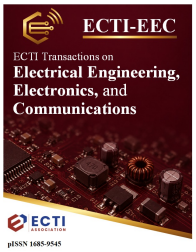
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IoT based Solar Power Forecasting cum Intelligent Scheduling Algorithm for Smart Microgrid System

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Abstract

To maintain reliability, cost-efficiency, and grid integration, solar-powered microgrids need accurate forecasting and effective scheduling. This study uses machine learning and optimization in an IoT framework to optimize solar PV microgrid scheduling with a Battery Energy Storage System (BESS). After smoothing solar and load data with a Kaufman Adaptive Moving Average (KAMA) and Infinite Impulse Response (IIR) filter, the forecasting module uses a Bidirectional Long Short-Term Memory (BiLSTM) network to accurately predict solar generation and load demand. A Mixed-Integer Linear Programming (MILP) model optimizes PV and BESS operations using these estimates to minimize costs and preserve energy balance and system stability. The suggested smart microgrid management solution is realistic and scalable since real-world data validates high forecasting accuracy and cost reduction. This study uniquely integrates financial time-series smoothing (KAMA), signal processing (IIR Filter), and deep learning-based sequence modeling (BiLSTM) to create a robust forecasting framework for Solar Power Generation and Load Demand prediction. These strategies have been used separately in various problems, but their combined use for renewable energy forecasting is novel. Solar-powered microgrids need precise forecasts and optimal scheduling to be reliable, cost-effective, and grid-integrated.

Keywords: Solar Power Forecasting, Smart Microgrid, Low-pass Adaptive Moving Average (LAMA), Kaufman's Adaptive Moving Average (LKAMA), Machine Learning (ML), Long Short-Term Memory (LSTM), Extreme Learning Machine (ELM).

I. Introduction

The penetration of distributed renewable energy, particularly solar photovoltaic (PV) systems, within smart grids is growing rapidly due to mounting environmental concerns and advances in clean energy technologies. Solar power, while clean and inexhaustible, exhibits inherent intermittency and variability, complicating efforts to maintain grid stability and cost-effective operation. In this context, solar-powered microgrids, i.e., clusters of photovoltaic generation, energy storage, and controllable loads, have emerged as promising solutions by offering flexibility and resilience. However, their reliability and economically efficient operation critically depends on two interlinked components: accurate forecasting of solar generation and load demand, and robust scheduling of resources such as battery energy storage systems (BESS) and grid exchange, as shown in Fig. 1 .

Machine Learning for Solar & Load Forecasting: Machine learning (ML) and deep learning techniques have shown marked improvements over conventional statistical or physical models in short-term solar irradiation and PV output forecasting. Recurrent neural networks (RNNs), especially Long Short-Term Memory (LSTM) architectures, are particularly effective for capturing temporal dependencies and adapting to non-linear patterns in solar and load time-series data. For example, Tang *et al.* applied an attention-based convolutional network with BiLSTM and achieved significant gains in PV output forecasting accuracy. Similarly, Lim *et al.* and Wang *et al.* demonstrated that hybrid CNN-LSTM models enhanced performance for short-term solar irradiance prediction.

However, preprocessing remains crucial due to the noisy and non-stationary nature of raw PV and load data . Our proposed pipeline combines the Kaufman Adaptive Moving Average (KAMA) and an Infinite Impulse Response (IIR) filter to smooth the data before feeding it into a BiLSTM network. This aims to isolate meaningful trends, reduce high-frequency

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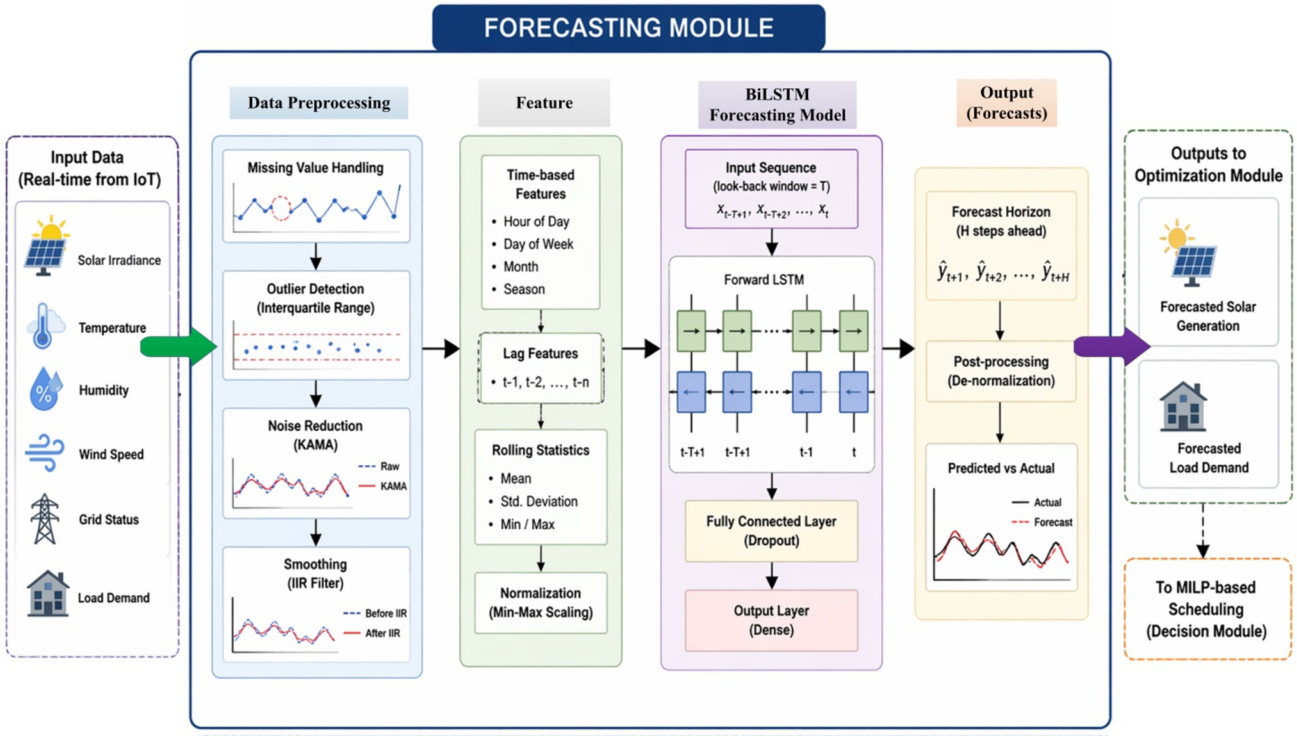


Fig. 1. Architecture of the proposed IoT-enabled forecasting module with KAMA–IIR preprocessing and Bidirectional Long Short-Term Memory-based prediction..

fluctuations, and enhance model operationalization in diverse weather conditions.

Optimization of Microgrid Scheduling with BESS: Predictive accuracy is essential not only for forecasting but also for enabling effective operational scheduling. Optimal scheduling in microgrids involves coordinating PV generators, BESS, and grid resources to meet demand while minimizing costs and maintaining reliability. Mixed-Integer Linear Programming (MILP) is widely adopted to model such problems with detailed system constraints and scheduling horizons.

Recent research has integrated ML-driven forecasting into MILP-based scheduling. Choi et al. developed a robust scheduling framework that combined GAN-based solar forecasting with BESS dispatch, driving revenue increases and grid incentives. Sun et al. implemented a microgrid dispatch using multi-objective bat algorithms informed by forecasted wind and solar generation via Gaussian process regression. Li et al. introduced adaptive rolling-horizon scheduling using LSTM-generated forecasts to optimize charging of electric vehicles in microgrids. These studies demonstrate how forecast-driven optimization enhances both economic performance and system resiliency.

Integrated BESS Scheduling for Economic & Reliable Microgrids: Coordinated dispatch of PV, BESS, and loads in microgrids presents a multi-objective optimization challenge involving cost minimization, battery lifecycle management, and grid support . The presence of forecasting uncertainty further complicates the task. Choi *et al.* tackled this by embedding forecast-error resilience within the MILP model. The combination of accurate forecasting and robust optimization enables microgrids to maintain performance under variability, optimizing charging/discharging, shaving peak demand, and reducing exchange costs with the main grid.

Contributions of This Work: Existing LSTM–MILP and CNN–LSTM frameworks often rely on conventional preprocessing and treat forecasting and Mixed-Integer Linear Programming scheduling as loosely coupled stages, leading to error propagation and limited adaptability. Moreover, most studies are evaluated on static datasets, limiting their real-time applicability. To address these gaps, this work proposes an IoT-enabled, end-to-end integrated framework with a cross-domain preprocessing approach using the Kaufman Adaptive Moving Average and the Infinite Impulse Response filter, followed by the Bidirectional Long Short-Term Memory and tightly coupled Mixed-Integer Linear Programming optimisation. This design improves forecasting accuracy and enables adaptive real-time scheduling. Building on these insights, this paper proposes a comprehensive IoT-enabled framework for solar microgrid scheduling that combines advanced forecasting with optimal dispatch.

1. **Two-stage preprocessing (KAMA + IIR)** to smooth solar and load data, reducing volatility and enhancing signal clarity.
2. **BiLSTM forecasting,** leveraging cleaned data to predict short-term solar output and demand with improved accuracy.
3. **MILP-based scheduling** using forecasted signals to optimally dispatch PV, BESS, and control grid exchange, subject to operational and economic constraints.
4. **Validation on real-world,** data showing improved fore-

casting metrics (MAE, MAPE) and optimized dispatch results—highlighting cost savings, reliability improvements, and smart-grid integration.

This integrated methodology advances state-of-the-art solar microgrid operation by tightly coupling ML-driven time-series forecasting and optimization. It enables data-driven decisions that enhance economic viability and grid reliability, supporting the broader adoption of intelligent microgrid systems for sustainable energy infrastructure.

II. LITERATURE REVIEW

Load forecasting and energy management in solar-driven microgrids have been significantly enhanced by recent advancements in artificial intelligence (AI) and machine learning (ML). Researchers have investigated several hybrid and adaptive modeling techniques to deal with the unpredictability of solar output and changing consumer demand. For example, in order to improve prediction accuracy and resilience under changeable irradiance conditions, a CNN-RNN hybrid deep learning model was created for multi-step load forecasting. In this model, CNNs capture spatial dependencies and RNNs model temporal dynamics [1]. In order to optimise microgrid scheduling, a predictive control framework was developed that incorporates forecasts based on deep learning. This framework effectively enhances energy efficiency and cost-effectiveness [2] .

Reinforcement learning (RL) and probabilistic load forecasting have been used to develop adaptive energy management systems that can handle uncertainty on the fly. By improving operational stability, energy efficiency, and supply-demand balancing, these techniques outperform traditional rule-based systems [3-5]. Furthermore, a bidirectional LSTM model developed for solar-assisted microgrids has proven to be quite accurate in both its predictions and its temporal consistency, two qualities that are crucial for reducing the need for energy storage and making the most efficient use of generation resources [1].

For real-time load prediction, Islam and Hossain [6] introduced a hybrid LSTM-PSO model that, in particular for isolated microgrids with limited storage, improves accuracy and decreases energy losses. For adaptive forecasting, other research has investigated CNN-LSTM hybrid architectures, which allow systems to respond well to non-stationary consumption trends and provide robust scheduling and balancing. A complementary advancement is the implementation of multi-agent energy management systems, which utilise AI-driven decentralised control to orchestrate distributed resources by utilising forecasted load data. This approach enhances grid autonomy and resilience [7]. Furthermore, robust optimisation frameworks have been developed to incorporate uncertainty in solar irradiance and load. These frameworks have resulted in dispatch and sizing methods that are viable in a variety of operating scenarios [8].

Furthermore, there are day-ahead scheduling methods that integrate predictive modelling with uncertainty-aware optimisation to increase economic benefit and reliability in solar microgrids [10], and a Grey Wolf Optimiser (GWO) that is integrated with GRU-based forecasting to decrease computational complexity and increase scheduling efficiency [9]. Forecasting using ensemble learning approaches has also been popular, frequently in conjunction with appropriate battery sizing, to improve storage utilisation and system reliability [5]. In order to improve energy matching in the long run, smart controllers that rely on online learning can adapt even more by constantly updating their forecasting models to follow changing load profiles [11].

Implementing spatiotemporal load forecasting has improved planning and infrastructure design by considering both the spatial and temporal variability of demand. This has allowed for the cost-efficient deployment of solar microgrid infrastructure [12]. Other methods that protect users' privacy have also evolved; for example, federated learning-based energy management allows for distributed PV system scalability and decentralised forecasting without compromising user privacy [13]. Improved real-time scheduling responsiveness is made possible by Transformer-based neural networks, which have recently been proposed for short-term load forecasting and outperform conventional recurrent designs in terms of accuracy and computing efficiency [14].

III. FORECASTING MODEL & PROBLEM STATEMENT

Optimizing microgrid performance requires highly accurate forecasts of solar power production and consumer demand. To accomplish this, sophisticated forecasting algorithms need to take into account a plethora of variables, such as the current time, the weather, and the patterns of user load. The models can detect demand trends, underlying patterns, and seasonal fluctuations since they are trained on preprocessed information of building energy usage and solar output.

Solar power forecasting typically relies on environmental variables—such as irradiation, weather patterns, temperature, and rainfall—alongside prior generation figures. In contrast, building load forecasting focuses on temporal markers like the hour, day, and month, combined with historical usage trends.To further enhance the accuracy of forecasts, ambient temperature is now used as an extra parameter. A BiLSTM, or Bidirectional LSTM, is a type of recurrent neural network (RNN) that reads data in both forward and backward directions, unlike standard LSTMs that only process sequences from past to future. By considering information from both sides of a sequence, BiLSTMs capture deeper context, making them highly effective for tasks such as natural language processing where understanding meaning depends on both previous and upcoming words. The projects data flow and overall system design are shown in Fig. 2.

This work adopts a unique preprocessing strategy that combines the Kaufman Adaptive Moving Average (KAMA) and an Infinite Impulse Response (IIR) filter to enhance the quality of time-series data prior to forecasting. KAMA, originally developed for financial time-series analysis, provides adaptive smoothing by dynamically adjusting its responsiveness based on signal volatility, thereby enabling effective trend extraction and initial noise reduction. In contrast, IIR filters, widely used

in digital signal processing, are computationally efficient and well suited for precise frequency response shaping.

In the proposed hybrid preprocessing framework, KAMA is first applied to the raw signal to suppress noise while preserving significant trends and abrupt changes. The output of the KAMA stage is subsequently processed using a low-pass IIR filter, to further attenuate high-frequency components or isolate specific frequency bands relevant to the application. This sequential combination leverages the complementary strengths of both techniques, resulting in robust noise reduction through adaptive smoothing and efficient, targeted frequency-domain filtering. While IIR filters may introduce non-linear phase distortion, this limitation can be mitigated, where necessary, using zero-phase filtering techniques available in standard signal processing toolkits.

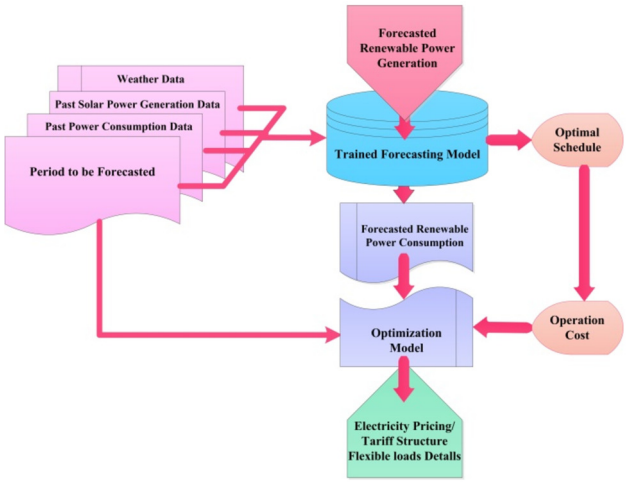


Fig. 2. Optimisation model input parameters, including forecasting model output.

A. Kaufman Adaptive Moving Average (KAMA) Filtering

For the purpose of preprocessing, the raw time-series data of Solar PV power and load demand are smoothed using the Kaufman Adaptive Moving Average (KAMA). Adapting to both steady and rapidly changing settings, KAMA dynamically modifies its smoothing coefficient based on the signal-to-noise ratio, unlike conventional moving averages. This is an improvement over exponential or simple moving averages, which tend to smooth out extreme fluctuations too much or keep too much noise. Instantaneous changes, such those caused by sporadic cloud cover, are easily captured by KAMA because it selectively filters out random oscillations while retaining significant signal patterns.

B. Infinite Impulse Response (IIR) Filtering

Utilising a low-pass Infinite Impulse Response (IIR) filter, the signals are further refined following KAMA smoothing. A major concern for real-time microgrid applications is the computational cost. IIR filters offer comparable filtering performance with much fewer coefficients compared to Finite Impulse Response (FIR) filters, which is a huge plus. In addition, IIR filters' feedback mechanism allows for a more precise frequency response, which in turn allows for a more efficient reduction of high-frequency noise that persists beyond the KAMA stage. That way, for future forecasting purposes, the signal will only contain the pertinent time dynamics of PV generation.

C. Bidirectional Long Short-Term Memory (BiLSTM) Forecasting

A Bidirectional Long Short-Term Memory (BiLSTM) neural network is fed the filtered PV output afterward. By incorporating memory cells and gating mechanisms, Bidirectional Long Short-Term Memory (BiLSTM) Recurrent Neural Networks (RNNs) are able to retain information over long time horizons, hence solving the vanishing gradient problem inherent in ordinary RNNs. For this reason, BiLSTM models outperform more conventional time-series methods like ARIMA, which have problems with nonlinearities, and shallow neural networks, which are unable to grasp temporal connections. By converting sequences of previous PV outputs into future values, a sliding-window training approach is utilised. In order to optimise the model and make accurate predictions of solar power trends under different situations, the goal is to minimise the mean squared error (MSE).

From a theoretical perspective, KAMA performs adaptive smoothing based on signal volatility, effectively preserving important trends and abrupt changes while reducing noise. However, it does not explicitly control the frequency spectrum of the signal. In contrast, the IIR filter provides precise frequency-domain filtering, efficiently attenuating high-frequency noise components that may persist after KAMA processing. Therefore, the sequential combination leverages complementary strengths: KAMA handles adaptive trend extraction, while IIR ensures targeted frequency refinement. To further support this, we have added an ablation study comparing four cases: (i) no preprocessing, (ii) KAMA only, (iii) IIR only, and (iv) combined KAMA–IIR preprocessing before the Bidirectional Long Short-Term Memory model. The results demonstrate that the combined approach consistently achieves lower forecasting errors (MAE and RMSE) than individual filtering methods, confirming the benefit of the hybrid preprocessing strategy.

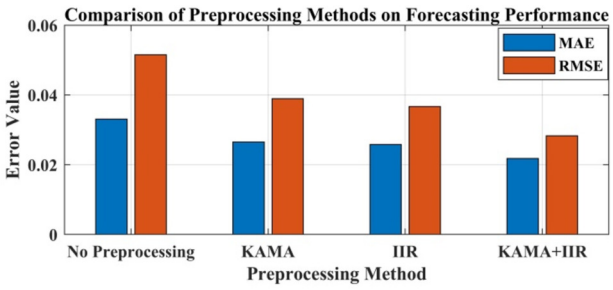


Fig. 3. Comparative analysis of preprocessing methods showing forecasting performance.

IV. PROBLEM FORMULATION

Microgrid optimisation is based on the principle of maximising income, especially in cases where the total load demand exceeds the energy generated by the photovoltaic (PV) system over a 24-hour period. When energy prices are high, the surplus can be sent back to the grid, allowing for efficient energy trading. Ensuring that dispatch methods maintain system balance and dependability while taking advantage of market dynamics to boost profitability, the proposed methodology explicitly accounts for the temporal unpredictability of both renewable generation and electricity prices.

The overarching goal is to find the best scheduling model for a grid-connected microgrid that maximises the use of renewable energy sources, guarantees reliable operation, and increases revenue through the sale of excess power. A photovoltaic (PV) plant and a battery energy storage system (BESS) are the components of the system that are being discussed here; they work together to adapt to changes in the demand for electricity. The scheduling model takes as inputs predicted PV output and load demand, which are acquired through a hybrid time-series forecasting pipeline that includes KAMA, a low-pass IIR filter, and an BiLSTM neural network. The system can be enhanced by including stochastic optimisation or resilient scheduling methods to tackle uncertainty in renewable generation and demand even further.

A. Dataset

All of the data used in this analysis came from the Liège Microgrid Open Data collection that is hosted on Kaggle. Complete time-series data on electrical parameters such as load consumption, renewable power output, battery state of charge, and more are provided by the high-resolution measurements taken from a real-world microgrid in Liège, Belgium. The raw data is captured every 5 seconds, allowing for a detailed examination of the dynamics of the microgrid in the short term. The data was aggregated to an hourly scale for the current scheduling scheme, which operates at a broader temporal resolution. To conduct resampling, we calculated the average values of load and renewable generation on an hourly basis. This yielded input series that were representative and could be used for operational optimisation.

The ESIOS platform of Red Eléctrica de España (REE) was used to get day-ahead electricity market pricing, along with the physical microgrid data [1]. These prices represent the Spanish market's real-time supply and demand balance; they are derived from the day-ahead auction clearing procedure and provide hourly resolution values. Accurate evaluation of market-driven energy management methods is made possible by their granularity and reliability, which make them ideal for inclusion into predictive scheduling models.

To maximize operational and financial efficiency, the suggested scheduling methodology employs a hierarchical framework for energy dispatch. Since solar photovoltaic (PV) output is both inexpensive and environmentally friendly, it is given top priority. Reducing operational costs and emissions, PV generation is directly distributed to satisfy local demand, eliminating the need to rely on foreign supply. When PV production is inadequate, the system then makes use of the Battery Energy Storage System (BESS), which transfers excess PV power during off-peak hours to a storage battery and vice versa during deficits. When PV and BESS aren't enough to cover the demand, the remaining amount is taken from the main utility grid. This sequential scheduling method maximizes the use of renewable energy sources, increases energy independence, and decreases grid stress caused by peak loads by putting PV first, then BESS, and last grid power.

B. Objective Function

$$\max \sum_t \Big[\lambda_{sell}(t)P_{grid,out}(t) - \lambda_{buy}(t)P_{grid,in}(t) - C_{deg}P_{batt,dis}(t) - C_{om}\Big] \quad (1)$$

Where $\lambda_{sell}(t)$: Selling price of electricity to the grid, $\lambda_{buy}(t)$: Buying price of electricity from the grid, C_{deg}: degradation cost coefficient, C_{om}: operation cost t: Total number of time steps (e.g., 24 for 24 hours).

The objective of the proposed microgrid optimization strategy is to maximize the net revenue generated over a 24-hour period. Revenue is earned through two primary sources: first, by exporting excess power generated by the Solar PV plant to the utility grid; and second, by discharging stored energy from the Battery Energy Storage System (BESS) and selling it to the grid. The income from these sources depends on the electricity selling price, which varies hourly.

On the cost side, the microgrid may need to import electricity from the utility grid in two scenarios: to directly supply the local load when renewable and stored energy are insufficient, and to charge the BESS during periods of low market prices. These imports incur a cost based on the hourly electricity buying price. The net revenue is calculated as the total revenue from power sales minus the total cost of electricity purchases. The optimization framework schedules energy flows among the Solar PV system, BESS, and the grid in a way that maximizes this net revenue while meeting demand and system constraints.

C. Constraints

Battery charging power limits dictate how quickly the battery can be replenished, whereas state-of-charge (SOC) boundaries define the allowable upper and lower charge levels. These SOC limits prevent both overcharging and excessive discharge, protecting the battery's lifespan from degradation or damage. The constraintsb incorporated into the objective function are the following:

1) **Power Balance:** The sum of power sources must meet the load demand at each time step:

$$\underbrace{\left(P_{\text{load}}^{\text{PV}}(t)+P_{\text{batt}}^{\text{PV}}(t)+P_{\text{grid}}^{\text{PV}}(t)\right)}_{\text{All PV output}}+\underbrace{\left(P_{\text{load}}^{\text{batt}}(t)P_{\text{grid}}^{\text{batt}}(t)\right)}_{\text{Battery discharge}}+\underbrace{\left(P_{\text{load}}^{\text{grid}}(t)+P_{\text{batt}}^{\text{grid}}(t)\right)}_{\text{Grid import}}$$
$$=\underbrace{D(t)}_{\text{Load demand}}+\underbrace{\left(P_{\text{batt}}^{\text{PV}}(t)+P_{\text{batt}}^{\text{grid}}(t)\right)}_{\text{Battery charging}}+\underbrace{\left(P_{\text{grid}}^{\text{PV}}(t)+P_{\text{grid}}^{\text{batt}}(t)\right)}_{\text{Export to grid}} \tag{2}$$

2) **Solar PV Generation:** The power generated by the PV system is limited by its maximum generation capacity:

$$O \le P_{pv,t} \le P_{pv,max,t} \quad \forall t \tag{3}$$

Where $P_{pv,max}(t)$ is the maximum power available from the PV system at time t, typically derived from weather or irradiance data.

3) **Battery State of Charge Dynamics:** The state of charge of the battery evolves based on charging and discharging:

$$SOC_t = SOC_{t-1} + \eta_{charge} P_{batt_{charge},t} - \frac{P_{batt_{discharge},t}}{\eta_{discharge}}, \quad \forall t \tag{4}$$

Where: η_{charge}: Charging efficiency, η_{charge}: Discharging efficiency.

4) **Battery Capacity Limits:** The state of charge must be within the battery's capacity limits:

$$SOC_{min} \le SOC_t \le SOC_{max} \quad \forall t \tag{5}$$

5) **Battery Charge/Discharge Limits:** The battery's charge and discharge rates are limited:

$$O \le P_{batt_charge,t} \le P_{batt_charge_max} \quad \forall t \tag{6}$$

$$O \le P_{batt_discharge,t} \le P_{batt_discharge_max} \quad \forall t \tag{7}$$

6) **Initial State of Charge:** The initial state of charge of the battery must be specified:

$$SOC_O = SOC_{init} \tag{8}$$

7) **Grid Power Constraints:** The power purchased from the grid must be non-negative:

$$P_{grid,t} \ge 0 \quad \forall t \tag{9}$$

These equations form the basis of the MILP model for solar PV scheduling and can be implemented in optimization frameworks like **Pyomo, Gurobi, CPLEX,** etc.

D. Solution Method

To evaluate the impact of the scheduling strategies for optimal storage systems, this study conducts a comparative analysis under practical operating conditions. Over the course of three representative days, the demand-side management strategy and the peak-valley price arbitrage strategy are applied to coordinate PV generation along with energy storage charging and discharging. BiLSTM was chosen because it can capture temporal dependencies in both forward and backward directions, allowing it to utilize past and future contextual information within a sequence. This is particularly beneficial for solar generation and load forecasting, where patterns are influenced by both preceding trends and upcoming temporal features (e.g., time of day, weather transitions). Compared to Gated Recurrent Unit (GRU), BiLSTM provides richer representational capability due to its dual-directional learning, which leads to improved accuracy for complex and highly variable signals.

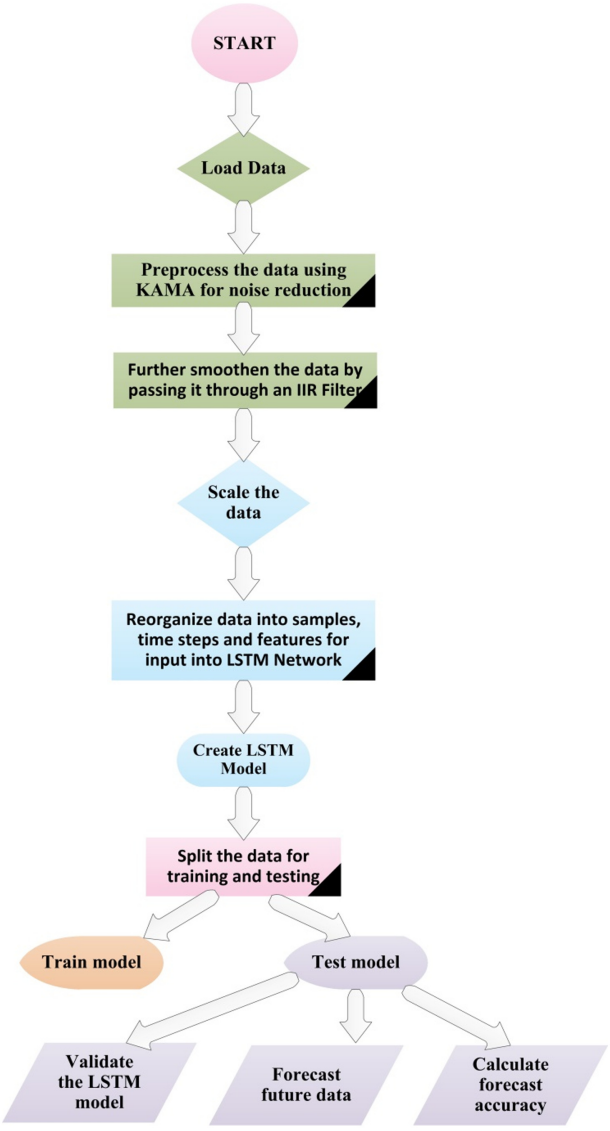


Fig. 4. Optimal scheduling flow chart of optical storage.

While CNN–LSTM architectures are effective in capturing spatial–temporal features, they introduce additional architectural complexity and computational overhead, which may not be justified for the primarily temporal nature of the dataset used in this work. Similarly, Transformer-based mod-

els, although powerful, typically require large-scale datasets and higher computational resources to achieve optimal performance. In contrast, BiLSTM offers a balanced trade-off between accuracy, model complexity, and computational efficiency, making it well-suited for real-time IoT-enabled microgrid applications. The overall framework of the optimization model is presented in Fig. 4. The detailed steps involved in formulating the PV-ESS optimization model are outlined as follows:

1. Using the forecasted PV output and the plant's load profile, the objective function and corresponding constraints are established. The primary goal of the PV-BESS optimization is to reduce the overall electricity expenditure. This optimization process must comply with several constraints, including maintaining system power balance, respecting the storage system's capacity limits, and satisfying the maximum demand requirements, along with other operational considerations.
2. The objective function and constraints serve as the basis for constructing the optimization model.
3. Check whether a new scheduling moment has arrived—if yes, proceed with the next step; if no, continue with the current scheduling policy.
4. With the defined objective function and constraints, the optimization model is solved using the GUROBI solver to determine the optimal charging and discharging power of the ESS. The solution provides scheduling outcomes under different weather scenarios.
5. Based on the model's solution results, the PV-BESS scheduling strategy is formulated to align with actual demand, aiming to smooth load variations, minimize electricity expenses, and enhance cost efficiency for plant users.

V. ANALYSIS OF APPLICATION RESULTS

This section presents a systematic evaluation of the proposed forecasting and scheduling framework. The analysis is divided into forecasting performance, optimization-based scheduling, and case study validation.

A. Forecasting Performance

The forecasting model was implemented in the Anaconda environment with Python 3.13, executed on an Intel Core i5-1135G7 processor (11th Gen, 4 cores, 8 threads). Preprocessing utilized the TA-Lib library for generating Kaufman Adaptive Moving Averages (KAMA), followed by a fourth-order Butterworth IIR filter designed in SciPy to smooth fluctuations. The processed data were then fed into a Bi-LSTM network with two layers of 128 neurons each, interleaved with dropout layers (20 % rate) to mitigate overfitting. Training was conducted on 936 samples spanning 13 May to 20 June 2019, with 65 % used for training, over 30 epochs with a batch size of 70.

B. Scheduling Optimization

After the forecasting stage, a Mixed-Integer Linear Programming (MILP) based day-ahead scheduling model was formulated in the Pyomo framework. The forecasted PV generation and load demand served as model inputs (Fig. 5). The Gurobi optimizer (v12.0.3) was employed to solve the model efficiently, producing optimal schedules within 68 iterations and 0.01 seconds.

TABLE I
SOLAR GENERATION FORECASTING METRICS.

Methodology	MAE	RMSE
BiLSTM	0.0331	0.0515
KAMA-IIR-BiLSTM	0.0218	0.0283

TABLE II
LOAD CONSUMPTION FORECASTING METRICS.

Methodology	MAE	RMSE
BiLSTM	0.0057	0.0089
KAMA-IIR-BiLSTM	0.0048	0.006

TABLE III
COMPARISON OF FORECASTING PERFORMANCE USING DIFFERENT PREPROCESSING METHODS.

Methodology	MAE	RMSE	MAPE (%)	R^2
No Preprocessing	0.0331	0.0515	5.82	0.912
KAMA only	0.0265	0.0389	4.67	0.935
IIR Only	0.0258	0.0367	4.52	0.941
Proposed (KAMA + IIR + BiLSTM)	0.0218	0.0283	3.95	0.962

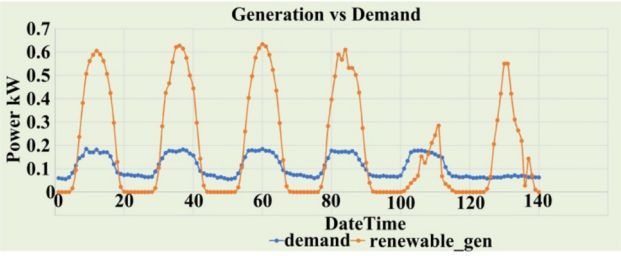
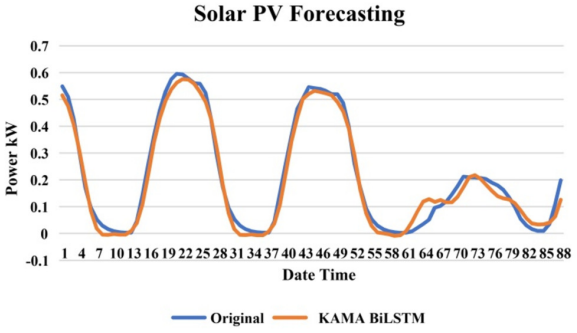
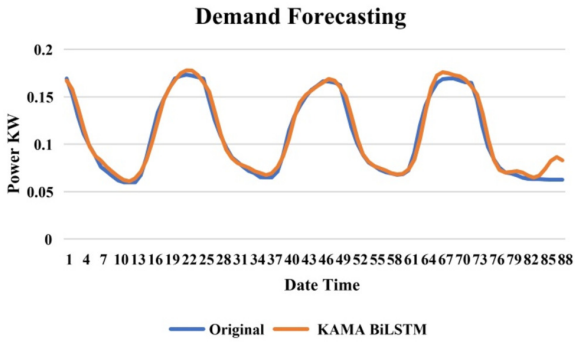


Fig. 5. Optimisation model input parameters, including forecasting model output.

The optimisation objective aimed to maximise economic returns by prioritising solar power usage for local demand and BESS charging, while exporting the surplus to the utility grid. The optimised dispatch strategy yielded a revenue of 0.0063 €/kWh, underscoring the economic feasibility of the approach. In (Fig. 6(a), (b) shown the solar and load generation forecasting are shown.



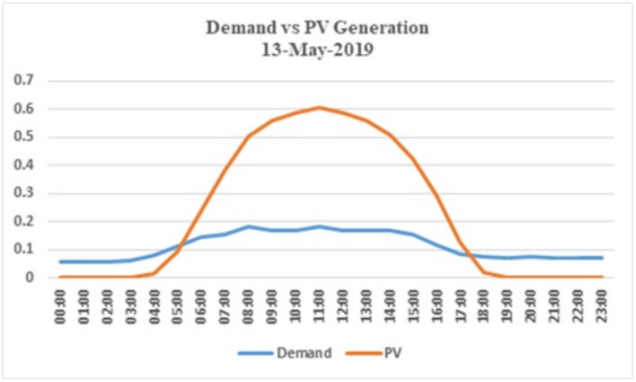
(a)



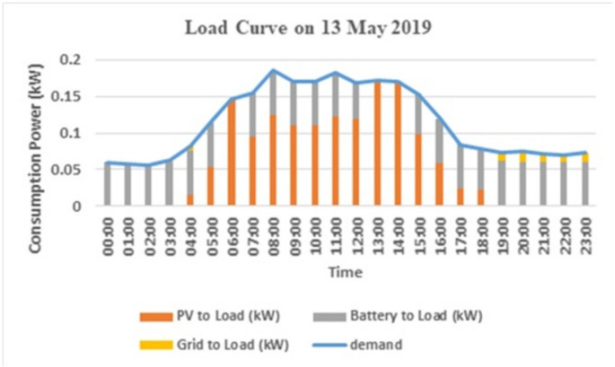
(b)

Fig. 6. (a) Solar Generation Forecasting, (b) Load Consumption Forecastings.

The scheduling framework was validated under three representative operating days: 13 May, 17 May, and 19 May 2019. In Fig. 7(a) illustrates solar generation and load demand profiles for 13 May 2019, while Fig. 7(b) presents the optimized scheduling outcome, highlighting effective utilization of solar power and storage to minimize surplus losses. Fig. 8(a) shows the PV generation versus demand on 17 May 2019, and Fig. 8(b) demonstrates how the MILP-based optimization achieves balanced dispatch while ensuring profitability through grid export. In Fig. 9(a) compares PV generation with load demand for 19 May 2019, and Fig. 9(b) depicts the corresponding optimized results, further confirming the capability of the strategy to adapt under varying conditions.

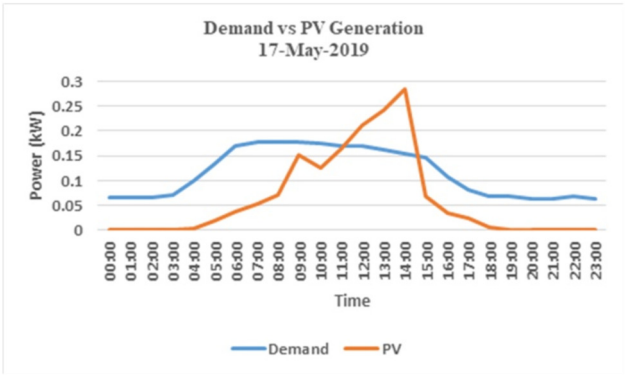


(a)

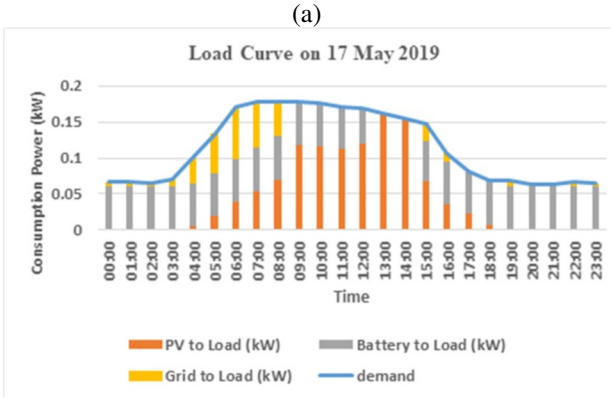


(b)

Fig. 7. (a) Solar Generation vs Load Demand on 13 May 2019, (b) Optimized results based on MILP based Scheduling Strategy on 13 May 2019.



(a)



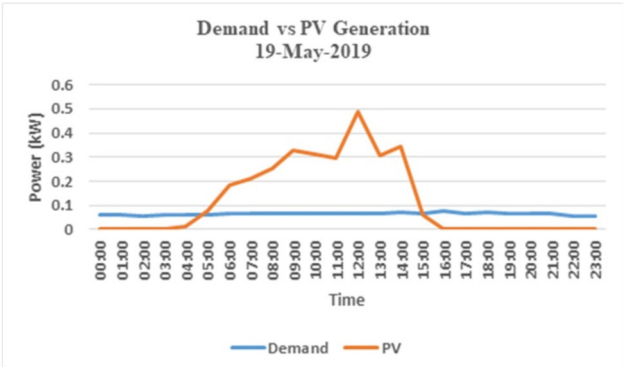
(b)

Fig. 8. (a) Solar Generation vs Load Demand on 17 May 2019, (b) Optimized results based on MILP based Scheduling Strategy on 17 May 2019.

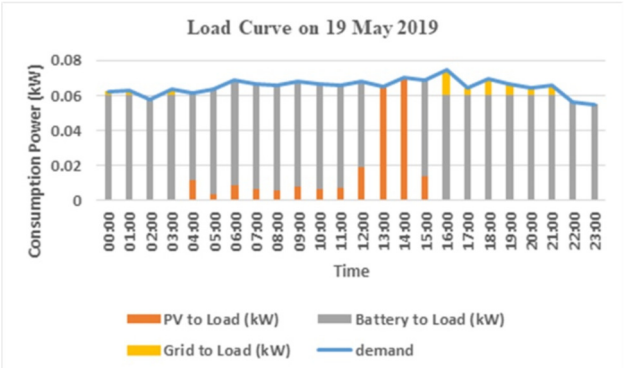
The integrated forecasting and scheduling framework demonstrates significant improvements in both accuracy and operational efficiency. By reducing forecasting errors through the KAMA-IIR-BiLSTM model, the scheduling optimization operates with more reliable inputs, minimizing imbalance and enhancing dispatch precision. The MILP-based scheduling ensures not only demand satisfaction and storage coordination but also profit maximization through grid interaction. Collectively, these results establish the practical value of the proposed PV-BESS management approach, offering both technical robustness and economic viability.

VI. Conclusion

In this study, an IoT-based solar power forecasting and intelligent scheduling framework was proposed for smart microgrids. The approach integrates advanced preprocessing techniques—Kaufman Adaptive Moving Average (KAMA) and an IIR filter—with a BiLSTM model to capture nonlinear patterns and improve forecasting accuracy across multiple time horizons. Building on these forecasts, an MILP-based scheduling algorithm was developed to optimize the charging and discharging of energy storage systems and to allocate power efficiently between local demand and grid interaction. Simulation results confirmed that the proposed method significantly outperforms traditional approaches, achieving smoother load balancing, reduced operational costs, and improved grid stability. These findings emphasize the importance of combining forecasting intelligence with optimization strategies to enhance



(a)



(b)

Fig. 9. (a) Solar Generation vs Load Demand on 19 May 2019, (b) Optimized results based on MILP based Scheduling Strategy on 19 May 2019.

the reliability and economic performance of renewable energy systems. Overall, the framework demonstrates strong potential for broader adoption in future smart microgrids, supporting sustainable, resilient, and cost-effective energy management.

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