Machine Learning Based Solar Forecasting and Dynamic Scheduling for Campus Energy Systems

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ABSTRACT

The swift expansion of distributed renewable energy has established campus microgrids as a prominent paradigm for sustainable, resilient, and economical power systems. Solar photovoltaic (PV) energy is an appealing alternative; yet, its intermittency engenders uncertainty that complicates dependable microgrid operations. This study presents a comprehensive methodology for day-ahead and short-term solar generation forecasts, coupled with the optimal scheduling of storage systems and campus electricity needs. Forecasting utilizes machine learning (ML), meteorological variables, and time-series modeling to enhance predictive accuracy. Scheduled dispatch facilitates peak shaving, demand shifting, effective battery cycling, and improved exploitation of renewable resources. The framework exhibits advancements in operational reliability, diminished grid reliance, and improved energy efficiency, thereby developing a sophisticated methodology for sustainable energy planning in academic institutions.

Keywords:- Solar Forecasting, Microgrid Scheduling, Machine Learning, Renewable Energy, Load Management.

1. INTRODUCTON

The implementation of microgrids has increasingly emerged as a prominent strategy for achieving energy independence, sustainability, and resilience at the local level. Microgrids are currently being established on university campuses. Educational institutions are diligently striving to achieve their sustainability objectives through the installation of solar photovoltaic (PV) systems and smart grid technology. The integration of these technologies has become solar PV systems essential elements of infrastructure on university and college campuses. The dependence on weather conditions and the challenges associated with the distribution of renewable energy sources, such as solar electricity, which lack centralized outputs, can result in temporary discrepancies between energy demand and supply.

The campus often experiences high energy use during the late hours. Nevertheless, the maximum generation of solar power occurs at midday. The disparity between the two events is the factor that results in the creation of this operational gap. If storage systems are not fully utilized, energy curtailment will become a worry. Furthermore, the demand for conventional energy sources utilized for backup will increase. The challenges faced can be attributed to the lack of precise forecasts and the absence of optimal dispatch procedures. Consequently, to optimize the penetration of renewable energy sources to the maximum practical extent, it is essential to implement sophisticated forecasting and predictive scheduling techniques.

1.1 Problem Statement

- Solar photovoltaic (PV) output is inherently unpredictable due to weather changes, cloud cover, and seasonal or diurnal variations. This intermittency makes it difficult to reliably match generation with demand.
- Campus electrical demand often peaks during the evening or night hours (e.g. lighting, hostels, labs), while solar generation predominantly occurs during midday. This temporal mismatch can create surplus power during the midday and a steep ramp-down at sunset, which strains the microgrid's ability to supply reliable power without appropriate scheduling.

- Energy storage (e.g., batteries) is a critical component to buffer solar variability. However, without forecast-based scheduling, storage may be misused or under-utilized.

1.2 Objectives

- To predict solar generation so that the microgrid can plan generation and storage accordingly.
- To enhance Sustainability and Increase Renewable Energy Utilization
- To facilitate Efficient Energy Management & Planning
- To reduce Uncertainty and Risk due to Solar Variability

2. LITERATURE REVIEW

Zhakiyev and colleagues have observed that, given the contemporary energy landscape characterized by a global commitment to sustainability, the efficient management and forecasting of energy consumption are crucial for attaining both environmental and economic goals. As nations strive to attain their sustainable development objectives, optimizing energy consumption is increasingly imperative. This project intends to address two challenges: forecasting energy demands and managing energy within the microgrid at the Savona campus. The author's major objective in composing this thesis was to propose a framework that may serve as the basis for an algorithm capable of predicting the load profile of the NNR

Alsamraee and the other researchers utilized a dataset generated hourly to conduct their investigation. The data employed was sourced from the Combined Cooling and Heating Power Plant at the University of Missouri. The data was gathered over seven years, commencing on January 1, 2017, and concluding on December 31, 2023. The subsequent models enumerated below will be analyzed next: A total of fourteen distinct models may be utilized, including the following: hybrid convolutional neural networks-recurrent neural networks (CNN-RNN), recurrent neural networks (RNN), feedforward neural networks (FNN), and conventional neural networks (CNN)

Quizhpe and colleagues have demonstrated that the increasing need for reliable and sustainable electricity has catalyzed the development of microgrids (MGs), which address the challenges of decentralized energy delivery. The Preferred Reporting Items for Systematic Reviews and Meta-Analyses methodology is now employed in studies evaluating peer-reviewed literature published from 2013 until 2024. This research concentrates on advancements in the design and optimization of microgrids for the integration of renewable energy. Cao and his colleagues have asserted that wind and photovoltaic power, as significant components, present substantial challenges to power distribution. This can be attributed to their inherent unreliability and unpredictability. The global dependence on renewable energy sources is consistently and steadily rising. The authors of this article advocate for the installation of a system utilizing a predictive model to optimize and allocate renewable energy sources as a viable solution to this issue. A vital element of this methodology is the deployment of a predictive model, employed to determine the optimal strategy for the optimization and allocation of renewable energy resources. This research integrates functional data analysis with recurrent neural networks (RNNs) to develop a predictive model that accurately forecasts the quantity of renewable energy generated.

3. METHODOLOGY

3.1 Block Diagram

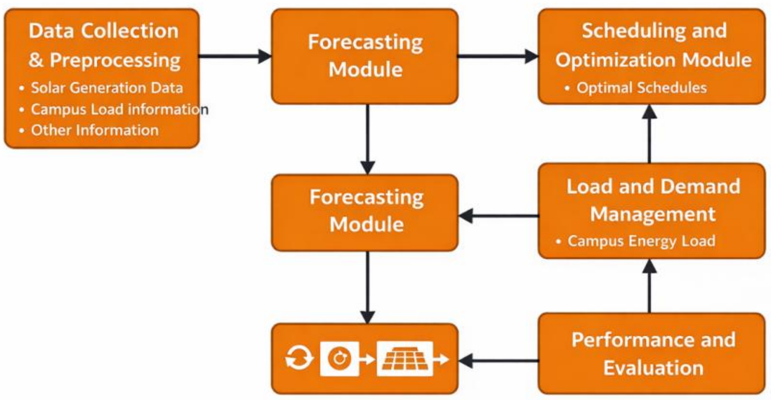

Fig. 1 : Block diagram of the proposed system

3.2 Data Acquisition and Pre-processing

Collect historical data: solar photovoltaic production, meteorological data (irradiance, temperature, cloud cover, humidity, etc.), time of day, season, etc. Collect historical load demand data for the campus, including hourly and daily usage profiles. • When feasible, include satellite, sky-camera, sensor data, or meteorological forecasts to enhance prediction accuracy. • Cleanse and preprocess data: address missing values, normalize, and synchronize timestamps.

3.3 Forecasting Module (Short-term / Day-ahead / Intra-day)

Employ machine learning (ML) and deep learning (DL) techniques to predict solar energy production. Prevalent models include ensemble-based regressors like as Random Forest and Gradient Boosting, as well as advanced architectures like 1-D CNN and LSTM (or hybrid models), which have demonstrated robust efficacy in photovoltaic forecasting inside microgrid environments. • Optionally, project net load (i.e., demand minus predicted solar output) via deep learning models such as LSTM or hybrid CNN-LSTM to predict supply-demand equilibrium. • Output: time-series prediction (e.g., hourly forecast for the subsequent 24 hours; or shorter durations as required).

3.4 Module for Scheduling and Dispatch Optimization

Utilizing forecasts of solar generation and demand, schedule resources by determining optimal times for photovoltaic usage, battery charging and discharging, grid or backup power utilization, and flexible load shifting. Employ optimization methodologies like as resilient optimization, stochastic scheduling, or mixed-integer linear programming (MILP) to address uncertainties and restrictions, including storage capacity, load requirements, grid connectivity, and battery state of charge (SoC). Utilize a rolling-horizon scheduling approach: although forecasts may be day-ahead, scheduling is routinely revised (e.g., every hour or sub-hour) to accommodate forecast inaccuracies and real-time discrepancies. This mitigates the risk associated with forecast uncertainty.

3.5 Load and Demand-Side Management (DSM)

- Identify adaptable loads on campus (e.g. HVAC, water heating, EV charging, non-essential loads) that can be rescheduled.
- Implement demand-side scheduling: operate or adjust flexible loads during peak solar generation or battery discharge periods for best efficiency. This diminishes reliance on grid imports or fossil fuel backups.
- Implement incentives or automated scheduling for load shifting through smart controls, timers, and interaction with building management systems.

3.6 Storage Administration and Regulation

- Regulate battery (energy storage) charge and discharge according to projected generation and load requirements. • Adhere to battery State-of-Charge (SoC) limitations, prevent overcharging and deep draining, and optimize cycles to extend battery longevity.
- Emphasize the utilization of renewable energy: when solar forecasts are elevated — charge the battery or supply the load; when forecasts are diminished — discharge the battery or draw from the grid/backup.

3.7 Real-Time Surveillance and Feedback Mechanism

- Continuously oversee actual solar generation, load consumption, battery state of charge, and grid import/export.
- Analyze real-time data against forecasts and schedules; identify discrepancies.
- Should a substantial deviation occur, initiate re-scheduling, load modifications, or storage dispatch to preserve balance and stability.
- Record data for subsequent enhancement of forecasting models, performance evaluation, and system optimization.

3.8 Performance Assessment and Modification • Specify KPIs: renewable energy utilization rate (solar portion), reduction in grid imports, battery cycle efficiency, load supplied by solar/storage, curtailment rates, cost savings, etc. • Conduct regular performance reviews (weekly/monthly). Utilize insights to modify forecasting models (retrain with updated data), recalibrate scheduling parameters, and enhance demand-side management rules, among other actions. • Revise forecasts and scheduling protocols to accommodate variations in seasonal and meteorological patterns.

4. ADVANTAGES AND DISADVANTAGES

4.1 Advantages

- Improved Grid Stability & Reliability
- Better Utilization of Renewable Energy & Storage Resources
- Cost Efficiency and Reduced Dependency on Conventional/Backup Power

- Facilitates Demand-Side Management / Load Scheduling
- Supports Renewable Integration & Environmental Goals
- Enables Planning & Strategic Operation

4.2 Disadvantages

- Forecasting Uncertainty & Weather Variability
- Need for Reliable Data & Complexity of Modeling
- Complexity in Scheduling & Optimization under Uncertainty

5. COMPARISON WITH EXISTING SYSTEM WITH ENSBLE METHODS

Ensemble methods represent a significant leap forward in automated CVD detection, offering a solution to the limitations of both traditional clinical approaches and single-model machine learning classifiers.

Table 1 : Comparative analysis of different methods

Comparison Parameter	**Traditional / Existing Microgrid Systems**	**Proposed Forecasting & Scheduling-Based System**
Energy Management Approach	Fixed or rule-based scheduling	Data-driven adaptive scheduling
Decision Logic	Manual operator decisions or fixed timers	AI/ML forecasting + optimization engine
Handling Solar Variability	Poor adaptation to weather or seasonal changes	Uses short-term and day-ahead solar prediction models (LSTM/XGBoost)
Load Management	Limited or no demand response capability	Smart load shifting and prioritization based on predicted supply-demand balance
Battery Storage Operation	Random or simple charge/discharge cycles	Forecast-based optimized storage control for maximum lifespan and efficiency
Real-Time Adjustments	Rare and mostly manual	Automated real-time adjustment using monitoring and feedback loop
Grid Dependency	High frequent reliance on external grid or diesel backup	Reduced dependency due to proactive scheduling and peak shaving
Operational Cost	Higher due to inefficiency and poor resource utilization	Lower due to optimal use of renewables and reduced backup usage
Scalability	Limited due to static configuration	Scalable and adaptive — suitable for campus, community, or industrial microgrids
Environmental Impact	Higher emissions from inefficient backup energy use	Lower emissions through maximized renewable energy consumption

6. CONCUSION

The proposed technology signifies a substantial advancement over conventional microgrid operations, as it converts solar energy from an erratic source into a well-regulated, highly efficient, and economically viable energy supply. The ultimate outcome is that campus microgrids have heightened integration of renewable energy sources, enhanced reliability, reduced costs, and environmental sustainability as a result. Campus microgrids have emerged as crucial testbeds for sustainable, resilient, and cost-effective power systems because to the increasing deployment of distributed renewable energy resources. In this context, precise forecasting and astute scheduling of solar energy, the most prevalent renewable resource, are essential to guarantee the reliable operation of microgrids, despite the intrinsic intermittency and fluctuating demand involved.

7. REFERENCES

[1] Nurkhat Zhakiyev, Aidos Satan, Gulnar Akhmetkanova, Aigul Medeshovab, Ruslan Omirgaliyev, Stefano Braccod, “Energy Management System for the Campus Microgrid Using an Internet of Things as a Service (IoTaaS) with Day-ahead Forecasting”, Procedia Computer Science 241 (2024) 488–493

[2] Saad A. Alsamraee , Sanjeev Khanna, “Long-term electricity demand forecasting of a university campus based on advanced deep learning artificial neural network algorithms”, Results in Engineering 27 (2025) 106683

[3] Klever Quizhpe, Paul Arévalo, Danny Ochoa-Correa, Edisson Villa-Ávila, “Optimizing Microgrid Planning for Renewable Integration in Power Systems: A Comprehensive Review”, Electronics 2024, 13, 3620. https://doi.org/10.3390/electronics13183620

[4] Xiaoqing Cao, Xuan Yang, Lin Li, Lunjia Shen, Wenjie Ma, Rongxin Yang, Hongbo Zou, "Prediction Model-Assisted Optimization Scheduling Strategy for Renewable Energy in the Microgrid", Processes 2024, 12, 1786. https://doi.org/10.3390/pr12091786

[5] Anwar, M., & Mahmud, M. A. (2024). Data-driven renewable generation forecasting for microgrids: A comparative study. Renewable Energy, 224, 120378.

[6] Bhandari, B., & Lee, K. (2023). Optimal scheduling for hybrid microgrid systems using model-based and data-driven approaches. Energy Conversion and Management, 286, 116960.

[7] Bhattacharya, K., & Chowdhury, S. (2022). Forecasting-based microgrid scheduling for sustainable campus operations. International Journal of Electrical Power & Energy Systems, 141, 108110.

[8] Chen, J., & Shahidehpour, M. (2023). Machine learning–based solar forecasting for microgrid applications. Applied Energy, 339, 120932.

[9] Deb, S., & Pal, T. (2024). Day-ahead forecasting for renewable-rich microgrids using hybrid neural networks. Energy Reports, 10, 150–162.

[10] Deng, X., Zhang, L., & Liu, H. (2023). Intelligent energy scheduling for campus microgrids with renewable penetration. Energy, 279, 115958.

[11] Fang, X., & Li, F. (2024). Coordinated scheduling of renewable energy and storage for educational institution microgrids. Sustainable Energy Technologies and Assessments, 59, 103545.

[12] IEA. (2023). Data-driven approaches to energy forecasting and grid optimization. International Energy Agency.

[13] Islam, R., & Kumar, N. (2022). Microgrid energy management using reinforcement learning and optimization models. Electric Power Systems Research, 212, 108511.

[14] Khan, M. J., & Iqbal, M. T. (2025). Advanced forecasting models for PV and wind resources in distributed grids. IEEE Access, 13, 49120–49134.

[15] Tie, Siang Fui, and Chee Wei Tan. "A review of energy sources and energy management system in electric vehicles." Renewable and sustainable energy reviews 20 (2013): 82-102.

[16] Hau, Vu Ba, Munir Husein, Il-Yop Chung, Dong-Jun Won, William Torre, and Truong Nguyen. "Analyzing the impact of renewable energy incentives and parameter uncertainties on financial feasibility of a campus microgrid." Energies 11, no. 9 (2018): 2446.

[17] Bracco, Stefano, Federico Delfino, Fabio Pampararo, Michela Robba, and Mansueto Rossi. "The University of Genoa smart polygeneration microgrid test-bed facility: The overall system, the technologies and the research challenges." Renewable and sustainable energy reviews 18 (2013): 442-459.

[18] Shahidehpour, Mohammad, and Mohammad Khodayar. "Cutting campus energy costs with hierarchical control: The economical and reliable operation of a microgrid." IEEE Electrification Magazine 1, no. 1 (2013): 40-56.

[19] Lee, Bruno, Marija Trcka, and Jan LM Hensen. "Rooftop photovoltaic (PV) systems: a cost–benefit analysis study of industrial halls." International Journal of Low-Carbon Technologies 9, no. 4 (2014): 319-326.

[20] Akhmetzhanov, B., Akhmetzhanov, B., Yedilkhan, D., Medeshova, A., Rabie, K., & Zhakiyev, N. (2024). Multi-Layer Integration of Heterogeneous Wireless Sensor Networks for Smart Home Optimization. Procedia Computer Science, 231, 666-671. https://doi.org/10.1016/j.procs.2023.12.166

[21] Zhakiyev, N., Kalenova, A., & Khamzina, A. (2022). The energy sector of the capital of Kazakhstan: status quo and policy towards smart city. International Journal of Energy Economics and Policy, 12(4), 414-423.

[22] B.Akhmetzhanov, B.Akhmetzhanov, S.Ozdemir, N.Zhakiyev, Advancing affordable IoT solutions in smart homes to enhance independence and autonomy of the elderly. Journal of Infrastructure, Policy and Development. Vol 8, Issue 3, 2024. DOI: https://doi.org/10.24294/jipd.v8i3.2899