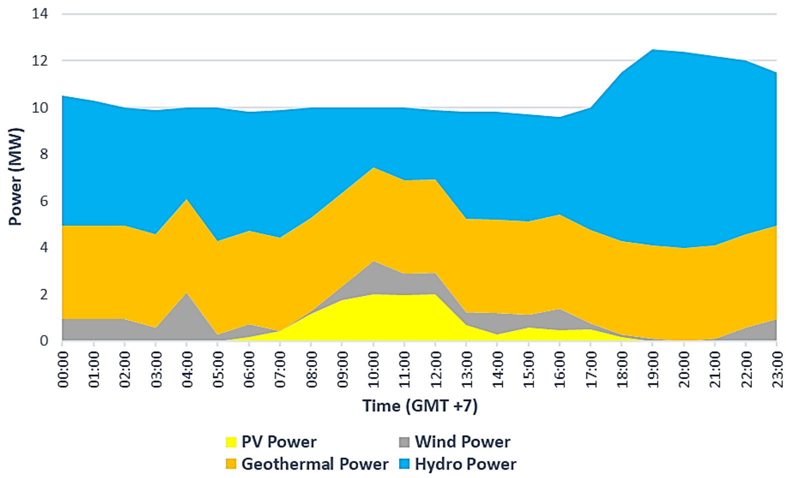


Figure 8. Hourly generation schedule showing demand and power plant contributions

3.3. Power system simulation results

The load flow simulation over a 24-hour cycle was conducted using the Newton-Raphson method to evaluate the operational feasibility of the proposed hybrid power system, which integrates intermittent renewable sources solar and wind with constant geothermal supply and a flexible hydropower plant. The goal was to determine how well the system could maintain voltage stability and minimize power losses while ensuring reliable energy delivery to meet hourly demand. The simulation was based on a generation schedule derived from short-term forecasting, reflecting realistic operating conditions.

To summarize the system's performance, four representative operational scenarios were selected: (1) maximum renewable generation (10:00), (2) minimum system load (16:00), (3) minimum renewable generation (20:00), and (4) peak demand period (19:00). The corresponding load flow results for each of these hours are presented in Table 2, which includes total system losses, percentage loss relative to total load, and the range of voltage levels observed across the system buses. Four representative operating conditions are presented to illustrate the system behavior under different renewable generation and loading scenarios. Complete hourly load flow outputs were generated during the simulation process; however, only representative cases are reported due to space limitations while still capturing the full range of observed operating conditions.

At 10:00, the system experienced its most favorable operating condition, driven by the high availability of solar and wind energy. During this hour, the hydropower plant operated at a reduced output, allowing the renewable sources to dominate generation. The total power loss was only 96.6 kW, accounting for 0.97% of the load, a strong indication of efficient transmission and minimal line congestion. Voltage levels across the network remained close to nominal, with a narrow range between 98.5% and 104.5%. In contrast, the scenario at 20:00 represents the most challenging condition. At this hour, solar output had dropped to zero, and wind contribution was minimal. Consequently, the hydropower plant ramped up significantly to meet demand. The system losses more than doubled compared to 10:00, reaching 228.3 kW, or 1.84% of the load. Voltage levels also deteriorated slightly, with the lowest value recorded at 96.2%, nearing the acceptable lower threshold for typical distribution systems. This illustrates the cost, both in terms of efficiency and power quality, of relying heavily on dispatchable resources during renewable shortfalls.

Table 2. Summary of load flow simulation results for key operating conditions

Condition	Power losses (kW)	Percentage of power loss to load consumption (%)	Lowest voltage (%)	Highest voltage (%)
Maximum PV and wind output (10:00)	96.6	0.97	98.5	104.5
Minimum load (16:00)	115.2	1.20	98.5	104.5
Minimum PV and wind output (20:00)	228.3	1.84	96.2	104.5
Peak load (19:00)	232.5	1.86	96.0	104.5

The simulation also captured performance under light load conditions at 16:00. Here, the demand was low, and solar generation was still moderately available. Despite this, losses reached 115.2 kW (1.20%), indicating that lower loads do not necessarily correlate with lower system losses, especially when generator dispatch and network impedance are not optimally balanced. Voltage levels remained relatively stable, further emphasizing the benefit of diversified power injection across the network. During the peak load condition at 19:00, the system was under significant pressure. Renewable input was declining, especially from solar PV, and wind speeds fluctuated. This required substantial contribution from the hydropower plant to maintain the supply-demand balance. Losses were the highest among all observed scenarios at 232.5 kW (1.86%), with the minimum voltage dropping to 96.0%. These results confirm the importance of timely hydropower response and underline the need for careful coordination between forecast accuracy and real-time dispatch.

The effectiveness of the proposed scheduling framework also depends on the operational flexibility of the hydropower plant. In this study, hydropower is assumed to have sufficient ramping capability to compensate for renewable fluctuations within each hourly scheduling interval. In practical systems, however, physical ramp-rate limitations, reservoir operating constraints, or water availability may reduce this flexibility. Under such conditions, delayed hydropower response could lead to temporary power imbalances, increased voltage deviations, or the need for additional balancing resources. Therefore, future studies should incorporate generator ramp-rate constraints and reserve requirements to evaluate the robustness of the proposed scheduling framework under more realistic operating conditions.

Evaluated across all 24 hours, the hybrid system demonstrated acceptable performance. Power losses stayed below 2% of total consumption a reasonable figure for systems with moderate geographic dispersion and renewable integration. Voltage levels remained within ±5% of nominal values throughout the day, confirming operational stability. The hydropower plant's flexibility proved critical in maintaining this balance, compensating effectively for the inherent variability of the solar and wind generators. The simulation results indicate that the system-maintained voltage levels within acceptable operating limits throughout the simulation period. More broadly, the simulation results highlight the value of combining real-time forecasting, responsive scheduling, and grid simulation tools in managing hybrid renewable systems. The integrated approach adopted in this study not only accommodates variability but also optimizes the role of dispatchable assets like hydropower. This synergy is essential for supporting high-penetration renewable energy transitions in modern power systems. These results indicate that the proposed framework is capable of supporting renewable-integrated power system operation within the assumptions of the adopted scheduling model and simulation environment, while maintaining acceptable voltage stability and system efficiency under the evaluated operating conditions.

From a quantitative perspective, the proposed system demonstrates low transmission loss levels ranging from 96.6 kW to 232.5 kW, corresponding to 0.97%–1.86% of total load demand. The system efficiency remains consistently above 98%, indicating efficient power delivery under varying renewable penetration levels. In terms of voltage performance, all bus voltages are maintained within 96.0%–104.5% of nominal values, which remains within the acceptable ±5% operational limit. These quantitative results confirm that the proposed scheduling framework is capable of maintaining both power quality and energy efficiency under highly variable operating conditions.

The satisfactory voltage performance is also influenced by the converter-interfaced operation of the photovoltaic and wind power plants. Under the assumptions adopted in this study, the grid-connected converters regulate active power injection according to the forecasted renewable generation while supporting stable grid integration. Consequently, variations in renewable output primarily affect the amount of dispatched power rather than causing significant voltage deviations, allowing the system to maintain bus voltages within acceptable operating limits throughout the simulation period.

Similar studies on renewable-integrated dispatch systems have also reported acceptable voltage regulation and loss levels under coordinated forecasting-based scheduling; however, most approaches evaluate either forecasting or dispatch separately without full system-level validation. The findings obtained in this study are consistent with previous studies reporting that renewable energy forecasting and power system scheduling are often treated as separate problems, resulting in limited operational integration between forecast outputs and dispatch strategies [13], [14]. In addition, previous scheduling approaches commonly rely on deterministic or predefined renewable generation data that cannot fully represent the real-time variability of solar and wind resources [15]. The results of this study demonstrate that the integration of real-time weather-based forecasting, generation scheduling, and load flow evaluation within a unified framework can support dynamic operational decision-making while maintaining acceptable voltage profiles and transmission losses. Furthermore, unlike previous works that mainly focus on forecasting accuracy or scheduling analysis independently, this study extends the existing literature by evaluating the system-level operational impact of forecast-based scheduling under varying renewable generation conditions [18]–[20].

The implications of these findings are both practical and technological for renewable-integrated power system operation. The proposed framework demonstrates that real-time renewable energy forecasting can be directly integrated with operational scheduling and system-level evaluation to support more adaptive and data-driven dispatch strategies. From a practical perspective, the coordinated use of hydropower and geothermal generation improves the capability of the system to accommodate renewable intermittency while maintaining acceptable voltage stability and transmission losses. In addition, the proposed approach provides a scalable foundation for future smart grid applications involving real-time monitoring, predictive energy management, and renewable energy integration under dynamic operating conditions.

In the Indonesian context, the proposed framework may be particularly applicable to isolated or weakly interconnected power systems where hydropower and geothermal resources are available to complement variable renewable generation. Day-ahead renewable forecasting can be used by system operators to prepare generation schedules before actual operation, allowing dispatchable hydropower resources to compensate for anticipated fluctuations in solar and wind output. Because the framework employs lightweight forecasting, spreadsheet-based scheduling, and conventional load flow analysis, it can also serve as a practical planning tool for utilities with limited computational resources while providing a foundation for future integration into more advanced energy management systems.

Despite the promising results, this work has several limitations. The forecasting model was developed using only three days of hourly observations and employed a univariate ARIMA approach that does not consider exogenous weather variables. In addition, the photovoltaic and wind power conversion models adopt simplified assumptions, including constant PV operating conditions and idealized wind turbine characteristics. The proposed scheduling framework is based on a rule-based dispatch strategy without economic optimization or uncertainty analysis, and the evaluation was performed on a representative 14-bus test system. Consequently, the scalability and robustness of the proposed framework under larger interconnected networks and more complex operating conditions require further investigation. Future work will address these limitations by incorporating longer datasets, advanced forecasting methods, optimization-based scheduling, and larger-scale power system models.

4. CONCLUSION

This work developed an integrated operational framework that combines real-time weather data acquisition, ARIMA-based renewable energy forecasting, generation scheduling, and power system simulation for hybrid renewable power systems. The proposed framework translates solar irradiance and wind speed forecasts into a 24-hour dispatch schedule involving photovoltaic, wind, geothermal, and hydropower plants, with hydropower serving as a flexible balancing resource. Forecast validation produced MAPE values of 18.43% for solar irradiance and 14.12% for wind speed, while load flow simulation confirmed satisfactory system performance, maintaining power losses below 2% and bus voltages within 96.0%–104.5% throughout the 24-hour operating period. The main scientific contribution of this work is the integration of renewable energy forecasting, operational scheduling, and system-level power flow evaluation into a unified workflow. Unlike previous studies that generally address forecasting and scheduling independently, the proposed framework directly links forecast outputs to dispatch decisions and validates their impact on system performance, providing a practical framework for evaluating renewable-integrated power system operation under the adopted modeling assumptions.

This work is limited by the use of a short forecasting dataset, simplified scheduling assumptions, and the absence of economic dispatch optimization and uncertainty analysis. In addition, the framework was evaluated on a 14-bus test system, which does not fully represent the complexity of large interconnected power networks. Future work should validate the framework using longer-term datasets, benchmark ARIMA against advanced forecasting methods such as LSTM and hybrid models, integrate optimal power flow or economic dispatch with battery energy storage systems (BESS), and evaluate its performance on larger transmission networks under real-time operating conditions. The proposed framework may also serve as a reproducible baseline for future studies on integrated renewable forecasting and generation scheduling, particularly for power systems with limited computational resources and in developing-country applications.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Novizon	✓			✓	✓					✓	✓			
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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
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Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that there is no conflict of interest regarding the publication of this research.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [S], upon reasonable request.

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