AI-Based Forecasting and Power Scheduling Framework for Smart Campus's Energy Optimization Using Locally Deployed Solar Grids

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Abstract– With the increasing emphasis on sustainability and cost-effective operations, educational and organizational campuses are progressively adopting localized renewable energy solutions such as solar power systems. This paper proposes an AI-driven framework to forecast and optimize the allocation and utilization of energy generated from sustainable sources deployed within campus environments. The proposed system follows a structured six-phase architecture comprising data logging, predictive modeling, and optimization of effective power distribution aligned with operational demands. Machine learning models are employed to forecast solar power generation based on weather data and Energy requirements of campus units with historical power consumption data, enabling real-time recommendations of energy-efficient operational schedules. The system ensures better energy utilization, supports sustainable campus management, and aims to reduce dependence on grid electricity. Unlike conventional power management systems, the proposed model integrates dual-predictive modules to align generation forecasts with load requirements in real-time.

Keywords—Electric Load Forecasting, Solar Power Forecasting, Energy Usage Pattern Recognition, Sustainable Energy Optimization, Dual-Predictive Energy Models, Campus Load Prediction, Smart Campus Solutions

I. INTRODUCTION

In recent years, the transition toward sustainable energy solutions has gained significant momentum, driven by growing concerns about environmental degradation, energy security, and rising utility costs. Among the available renewable energy technologies, **solar power** has emerged as one of the most accessible, abundant, and scalable options for decentralized energy generation [1], [2]. Its ability to harness energy from an environmentally clean and inexhaustible source makes it especially appealing to institutional campuses aiming to reduce their carbon footprint while simultaneously lowering operational expenses.

However, despite the growth in solar adoption, its integration into real-world infrastructures—such as university or organizational campuses—poses unique challenges.

The availability of solar energy is **intermittent and unpredictable**, varying based on weather conditions, time of day, cloud cover, and seasonal fluctuations [3], [4]. Simultaneously, the power demand across a campus is **non-uniform and dynamic**, affected by factors such as academic schedules, building occupancy, and equipment usage [5]. This creates a mismatch between energy generation and consumption, which, if left unaddressed, can lead to inefficiencies and wastage of available renewable energy.

To bridge this gap, intelligent systems are essential—systems that are not only capable of forecasting solar energy generation but also predicting energy demand with high accuracy. Artificial Intelligence (AI) and Machine Learning (ML) have shown great potential in energy-related applications, especially for **solar forecasting** and **load demand prediction**, by leveraging historical and environmental data to detect patterns and predict outcomes [6], [7].

This paper proposes a smart, AI-powered energy optimization framework specifically designed for campus-scale infrastructures. It integrates **dual-predictive models**—one for forecasting solar power based on real-time and historical weather data, and another for predicting campus energy consumption based on usage logs and zone-level load profiles. These models feed into a **constraint-based optimization engine** that aligns predicted supply with prioritized operational demands.

The result is a **real-time, data-driven energy scheduler** that recommends feasible operational hours for campus zones while minimizing dependency on grid electricity. By implementing this approach, the system enhances energy efficiency, reduces operational costs, and supports sustainability goals in educational institutions. Additionally, the architecture is designed to be **modular, scalable, and adaptable** to a wide range of environments, including smart cities and rural microgrids.

II.LITERATURE REVIEW

B. Yildiz, J. I. Bilbao, and A. B. Sproul (2017) [13]. This study presents a review and analysis of regression and machine learning models for electricity load forecasting in commercial buildings. It compares various techniques, highlighting their strengths and weaknesses in predicting energy consumption patterns. The research emphasizes the importance of accurate load forecasting for efficient energy management and grid stability.

D. Solyali (2020) [14]. This paper provides a comparative analysis of machine learning approaches for short- and long-term electricity load forecasting. It evaluates the performance of different algorithms in the context of the energy sector, examining their accuracy and suitability for different forecasting horizons. The study contributes to understanding the capabilities of ML in improving energy prediction.

A. A. Ajiboye, S. I. Popoola, et al. (2022) [10]. This work discusses data-driven optimal planning for hybrid renewable energy system management in a smart campus setting. It explores strategies for integrating renewable energy sources and optimizing their utilization to enhance energy efficiency and sustainability. The research highlights the role of data analysis in effective energy management within campus environments.

A. M. Eltamaly, M. A. Alotaibi, et al. (2021) [11]. This paper introduces an IoT-based hybrid renewable energy system designed for a smart campus. It investigates the integration of Internet of Things technologies with renewable energy systems to enable intelligent monitoring and control of energy generation and consumption. The study demonstrates the potential of IoT in creating smart and sustainable energy infrastructures.

E. Aguilar Madrid and N. Antonio (2021) [12]. This study focuses on short-term electricity load forecasting using machine learning techniques. It explores the application of ML algorithms to predict electricity demand over short time periods, which is crucial for real-time energy management and grid operation. The research contributes to the development of accurate and efficient load forecasting methods.

N. Shirzadi, A. Nizami, M. Khazen, and M. Nik-Bakht (2021) [15]. This work explores the application of machine learning and deep learning techniques for medium-term regional electricity load forecasting. The study investigates the effectiveness of these advanced methods in predicting electricity demand over a regional scale for a timeframe beyond the immediate short term. The research contributes to understanding the capabilities of AI in addressing forecasting challenges for broader energy planning.

Gholizadeh and Musilek (2021) [17]introduced a federated learning approach to short-term electricity load forecasting, addressing privacy concerns associated with centralized data collection. Their method clusters clients based on hyperparameters to enhance convergence speed and model accuracy. The study demonstrated that federated learning could achieve a root mean squared error (RMSE) of 0.117 kWh for individual load predictions, highlighting its potential in decentralized energy systems.

Li et al. (2018) [18] proposed a hybrid model integrating Empirical Mode Decomposition (EMD) with Long Short-Term Memory (LSTM) networks for short-term load forecasting. The EMD technique decomposes complex load signals into simpler components, which are then processed by LSTM networks optimized using particle swarm optimization. This approach effectively captures nonlinear patterns in load data, resulting in improved forecasting accuracy compared to traditional methods.

Chen et al. (2018) developed a short-term load forecasting model utilizing deep residual networks (ResNets). By incorporating residual learning, the model addresses the vanishing gradient problem common in deep networks, enabling the capture of complex temporal dependencies in load data. The study reported that this architecture outperformed conventional deep learning models in terms of forecasting accuracy and generalization capabilities.

III. RESEARCH GAP

Despite the growing interest in smart campus energy management and the increasing adoption of renewable energy sources like solar power, a significant gap remains in the development of fully integrated and intelligent systems capable of accurately forecasting both energy supply and demand to optimize real-time energy scheduling. Many existing approaches either focus solely on forecasting one aspect (either solar generation or load demand) or lack the sophisticated AI-driven optimization necessary for dynamic and efficient energy utilization. Furthermore, few frameworks adequately address the integration of these predictions into real-time scheduling mechanisms that can proactively adjust campus energy consumption to maximize self-sufficiency and minimize reliance on the external grid. This limitation leads to suboptimal usage of renewable energy and continued dependence on less sustainable and cost-effective energy sources. Addressing this gap can unlock substantial benefits, including reduced energy costs, improved grid stability, and a significant decrease in the carbon footprint of campus operations. The aim of this study is to design and develop an AI-Driven Solar Power Forecasting and Load Scheduling Framework that utilizes machine learning models to predict both solar energy generation and campus energy demand, and subsequently employs an optimization engine to generate real-time schedules for enhanced energy efficiency and reduced grid dependency.

IV. EXISTING SYSTEM

Most existing campus energy systems rely on manual scheduling, timer-based automation, and real-time monitoring. While some use IoT-enabled dashboards for visualization, they lack predictive capabilities. These systems do not forecast solar generation or dynamically match energy supply with demand. As a result, they fall short in optimizing renewable energy use under varying conditions. Machine learning integration is largely absent in current solutions.

● Most campus energy systems focus on real-time monitoring and manual control.

● Timer-based or rule-based mechanisms are common, lacking adaptability to dynamic usage or solar availability.

● Some systems use IoT devices and dashboards for consumption visualization, but offer limited automation.

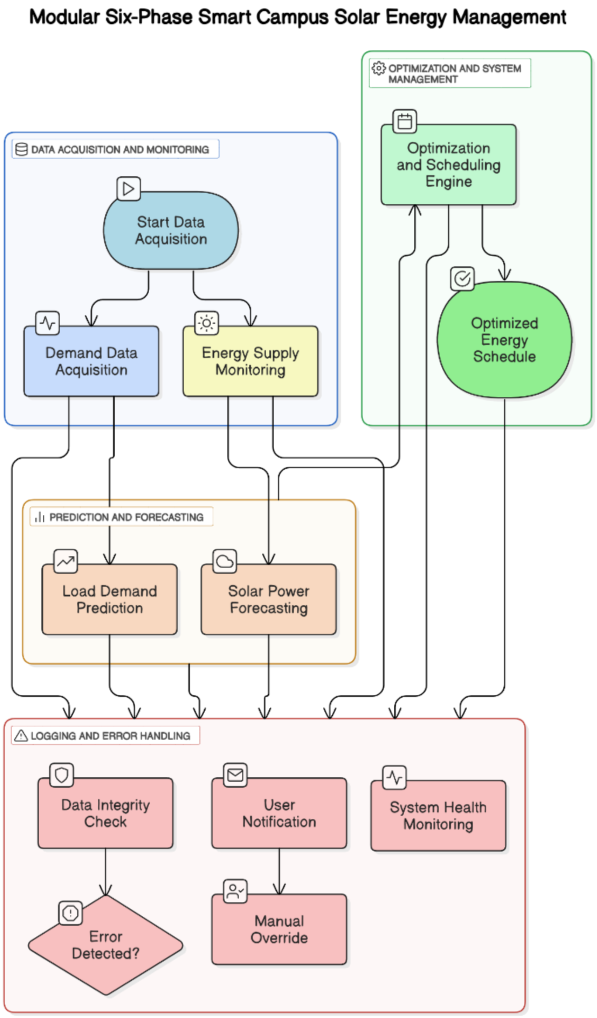
● No integration of AI/ML for forecasting solar power or predicting load demand in most current setups.

● Typically, they do not support dual-predictive scheduling for aligning generation and consumption.

V. PROPOSED SYSTEM

This AI-based framework optimizes energy management on smart campuses with local solar grids. It uses dual-predictive models to forecast solar power generation and campus energy demand. An intelligent decision engine then aligns predicted supply with demand, and a real-time scheduler suggests optimal times for energy-intensive activities. By minimizing reliance on the external grid and maximizing solar energy utilization, the system aims to enhance sustainability and reduce energy costs. Its modular design allows for future expansion and integration with real-time data sources. The

framework incorporates several key features to achieve intelligent energy optimization:



System Flow Diagram

● Dual-Predictive Modeling for solar generation and campus energy demand forecasting.

● Intelligent Optimization aligning predicted supply with demand and suggesting energy saving actions.

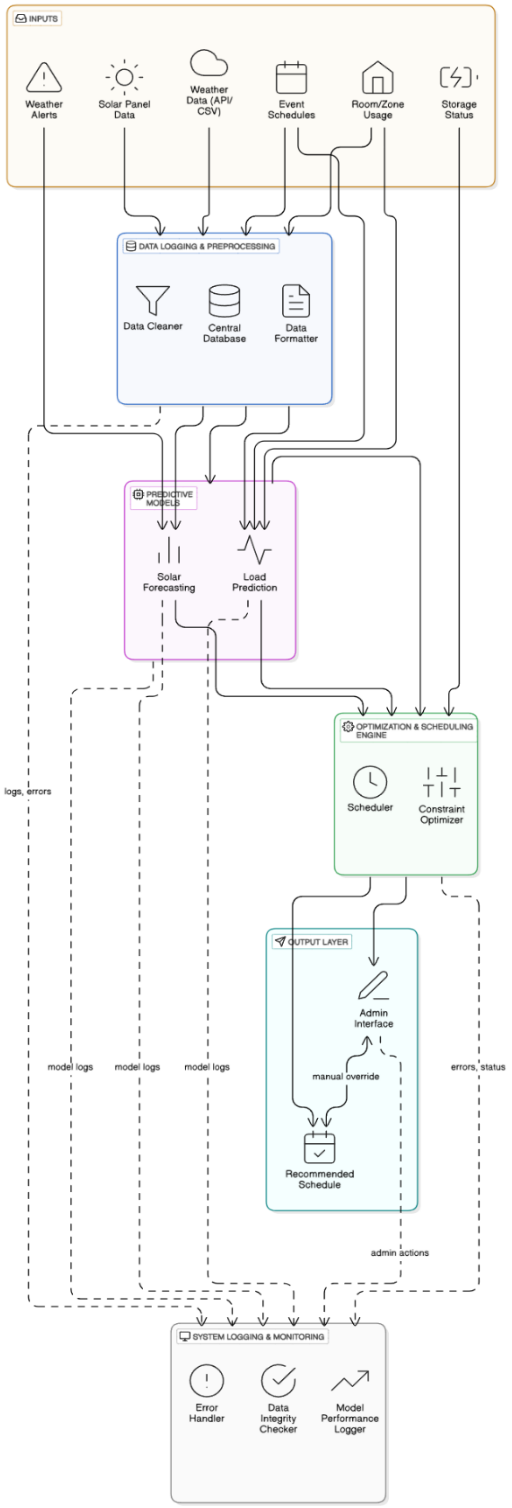
● Real-time Scheduling recommending optimal times for high-consumption activities.

● Modular Six-Phase Architecture for structured data handling, and decision-making.

● Data-Driven Approach leveraging historical data and machine learning for predictions.

● Focus on Sustainability by reducing grid reliance and energy costs.

● Scalable and Adaptable design for various campus and community applications



System Architecture Diagram

The approach taken in this project centers around the utilization of Python for the core development and data management. The system begins with data acquisition from solar panels, weather APIs, and campus energy consumption logs.

This data is then preprocessed and stored for subsequent analysis and model training. Machine learning models are developed using libraries like Scikit-learn to forecast both solar energy generation and campus energy demand.

The predicted energy supply and demand are then used by an optimization engine to generate energy schedules.

These schedules aim to optimize energy usage and reduce reliance on external power grids. Interactive 9components are used to present the schedules and relevant energy data, providing a user-friendly experience.

By utilizing Python's data manipulation capabilities, machine learning libraries, interactive components, and structured data handling, the system offers a solution for optimizing energy consumption and promoting sustainable energy use within a smart campus.

VI. CONCLUSION AND FUTURE SCOPE

The project results showcase the system's ability to accurately predict solar power and energy demand, leading to the generation of effective energy schedules. The system successfully optimizes energy usage, enabling reduced reliance on external power grids and cost savings. Visual representations of energy data and schedules enhance user understanding and decision-making.

The system's data-driven approach facilitates improved energy efficiency and sustainability within smart campus environments. In summary, the developed framework offers a practical and beneficial solution for optimizing energy management and promoting the use of renewable energy

The results of this study demonstrate the effectiveness of the AI-Driven Solar Power Forecasting and Load Scheduling Framework for smart campus energy optimization. The dual predictive models accurately forecast solar energy generation and campus energy demand, indicating their reliability in predicting energy supply and consumption patterns.

The system's schedule generation effectively aligns energy availability with operational requirements, providing actionable plans for energy usage. The integration of predictive capabilities with a constraint-based optimization engine enables dynamic energy allocation and reduces reliance on the external grid. Furthermore, the system's modular design and use of Python facilitate scalability and user-friendly interaction.

A thorough review of existing campus energy management systems reveals both strengths and weaknesses. Many of the systems reviewed rely on manual scheduling, timer-based automation, or basic monitoring dashboards.

While these systems provide some level of control and visibility, they typically lack the predictive capabilities and intelligent optimization necessary for efficient renewable energy integration. Furthermore, most of these tools do not adequately address the dynamic nature of energy supply and demand in a smart campus environment. On the positive side, studies in the literature review demonstrate the potential of machine learning for accurate energy forecasting, which aligns with our approach.

However, these studies often focus on specific aspects of energy management (e.g., load forecasting or solar forecasting) rather than providing a comprehensive framework for integrated energy optimization and scheduling, which is a gap our study aims to address. By offering dual predictive modeling and real-time schedule generation, the proposed system provides a more holistic and actionable solution for smart campus energy management.

Future development of the system should prioritize integrating IoT sensors for real-time energy flow tracking and device-level control. Incorporating advanced deep learning models and expanding the training dataset will enhance forecasting accuracy. A comprehensive web dashboard with secure login, reporting, and control functionalities is recommended. Automating real-time weather data ingestion via APIs will improve forecast precision. Furthermore, implementing predictive maintenance alerts based on energy consumption anomalies would enable proactive maintenance

This study presented the design and implementation of an AI-Driven Solar Power Forecasting and Load Scheduling Framework, a system that leverages machine learning models to predict solar energy generation and campus energy demand. Unlike traditional systems that rely on static schedules or basic monitoring, this project offers a dynamic, optimized approach, guiding energy usage through intelligent scheduling and real-time adjustments.

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