

Article

Integrated Data-Driven and Interaction-Based Evaluation of Hybrid PV–Wind Systems for Sustainable Urban Park Lighting Design

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Abstract

The growing demand for sustainable urban infrastructure requires reliable and energy-efficient lighting solutions, particularly for urban parks characterized by dynamic energy consumption patterns. This study proposes an integrated analytical framework combining deterministic energy system modeling, a novel interaction-oriented metric, and machine learning techniques to evaluate hybrid photovoltaic (PV)–wind systems for urban park lighting applications. Multi-year hourly meteorological and lighting-demand data from millet gardens in Balıkesir and Çanakkale, Türkiye, were analyzed. A Hybrid Energy Synergy Index (HESI) was introduced to quantify the degree of concurrent contribution and coordination between PV and wind resources relative to lighting demand. The results show substantial demand variability, with an average daily demand of approximately 1609 kWh and peak values exceeding 25,600 kWh. Photovoltaic generation dominated total renewable energy production (92.95%), whereas wind energy contributed 7.05%. The average HESI value (≈ 0.113) indicated weak source coordination, accompanied by persistent energy deficits that occasionally exceeded $-20,000$ kWh. Reliability analysis revealed severe system inadequacy, with a reliability rate of only 0.000547 (0.055%). Within the evaluated design space, the highest-performing configuration consisted of 49 PV panels and 19 wind turbines; however, reliability improvements remained limited, indicating that capacity expansion alone is insufficient to ensure satisfactory performance. Machine learning models achieved high predictive accuracy for HESI forecasting ($R^2 = 0.9902$; $MAE = 0.0027$), while explainable artificial intelligence identified solar radiation and wind speed as the dominant environmental drivers. The results highlight the importance of integrating renewable energy capacity planning with energy storage support, improved source coordination, and adaptive energy management strategies to enhance the reliability of sustainable urban lighting systems.

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Keywords: hybrid renewable energy systems; urban park lighting systems; building lighting systems; machine learning; sustainable built environment

1. Introduction

The rapid expansion of urbanization and the increasing energy demands of modern cities have intensified the need for sustainable and efficient infrastructure solutions. Urban lighting systems, particularly street and park lighting, constitute a significant share of municipal energy consumption and operational costs. Traditional grid-dependent lighting systems are not only energy intensive but also contribute substantially to carbon emissions, making their transformation a critical component of smart city development strategies [1,2].

In response to these challenges, renewable energy-based lighting systems have gained considerable attention as viable alternatives. Among these, photovoltaic (PV) systems have been widely explored due to their environmental benefits and declining costs, offering sustainable solutions for urban lighting applications [3]. However, the inherent intermittency of solar energy presents operational limitations, particularly during unfavorable weather conditions or nighttime periods [4].

To mitigate these limitations, hybrid renewable energy systems integrating solar and wind resources have been proposed as more reliable alternatives. Several studies have demonstrated that combining these energy sources improves system stability and reduces dependency on conventional power supply [5–7]. Hybrid solar–wind street lighting systems, in particular, provide continuous power generation by exploiting the complementary characteristics of solar irradiance and wind availability [7,8]. Furthermore, techno-economic analyses confirm that such systems can achieve favorable performance in terms of cost efficiency, emissions reduction, and energy autonomy [8,9].

Parallel to advancements in energy generation technologies, smart lighting systems enhanced by Internet of Things (IoT) and intelligent control mechanisms have emerged as an effective approach for optimizing energy consumption. IoT-based lighting systems enable adaptive control of illumination levels based on environmental conditions and user activity, leading to significant energy savings and improved operational efficiency [10,11]. Additionally, machine learning-based intelligent control systems have been developed to dynamically regulate lighting behavior, further reducing energy consumption while maintaining user comfort and safety [12].

Recent studies have also explored the application of advanced optimization and energy management techniques to improve system performance. For example, hybrid optimization frameworks combining metaheuristic algorithms and neural networks have demonstrated high efficiency in managing energy flows in PV-powered lighting systems [13]. Similarly, integrated planning tools and energy management approaches have been proposed to support the design and operation of complex microgrid-based systems [14].

Despite these advancements, the reliability of hybrid energy systems remains a major concern due to the variability of renewable resources and demand fluctuations. Several studies have emphasized the importance of proper system sizing, energy storage integration, and reliability analysis to ensure stable operation of isolated or off-grid microgrids [15,16]. In particular, the selection of appropriate component sizes and energy storage capacities plays a crucial role in balancing supply and demand while maintaining system reliability [16].

Another critical aspect of urban lighting systems is their application in urban parks and green spaces. These environments present unique challenges due to their spatial diversity, user-driven demand patterns, and ecological considerations. Studies have shown that lighting design in such areas must balance safety, user comfort, and environmental sustainability, including minimizing light pollution and preserving natural ecosystems [17]. Moreover, the spatial and landscape characteristics of urban green areas, such as millet gardens, significantly influence lighting requirements and system design considerations [18,19].

In addition to system design and optimization, data-driven approaches have become increasingly important for predicting energy demand and improving system performance. Machine learning techniques have been widely applied to forecast energy generation and consumption, enabling more accurate and adaptive system management [20]. Advanced explainable machine learning approaches further enhance interpretability by identifying key drivers of system behavior, particularly under varying weather conditions [21]. These approaches have also been extended to broader energy systems, including demand prediction in renewable-integrated infrastructures [22].

Nevertheless, despite substantial advances in renewable energy integration, intelligent lighting control, and energy system optimization, important research gaps remain. Existing studies predominantly evaluate hybrid renewable energy systems using aggregate performance indicators such as energy yield, Loss of Power Supply Probability (LPSP), Loss of Load Probability (LOLP), Loss of Load Expectation (LOLE), capacity factor, or conventional reliability metrics. While these indicators provide valuable information regarding system adequacy and operational performance, they do not explicitly quantify the degree of interaction and coordination between renewable energy sources over time. As a result, the contribution of source coordination and interaction to supply–demand matching remains insufficiently understood. Furthermore, most studies consider energy generation, demand modeling, reliability assessment, and predictive analytics as separate tasks rather than components of an integrated analytical framework. The combined application of interaction-based performance assessment, reliability evaluation, machine learning forecasting, and explainable artificial intelligence in urban park lighting systems therefore remains limited in the current literature.

To address these limitations, this study proposes an integrated analytical framework for hybrid renewable energy-based urban park lighting systems. The framework combines deterministic system modeling, interaction-based performance evaluation, and machine learning-driven predictive analysis within a unified structure. In particular, a novel metric is introduced to quantify the interaction between photovoltaic and wind energy sources, thereby enabling a more comprehensive and interpretable evaluation of system performance.

The main contributions of this study can be summarized as follows: First, a comprehensive hybrid renewable energy framework is developed specifically for urban park lighting systems, enabling a more realistic representation of energy demand and supply interactions. Second, the study integrates photovoltaic and wind energy modeling with dynamically varying demand patterns, thus reflecting real-world operational conditions. Third, a novel interaction-oriented metric, the HESI, is introduced to quantify the simultaneous contribution of photovoltaic and wind resources. Unlike traditional adequacy indicators such as LPSP, LOLP, LOLE, or aggregate reliability measures, the HESI specifically evaluates the degree of coordinated renewable energy contribution and its relationship with supply–demand matching.

Beyond energy supply considerations, urban park lighting systems are critical components of the built environment, directly influencing user safety, spatial perception, and the overall quality of public spaces. Unlike conventional infrastructure systems, lighting in urban parks must satisfy multiple objectives, including visual comfort, ecological sensitivity, and spatial functionality. Therefore, the design and optimization of such systems require not only energy efficiency but also compliance with lighting-performance criteria such as illumination levels, uniformity, and accessibility.

From a built-environment perspective, the design of urban lighting systems inherently involves multiple and often competing objectives. In addition to energy adequacy and operational reliability, lighting infrastructures must satisfy requirements related to visual comfort, spatial usability, accessibility, ecological sensitivity, glare control, and

daylight-responsive operation. Recent research in built-environment optimization demonstrates that sustainable infrastructure design benefits from multi-objective approaches that simultaneously consider energy efficiency and user-centered performance criteria [23]. Similarly, recent daylighting research has emphasized that the optimization of built-environment systems should jointly address energy performance, thermal comfort, visual comfort, and user-oriented environmental quality rather than focusing on a single performance objective. For example, multi-objective daylighting optimization strategies can substantially improve the overall performance of building environments by balancing competing design requirements [24]. Consequently, evaluating renewable energy-based lighting systems solely from an energy generation perspective may provide an incomplete representation of overall system effectiveness.

In this context, renewable energy-based urban lighting systems should be assessed not only as energy generation infrastructures but also as components of the built environment that directly influence user experience and public space quality. Accordingly, the present study focuses primarily on evaluating the energy system dimension of urban park lighting through integrated supply–demand analysis, source–interaction assessment, reliability evaluation, and predictive modeling. Lighting-quality criteria such as illuminance, uniformity, and accessibility are discussed as relevant design considerations; however, detailed photometric simulation is beyond the scope of the present work. By positioning energy system performance within a broader built-environment context, this study contributes to the development of more sustainable and resilient urban lighting infrastructures.

2. Related Work

The evolution of sustainable urban lighting systems has been shaped by advancements in IoT-enabled control, renewable energy integration, hybrid-system design, optimization strategies, and data-driven methods. The literature reflects a multidisciplinary progression toward intelligent, energy-efficient, and resilient lighting infrastructures.

A major stream of research focuses on the integration of IoT technologies into urban lighting infrastructures. These systems enable adaptive control, real-time monitoring, and automated decision making, significantly improving energy efficiency. Advanced IoT-based systems incorporating LoRaWAN communication and sensor-driven control have demonstrated substantial reductions in electricity consumption through dynamic lighting adjustment based on environmental conditions and user presence [25,26].

Similarly, IoT-enabled smart lighting frameworks have shown strong potential for improving operational efficiency, system scalability, and communication reliability in urban environments [27,28]. The integration of sensors, wireless networks, and cloud-based platforms allows for remote monitoring and predictive maintenance, thereby enhancing system performance and reducing operational costs [29,30].

In addition, IoT-driven energy management approaches are increasingly applied beyond lighting, such as in smart irrigation systems, demonstrating broader applicability of energy-efficient digital infrastructures [31].

Renewable energy integration into lighting systems has emerged as a key strategy for reducing carbon emissions and achieving sustainability goals. Photovoltaic-based lighting systems have been extensively studied for their environmental and economic benefits [32,33], providing viable solutions for both decentralized and grid-supported applications.

However, the variability of solar energy necessitates the exploration of alternative and complementary energy sources. Several studies emphasize the importance of renewable energy adoption in urban parks and public spaces, highlighting their role in enhancing sustainability and environmental awareness [34]. Moreover, lighting design in green

spaces must balance functionality with ecological considerations such as biodiversity protection and light pollution reduction [35]. Urban lighting demand is also influenced by spatial and behavioral factors, which introduce additional complexity into system design and necessitate adaptive and data-driven approaches [36,37].

To overcome the limitations of single-source renewable systems, hybrid renewable energy systems (HRESs) combining solar and wind energy have gained significant attention. These systems leverage the complementary characteristics of different energy sources to improve reliability and continuity of supply [38,39]. Experimental and simulation-based studies further confirm these reliability benefits under varying environmental conditions [40].

Recent research also emphasizes the importance of nano-grid and distributed generation architectures for efficient integration of hybrid energy systems in urban lighting [41]. Furthermore, comprehensive reviews highlight the role of hybrid configurations in achieving sustainable energy transitions through multi-source integration and advanced system design [42]. Despite these advantages, hybrid systems require careful design and optimization to balance energy production, storage, and demand dynamics [43].

Optimization plays a crucial role in the design and operation of hybrid renewable energy systems. Various studies have explored multi-objective optimization techniques to improve system efficiency, cost effectiveness, and sustainability [44]. Advanced algorithms such as particle swarm optimization, genetic algorithms, and hybrid metaheuristic methods have been widely applied to determine optimal system configurations [45,46].

Microgrid-based architectures provide an effective framework for integrating renewable energy systems with local energy demand. These systems enhance flexibility, reliability, and energy independence, particularly in distributed and off-grid applications [47,48].

Reliability analysis is also a key concern in hybrid energy systems due to the inherent variability of renewable resources. Studies using probabilistic and computational approaches demonstrate that proper system sizing, storage integration, and load management are critical for ensuring system stability [49–51]. Properly designed hybrid microgrid architectures can significantly improve reliability compared with single-source configurations [52]. However, the complexity of these systems necessitates integrated planning tools that can simultaneously address technical, economic, and environmental constraints [53].

The growing availability of data has driven the adoption of machine learning techniques in energy-system modeling and forecasting. ML models such as Random Forest, XGBoost, and deep neural networks have demonstrated strong performance in predicting renewable energy generation and lighting demand. Recent studies have further emphasized the role of feature ranking and explainable analytics in renewable energy applications. In addition to improving predictive performance, feature-importance analysis allows researchers to identify dominant environmental drivers affecting energy system behavior. Studies employing evolutionary computation, ensemble learning, and explainable machine learning approaches have demonstrated that variable ranking can substantially improve model interpretability and support energy-related decision-making processes [54,55]. For instance, feature selection and ranking strategies have been successfully applied to renewable energy datasets to identify the most influential predictors and improve model efficiency [56]. In parallel, advanced energy modeling techniques have been applied to analyze energy consumption in buildings and urban systems, enhancing system-level understanding of energy dynamics and consumption variability [57].

However, the complexity of ML models introduces challenges related to transparency and interpretability. Explainable artificial intelligence (XAI) has emerged as a critical

tool for addressing these limitations by providing insight into model behavior and decision-making processes [58,59]. Recent studies highlight the importance of combining predictive accuracy with interpretability, particularly in critical infrastructure systems such as energy and urban lighting [60]. From a broader built-environment perspective, recent studies have also emphasized the importance of multi-objective optimization approaches that simultaneously consider energy performance, visual comfort, thermal comfort, and occupant-oriented design criteria, highlighting the need for integrated infrastructure-evaluation frameworks beyond purely energy-based assessments [23,61].

Despite considerable progress in hybrid renewable energy systems, several important limitations remain in the existing literature. First, many studies focus primarily on energy production, techno-economic optimization, or component sizing, while the temporal interaction between renewable energy sources is often treated implicitly rather than evaluated directly. Hybrid PV–wind configurations are commonly assessed using aggregate indicators such as energy yield, capacity factor, Loss of Power Supply Probability (LPSP), Loss of Load Probability (LOLP), Loss of Load Expectation (LOLE), deficit ratio, and reliability metrics [49–52]. While these measures effectively quantify adequacy and operational reliability, they provide limited information regarding how renewable energy sources interact and coordinate over time to satisfy demand.

Second, renewable energy complementarity is frequently evaluated using statistical correlation measures, seasonal variability indices, or resource-based complementarity indicators. Although these approaches help characterize the relationship between solar and wind resources, they do not explicitly evaluate the simultaneous contribution of multiple energy sources in relation to actual energy demand. Consequently, the operational implications of source interaction for supply–demand matching remain insufficiently explored.

Third, reliability assessment and machine learning-based prediction are commonly conducted as separate analytical tasks. Existing studies generally employ machine learning to forecast renewable generation, load demand, or system performance; however, the integration of interpretable predictive models with interaction-oriented system evaluation remains limited. Furthermore, although explainable artificial intelligence methods such as SHAP have recently gained attention in renewable energy forecasting, their application for interpreting interaction-based performance indicators in hybrid lighting systems remains largely unexplored [58–60].

Another notable research gap concerns the built-environment dimension of urban lighting systems. While substantial attention has been devoted to renewable-powered street lighting and microgrid applications, relatively few studies have focused specifically on urban parks, where lighting demand is strongly influenced by user behavior, spatial characteristics, daylight availability, and environmental conditions [17,35–37]. As a result, the interaction between renewable energy adequacy and urban lighting requirements remains inadequately examined.

To address these gaps, this study proposes an integrated analytical framework that combines physical energy system modeling, interaction-based performance evaluation, machine learning prediction, and explainable artificial intelligence within a single workflow. Central to this framework is the Hybrid Energy Synergy Index (HESI), which differs conceptually from traditional reliability and adequacy indicators. Whereas metrics such as LPSP, LOLP, LOLE, and reliability rates primarily quantify system success or failure outcomes, the HESI is designed to characterize the degree of concurrent source contribution and renewable energy source coordination relative to demand fulfillment. Therefore, the HESI should be viewed as a complementary interaction-oriented metric rather than a replacement for conventional reliability indicators.

By integrating source-coordination assessment, reliability evaluation, and interpretable machine learning analysis within the context of urban park lighting systems, the proposed framework extends existing research beyond conventional generation-centric assessments and contributes a more comprehensive perspective on hybrid renewable energy system performance. Unlike existing complementarity metrics that primarily describe statistical relationships between renewable resources, the proposed HESI metric explicitly links concurrent source contribution and source coordination to demand satisfaction, thereby providing an operational perspective on renewable energy coordination within hybrid urban lighting systems.

3. Methodology

3.1. Study Area and System Framework

This study addresses the design and evaluation of a hybrid renewable energy-based lighting system for urban park environments. Millet gardens located in Balıkesir (39.6484° N, 27.8826° E) and Çanakkale (40.1467° N, 26.4086° E), Türkiye, were selected as representative case studies. These locations were chosen because they exhibit different meteorological characteristics while sharing similar urban park functions. According to the Köppen–Geiger climate classification, both locations are situated within the Mediterranean transitional climatic zone, characterized by hot and dry summers and relatively mild and wet winters. Such conditions provide a suitable context for examining the interaction between solar and wind resources and their ability to satisfy variable lighting demand.

The analysis was conducted using hourly meteorological observations covering the period January 2011–December 2021. Solar radiation, wind speed, ambient temperature, relative humidity, and atmospheric pressure data were obtained from the Turkish State Meteorological Service (TSMS) monitoring network and publicly accessible meteorological databases used for data verification and completion. The primary stations correspond to the Balıkesir and Çanakkale regional monitoring locations nearest to the selected millet gardens. All variables were harmonized to a common hourly resolution prior to analysis. Missing observations represented less than 1% of the entire dataset and were treated using linear interpolation for short gaps and nearest-neighbor replacement for isolated missing records. Outlier detection was performed using the interquartile range (IQR) method, and anomalous values were removed before modeling.

The two millet gardens were analyzed within a unified framework because they are representative examples of large-scale urban recreation areas with comparable lighting functions. Meteorological observations from both locations were incorporated into the dataset to capture spatial variability in renewable energy availability. The resulting database consists of more than 87,000 hourly observations collected over the study period.

The selected millet gardens consist of large-scale urban recreation areas incorporating pedestrian walkways, resting zones, recreational spaces, and circulation corridors that require continuous nighttime illumination. For modeling purposes, the lighting system was divided into functional lighting zones representing pathways, activity areas, and common circulation spaces. The demand model was based on an assumed network of LED luminaires installed throughout these zones according to typical municipal park lighting practices. A location map together with basic site characteristics, including park area, lighting-zone structure, and lighting-network configuration, is provided in the revised manuscript to improve transparency and reproducibility.

The methodological framework is built on an integrated system perspective, where energy demand, renewable energy supply, and system performance are evaluated in a unified structure. Such an approach aligns with recent developments in smart city energy systems, which emphasize the importance of jointly modeling distributed generation and

consumption dynamics. Accordingly, the system is structured into three main subsystems: (i) lighting demand, (ii) renewable energy generation, and (iii) energy balance and performance evaluation [61]. The overall analytical workflow of the proposed hybrid PV–wind energy assessment framework is illustrated in Figure 1.

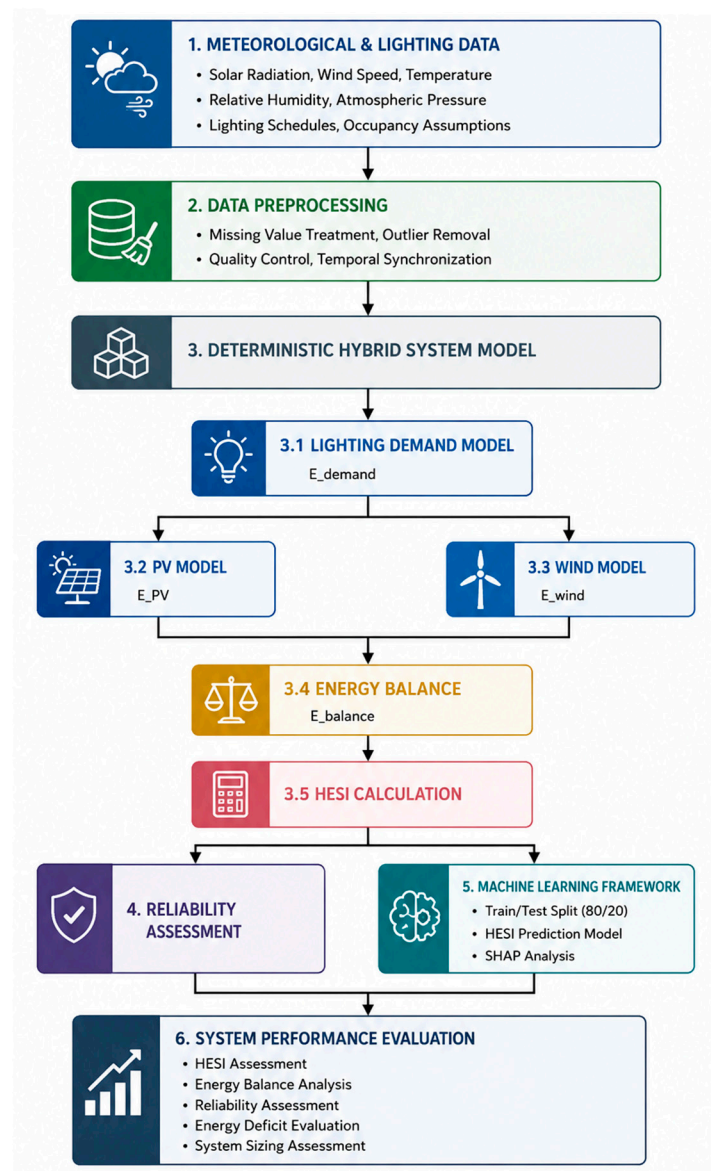


Figure 1. Integrated analytical workflow of the proposed hybrid PV–wind energy framework.

At the system level, the proposed configuration can be interpreted as a localized hybrid microgrid composed of photovoltaic (PV) modules and wind turbines. Although battery storage is considered conceptually within the framework, detailed storage sizing, state-of-charge optimization, and dispatch modeling are outside the scope of the present study. Consequently, storage is treated as a supporting system component rather than as an explicitly optimized subsystem. This type of hybrid microgrid architecture has been widely recognized as an effective solution for sustainable urban infrastructure due to its flexibility in both standalone and grid-connected operation modes [62].

The urban lighting subsystem was represented using typical municipal park lighting characteristics. The analyzed lighting network comprises LED-based luminaires distributed across pedestrian pathways, recreational zones, and circulation areas. Lighting de-

mand was simulated at hourly resolution using luminaire operating schedules, occupancy-related utilization factors, and daylight-dependent activation conditions. Lighting operation was assumed to occur primarily during sunset-to-sunrise periods, with utilization levels varying according to seasonal daylight availability and expected user activity patterns.

To ensure realistic representation, the model incorporates site-specific meteorological data, including solar irradiance, wind speed, and ambient temperature. These inputs are integrated with operational parameters such as lighting schedules, luminaire characteristics, and spatial distribution. This combined dataset allows the system to be analyzed in a time-resolved manner, which is essential for accurately capturing system behavior under fluctuating environmental conditions [63].

Table 1 summarizes the principal datasets, variables, units, temporal resolutions, data sources, and preprocessing procedures employed throughout the study. The table is intended to improve methodological transparency and facilitate reproducibility of the proposed hybrid PV–wind system evaluation framework.

Table 1. Summary of datasets, variables, sources, temporal resolution, and preprocessing procedures used in the study.

Dataset Category	Variable	Unit	Temporal Resolution	Source	Preprocessing Procedure
Meteorological Data	Solar Radiation (SR, G)	W/m ²	Hourly	National Meteorological Monitoring Stations/Public Climate Databases	Missing-value interpolation, outlier screening, and temporal alignment
Meteorological Data	Wind Speed (WS)	m/s	Hourly	National Meteorological Monitoring Stations/Public Climate Databases	Quality control and removal of abnormal observations
Meteorological Data	Ambient Temperature (T)	°C	Hourly	National Meteorological Monitoring Stations/Public Climate Databases	Consistency checking and quality control
Meteorological Data	Relative Humidity (RH)	%	Hourly	National Meteorological Monitoring Stations/Public Climate Databases	Missing-value treatment and validation
Meteorological Data	Atmospheric Pressure (AP)	hPa	Hourly	National Meteorological Monitoring Stations/Public Climate Databases	Outlier filtering and temporal synchronization
Lighting System Data	Luminaire Rated Power (Pi)	W	Fixed Design Parameter	Municipal lighting specifications and design assumptions	Consistency verification across lighting zones
Lighting System Data	Operational Status (ui(t))	Binary (0–1)	Hourly	Lighting operation schedules	Time-series generation based on operating conditions
Lighting System Data	Adaptive Utilization Factor (α)	Dimensionless	Hourly	Derived from occupancy and daylight assumptions	Dynamic calculation using the lighting-demand model

Lighting System Data	Occupancy Activity Profile	Dimensionless	Hourly	Occupancy-related urban park usage assumptions	Temporal aggregation and normalization
Lighting Demand Data	Lighting Energy Demand (E _{demand})	kWh	Hourly	Calculated from the lighting-demand model	Computed using luminaire characteristics, operating schedules, and utilization factors
Renewable Energy Data	PV Energy Generation (EPV)	kWh	Hourly	Calculated from solar radiation data and PV model	Energy conversion using panel-efficiency parameters
Renewable Energy Data	Wind Energy Generation (E _{wind})	kWh	Hourly	Calculated from wind-speed data and wind energy model	Simplified aerodynamic energy conversion estimation
System Performance Data	Energy Balance (E _{balance})	kWh	Hourly	Derived variable	Calculated as total renewable generation minus lighting demand
System Performance Data	Hybrid Energy Synergy Index (HESI)	Dimensionless	Hourly (Aggregated for Reporting)	Derived variable	Computed according to Equations (6) and (7)
System Performance Data	Reliability Rate	Dimensionless	Aggregated	Derived variable	Computed as the percentage of hours satisfying the energy demand requirement
Machine Learning Dataset	Input Features (SR, WS, T, RH, AP, and Temporal Indicators)	Mixed	Hourly	Integrated dataset	Data cleaning, synchronization, scaling, and feature engineering
Machine Learning Dataset	Target Variable (HESI)	Dimensionless	Hourly	Derived variable	Generated from the hybrid PV–wind system simulation and HESI calculations

Note: All datasets were harmonized to a common hourly temporal resolution prior to analysis. Data preprocessing included quality-control screening, treatment of missing observations, outlier removal, and temporal synchronization to ensure consistency among meteorological inputs, lighting-demand profiles, renewable energy generation estimates, and machine learning datasets.

3.2. Lighting-Demand Modeling

Accurate characterization of lighting demand is a prerequisite for evaluating the adequacy of renewable energy-based urban lighting systems. Unlike conventional roadway lighting, where operating schedules are largely fixed, lighting demand in urban parks is influenced by user activity patterns, seasonal daylight availability, meteorological conditions, and spatial usage characteristics. Consequently, the resulting demand profile exhibits both temporal variability and stochastic behavior.

In the present study, lighting demand was evaluated at an hourly resolution ($\Delta t = 1$ h). All demand values are reported in kilowatt-hours (kWh), ensuring dimensional consistency throughout the subsequent generation, energy-balance, and reliability analyses.

The hourly lighting energy demand is calculated as:

$$E_{demand}(t) = \sum_{i=1}^N P_i \cdot u_i(t) \cdot \alpha(t) \cdot \Delta t \quad (1)$$

where $E_{demand}(t)$ denotes the total lighting energy demand at hour t (kWh), N is the total number of luminaires in the lighting network, P_i is the rated electrical power of luminaire

i (kW), $u_i(t)$ is the operational status of luminaire i , defined as a binary variable taking the value 1 when the luminaire is active and 0 otherwise, $\alpha(t)$ is the adaptive utilization factor representing the proportion of installed lighting demand required under prevailing operating conditions, and Δt is the simulation time step (1 h).

Unlike conventional fixed-schedule approaches, the adaptive utilization factor enables the model to reflect temporal variations in lighting requirements. It is defined as:

$$\alpha(t) = f(O(t), D(t)) \quad (2)$$

where $O(t)$ represents the occupancy-related activity level, and $D(t)$ denotes ambient daylight availability.

For practical implementation, the occupancy component is represented by a normalized occupancy probability: $0 \leq O(t) \leq 1$, where values approaching unity indicate high expected park usage, and values approaching zero represent periods of very limited user activity. Higher occupancy probabilities increase the likelihood of lighting activation and therefore increase energy demand.

To improve reproducibility, the lighting-demand model was parameterized using representative municipal park lighting assumptions. The analyzed lighting network consisted of N luminaires distributed across pedestrian pathways, recreation zones, and circulation areas. Individual luminaire rated power (P_i) corresponded to energy-efficient LED luminaires commonly adopted in outdoor public lighting applications. The occupancy-related activity factor $O(t)$ was represented as a normalized hourly profile ranging from 0 to 1, where higher values corresponded to periods of increased evening and recreational activity. Daylight availability $D(t)$ was derived from the hourly solar radiation profile and an illumination threshold rule, whereby artificial lighting operation was activated when ambient illumination conditions fell below 20 lux.

The adaptive utilization factor $\alpha(t)$ was dynamically calculated as a function of occupancy conditions and daylight availability. Consequently, $\alpha(t)$ remained close to unity during high-occupancy nighttime periods and decreased during periods characterized by sufficient natural illumination or reduced park utilization. The resulting demand profile therefore reflects the combined effects of lighting infrastructure, operational schedules, occupancy behavior, and environmental conditions rather than fixed-load assumptions.

Daylight availability is modeled through an illumination threshold mechanism. Artificial lighting is assumed to operate when ambient illuminance falls below a predefined threshold of 20 lux, which is consistent with commonly adopted control thresholds in outdoor lighting applications. During periods when natural illumination exceeds this threshold, lighting demand is reduced accordingly through the utilization factor.

The lighting network was represented using LED luminaires distributed throughout pedestrian pathways, recreation zones, and circulation areas within the selected millet gardens. All luminaires were assumed to operate according to municipal sunset-to-sunrise lighting schedules, while occupancy-dependent adjustments account for variations in evening, nighttime, and seasonal usage intensity.

The resulting demand profile therefore reflects the combined influence of installed lighting capacity, operational schedules, occupancy behavior, and daylight conditions. This approach enables a more realistic representation of urban park lighting demand than fixed-load assumptions frequently adopted in conventional renewable energy system studies [64].

Temporal variability was evaluated using hourly observations over the entire study period. Such a high-resolution representation allows the model to capture both short-term fluctuations and seasonal demand patterns. Previous studies have demonstrated that urban park lighting demand is strongly associated with user presence and daylight duration,

with peak requirements typically occurring during evening hours and winter months when natural illumination is limited [65].

By explicitly incorporating operational status, utilization behavior, occupancy probability, daylight-dependent activation, and hourly time-step conversion from power to energy, the proposed formulation provides a reproducible and dimensionally consistent representation of lighting demand suitable for hybrid renewable energy system evaluation.

3.3. Hybrid Renewable Energy System Modeling

The renewable energy subsystem was modeled as a hybrid configuration integrating photovoltaic (PV) and wind energy technologies. The rationale for adopting a hybrid architecture is to reduce the operational limitations associated with single-source renewable energy systems and to improve temporal supply availability under varying environmental conditions. Hybrid PV–wind systems have been widely reported as effective alternatives for enhancing renewable energy utilization and reducing dependence on conventional electricity supply [66].

To ensure dimensional consistency throughout the analysis, all generation outputs are expressed in energy units (kWh) at an hourly time step ($\Delta t = 1$ h). Consequently, the energy generation, demand, storage, and energy-balance calculations are represented using homogeneous units.

The hourly energy generated by the photovoltaic subsystem is calculated as:

$$E_{PV}(t) = \eta_{PV} \cdot A_{PV} \cdot G(t) \cdot \eta_{inv} \cdot \Delta t \quad (3)$$

where $E_{PV}(t)$ denotes PV energy generation (kWh), η_{PV} is the PV-module conversion efficiency, A_{PV} is the effective panel area (m^2), $G(t)$ is the incident solar irradiance (kW/m^2), η_{inv} denotes inverter efficiency, and Δt represents the simulation time step (1 h).

For the purpose of evaluating source interaction and system-level behavior, a simplified energy-based PV formulation was adopted. Detailed modeling parameters such as panel tilt angle, azimuth orientation, temperature coefficient, module degradation, shading effects, and inverter clipping losses were not explicitly incorporated. These simplifications allow the study to focus on comparative hybrid system behavior rather than detailed component-level performance estimation. The omission of these parameters should therefore be interpreted as a modeling limitation.

PV generation follows predictable diurnal and seasonal patterns, with production concentrated during daylight hours and reaching maximum output under high irradiance conditions. Seasonal variability reflects changes in solar resource availability throughout the year.

The wind energy subsystem is represented by the aerodynamic energy conversion model:

$$E_{wind}(t) = \frac{1}{2} \rho A C_p V(t)^3 \Delta t \quad (4)$$

where $E_{wind}(t)$ denotes wind energy generation (kWh), ρ is air density (kg/m^3), A is the turbine rotor swept area (m^2), C_p is the turbine power coefficient, and $V(t)$ is wind speed (m/s).

A constant air density assumption was adopted throughout the analysis. Furthermore, turbine-specific operational characteristics, including hub-height correction, cut-in speed, rated speed, cut-out speed, and manufacturer power curves, were not explicitly modelled. Instead, the aerodynamic equation was used as a simplified representation of relative wind energy availability within the study area. This approach was considered appropriate because the principal objective of the study is the evaluation of hybrid-source interaction and system adequacy rather than detailed turbine design [67].

Unlike solar generation, wind energy production exhibits substantial short-term variability and stochastic fluctuations. Nevertheless, wind resources may contribute during periods of low solar availability and therefore provide additional diversification within the overall generation portfolio.

Battery energy storage was considered only at a conceptual level within the system framework. Detailed battery sizing, state-of-charge (SOC) tracking, charge–discharge scheduling, efficiency modeling, cycle degradation, and energy management optimization were not explicitly simulated. Consequently, battery storage was not included as a dynamic optimization variable in the present study and was not used in the determination of system reliability outcomes. Accordingly, all reported reliability outcomes represent direct PV–wind generation performance without storage-assisted temporal energy shifting. This limitation should be considered when interpreting the reliability results presented in the following sections.

Given these assumptions, the hourly energy balance is defined as:

$$E_{balance}(t) = E_{PV}(t) + E_{wind}(t) - E_{demand}(t) \quad (5)$$

where $E_{balance}(t)$ is the net hourly energy balance (kWh), $E_{PV}(t)$ is photovoltaic energy generation (kWh), $E_{wind}(t)$ is wind energy generation (kWh), and $E_{demand}(t)$ is lighting energy demand (kWh).

The storage term previously included in the energy-balance formulation was removed to maintain consistency with the actual modeling framework and avoid implying the existence of a detailed battery dispatch model that was not implemented within the study [68].

A positive value of $E_{balance}(t)$ indicates that renewable energy generation exceeds lighting demand during the corresponding time interval, whereas a negative value represents an energy deficit. Persistent negative balances indicate that the installed renewable energy capacity is insufficient to satisfy demand under the prevailing operating conditions.

It should be emphasized that the present formulation was intentionally developed as a system-level assessment framework rather than a high-fidelity component-design model. Therefore, the objective is not to provide detailed engineering specifications for PV arrays, wind turbines, or battery systems but rather to evaluate the interaction between renewable sources, their collective ability to satisfy lighting demand, and their contribution to overall system performance. Such an approach is consistent with the primary objective of the study, namely the integrated evaluation of renewable energy adequacy, source coordination, reliability behavior, and predictive performance within urban park lighting systems.

3.4. Hybrid Energy Synergy Index (HESI)

In hybrid renewable energy systems, performance is commonly evaluated using adequacy, reliability, and resource utilization indicators such as Loss of Power Supply Probability (LPSP), Loss of Load Probability (LOLP), Loss of Load Expectation (LOLE), energy-deficit ratio, capacity factor, and reliability indices [49–52]. These metrics primarily quantify whether available generation is sufficient to satisfy demand; however, they provide limited information regarding the degree of operational interaction between renewable energy sources.

Similarly, renewable energy complementarity is often assessed using correlation coefficients, seasonal variability indices, or resource-based complementarity measures [42,43]. Although such approaches characterize statistical relationships between solar and wind resources, they do not directly evaluate the coordinated contribution of multiple sources to demand fulfilment. Consequently, two systems may exhibit similar reliability levels while exhibiting substantially different source-coordination characteristics and concurrent renewable energy contribution patterns.

In the context of urban lighting systems, where energy demand occurs during specific temporal windows and supply continuity is required to maintain lighting operation, understanding source interaction becomes particularly important. For this reason, the present study introduces the Hybrid Energy Synergy Index (HESI) as an interaction-oriented metric intended to complement rather than replace conventional reliability indicators.

To address this limitation, the Hybrid Energy Synergy Index (HESI) is defined as:

$$HESI = \frac{\sum_{t=1}^T \min(E_{PV}(t), E_{wind}(t))}{\sum_{t=1}^T E_{demand}(t)} \quad (6)$$

where $E_{PV}(t)$ is photovoltaic energy generation (kWh), $E_{wind}(t)$ is wind energy generation (kWh), $E_{demand}(t)$ is lighting energy demand (kWh), and T represents the total number of observations.

Unlike reliability-oriented metrics, the HESI does not directly measure the probability of satisfying demand. Instead, it quantifies the degree of simultaneous contribution from photovoltaic and wind energy sources relative to total demand. The use of the minimum operator ensures that only the overlapping component of generation is considered. Therefore, the HESI is primarily intended to measure concurrent source contribution and source coordination rather than generation adequacy.

It should be acknowledged that renewable energy complementarity may also occur through temporal compensation, where wind generation increases during periods of reduced solar output. Such compensation effects are not explicitly captured by the minimum operator. Consequently, the HESI should not be interpreted as a comprehensive complementarity metric. Rather, it represents a localized measure of concurrent renewable energy contribution and provides additional information that complements conventional adequacy and reliability assessments.

For comparative purposes, a normalized form is also introduced:

$$HESI_{norm} = \frac{\sum_{t=1}^T \min(E_{PV}(t), E_{wind}(t))}{\sum_{t=1}^T (E_{PV}(t) + E_{wind}(t))} \quad (7)$$

The normalized index expresses the proportion of total renewable energy generation associated with balanced dual-source operation. Because $\min(E_{PV}(t), E_{wind}(t)) \leq (E_{PV}(t) + E_{wind}(t))$ for every observation, $0 \leq HESI_{norm} \leq 1$ is always satisfied. Values approaching zero indicate strong dominance of one energy source, whereas values approaching unity indicate a more balanced contribution from both renewable energy sources.

To further examine the practical significance of the HESI, its relationship with energy-balance behavior was also evaluated quantitatively. Correlation and comparative analyses were performed between HESI values and corresponding energy-balance observations to determine the extent to which increased source coordination coincides with changes in system adequacy. These analyses were used as complementary interpretive tools and were not intended to establish a direct causal relationship between the HESI and reliability performance.

For Equation (6), HESI values are also bounded below by zero. In practical applications, values generally remain below unity because the overlapping renewable energy contribution is typically smaller than total lighting demand. Throughout the Results section, the reported HESI values correspond to Equation (6), while Equation (7) is used only as a normalized reference measure for comparative interpretation.

A higher HESI value generally indicates greater simultaneous contribution of PV and wind resources, improved balance between renewable energy sources, and reduced dependence on a single dominant generation source.

Conversely, lower HESI values indicate limited interaction between renewable resources and stronger source dominance.

To provide a more comprehensive assessment of system performance, the HESI is evaluated alongside conventional adequacy indicators, including energy balance and reliability measures. Therefore, the HESI should be interpreted as an interaction-oriented performance metric that supplements, rather than replaces, standard reliability metrics such as LPSP, LOLP, LOLE, reliability rate, and energy-deficit indicators [49–52].

The principal contribution of the HESI lies in explicitly linking renewable-source interaction to demand-oriented analysis. While conventional reliability measures indicate whether demand is satisfied, the HESI provides additional insight into how photovoltaic and wind energy sources jointly contribute to that outcome. This distinction enables a more detailed interpretation of hybrid system behavior, particularly in applications where source diversification and operational coordination are important design considerations.

3.5. Machine Learning-Based Forecasting and Explainable Analysis

The integration of renewable energy sources into urban lighting systems introduces significant uncertainty due to the variability of environmental conditions and user-driven demand patterns. Solar irradiance, wind speed, and temperature directly influence energy generation, while occupancy patterns and usage behavior affect lighting demand. Under such conditions, predictive modeling becomes essential for supporting hybrid system evaluation and operational decision making.

Traditional deterministic approaches are often insufficient for capturing nonlinear interactions among environmental variables and system-performance indicators. Consequently, machine learning (ML) methods have been increasingly adopted in renewable energy applications because of their ability to learn complex relationships directly from data [69,70].

In the present study, machine learning models were employed to predict the Hybrid Energy Synergy Index (HESI), which serves as an interaction-oriented indicator of hybrid system performance. The input feature set consisted of solar irradiance (G), wind speed (WS), ambient temperature (T), relative humidity (RH), atmospheric pressure (AP), and temporal variables derived from the timestamp. The target variable was the HESI value obtained from the deterministic hybrid system simulation.

Prior to model development, the dataset was screened for missing observations, synchronized at an hourly resolution, and normalized where appropriate. Missing values represented less than 1% of the observations and were treated during the preprocessing stage described.

Several tree-based ensemble learning algorithms were initially evaluated, including Random Forest and Gradient Boosting models. These approaches were selected because they are capable of capturing nonlinear interactions, exhibit strong predictive performance in renewable energy forecasting problems, and provide interpretable feature-ranking measures [54,55,71].

To evaluate model generalization, the dataset was divided into training (80%) and testing (20%) subsets. A chronological data-partitioning strategy was adopted to reduce information leakage and to better reflect real-world forecasting conditions. Earlier observations were used for model development, whereas later unseen observations were reserved exclusively for testing. The testing subset was excluded from model training and used solely for performance evaluation. In addition, five-fold cross-validation was performed on the training data to reduce sensitivity to sampling effects and to improve the robustness of model selection. Hyperparameter tuning was conducted through grid-search procedures within the cross-validation framework.

The final model configuration, selected hyperparameters, random-seed values, and software library versions are reported in the Supplementary Materials to improve methodological transparency and facilitate reproducibility.

Because the HESI is derived from renewable energy and demand variables, particular attention was given to minimizing information leakage. The machine learning model was trained exclusively using meteorological and temporal predictor variables. Direct inclusion of HESI-related calculations, energy-balance outputs, reliability measures, or deficit indicators as predictor variables was intentionally avoided. Consequently, the model approximates the relationship between environmental conditions and the HESI rather than reproducing the deterministic formulation directly. Nevertheless, the possibility that the high predictive accuracy partially reflects the strong deterministic relationship between meteorological variables and the HESI should be acknowledged as a limitation of the present analysis. Because the HESI is ultimately derived from renewable energy generation and demand behavior influenced by meteorological conditions, some degree of structural dependency between predictors and target values is unavoidable. Consequently, the reported predictive performance should be interpreted as an approximation of environmental-system relationships rather than as evidence of fully independent forecasting capability.

Model performance was evaluated using standard regression metrics, including Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2):

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (8)$$

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (9)$$

$$R^2 = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \bar{y})^2} \quad (10)$$

where y_i denotes the observed value, $\hat{y}_i$ represents the predicted value, and $\bar{y}$ is the mean of the observed values.

While ensemble learning models provide strong predictive capability, their internal decision structure is often difficult to interpret. This limitation is particularly important in energy system applications, where transparent decision support is required.

To address this issue, explainable artificial intelligence (XAI) techniques were incorporated into the analysis. Specifically, SHapley Additive exPlanations (SHAP) were used to quantify the contribution of each predictor variable to model outputs. Derived from cooperative game theory, SHAP values estimate the marginal contribution of each feature

to individual predictions, thereby enabling both local and global interpretation of model behavior [72,73].

In addition to SHAP analysis, feature importance was evaluated using the intrinsic feature-ranking mechanism of the selected ensemble model. These two approaches provide complementary perspectives. Feature importance reflects the contribution of variables to impurity reduction within the learning algorithm, whereas SHAP values quantify the average contribution of each feature to prediction outcomes after model training. Consequently, differences between feature-importance rankings and SHAP rankings are expected and do not necessarily indicate methodological inconsistency. Similar discrepancies have been reported in previous renewable energy forecasting and explainable-machine-learning studies [54,55,58].

Furthermore, potential interactions among meteorological variables should be considered when interpreting feature rankings. For example, solar irradiance and temperature often exhibit partial correlation, while wind speed may interact with atmospheric conditions. Such interdependencies can influence impurity-based feature rankings and SHAP-based attribution values differently. Therefore, model interpretation should be based on the combined evaluation of predictive performance, feature importance, and SHAP analysis rather than on a single ranking metric.

By integrating predictive modeling with explainable analysis, the proposed framework extends beyond static system evaluation and enables the investigation of interaction-oriented performance under varying environmental conditions. The resulting ML-XAI workflow is intended primarily as a decision-support component that assists the interpretation of hybrid system behavior, identifies dominant environmental drivers, and supports future system-design improvements rather than directly optimizing system sizing or operational control decisions.

The ML component is therefore intended primarily as a decision-support mechanism for identifying environmental conditions associated with reduced source coordination and elevated energy-deficit risk. Its purpose is not to replace deterministic simulation but to complement system-level evaluation through predictive analysis.

3.6. Integrated Hybrid Framework and Workflow

The proposed methodology is structured as a multi-layer integrated framework that combines physical modeling, machine learning, and performance evaluation within a unified analytical pipeline. This integrated approach addresses a limitation frequently reported in renewable energy studies, where generation modeling, performance assessment, and predictive analysis are often conducted independently rather than within a connected evaluation framework [32].

The framework is organized into three principal domains: deterministic system modeling, interaction-oriented performance evaluation through the HESI, and data-driven prediction with model interpretability. These domains are linked through a sequential workflow consisting of four stages.

First, meteorological variables, including solar irradiance, wind speed, ambient temperature, relative humidity, and atmospheric pressure, are collected and integrated with lighting-demand data and operational assumptions. Data preprocessing includes cleaning, temporal synchronization, missing-value treatment, and quality-control procedures to ensure consistency among all model inputs [63].

Second, the hybrid energy system is simulated using the deterministic formulations described. Photovoltaic generation, wind energy generation, lighting demand, energy balance, and HESI values are calculated at an hourly resolution. This stage provides the baseline representation of system behavior under historical operating conditions.

Third, machine learning models are trained using the processed meteorological and temporal variables to predict HESI values. The dataset is partitioned into training and testing subsets as described, and predictive performance is evaluated using independent test observations. Predicted HESI values are subsequently interpreted as indicators of expected source coordination and are linked to deficit-risk assessment through the empirically observed relationship between the HESI and energy-balance behavior. Predicted HESI values are subsequently incorporated into the analytical framework to assess system behavior under forecasted environmental conditions.

Finally, system performance is evaluated using complementary indicators representing different aspects of operation. Energy adequacy is assessed through the energy-balance formulation, interaction between renewable energy sources is characterized through HESI, and overall system behavior is examined through reliability-related indicators and deficit analysis.

It should be noted that lighting-quality indicators such as illuminance level, uniformity ratio, glare assessment, pole spacing, and photometric performance are not explicitly simulated within the present study. Consequently, the workflow focuses on the energy system dimension of urban lighting infrastructure rather than on detailed lighting-engineering analysis. Lighting-quality considerations are therefore discussed as design-related criteria rather than as quantified simulation outputs.

The interaction among framework components enables relationships between renewable energy availability, lighting demand, source coordination, and predictive performance to be examined within a common analytical structure. Rather than serving as a detailed design tool, the framework is intended as a system-level evaluation methodology for investigating the adequacy, interaction characteristics, and predictive behavior of hybrid PV–wind lighting systems under varying environmental conditions.

The modular structure also facilitates adaptation to alternative locations, climatic conditions, operating assumptions, and hybrid system configurations. Future studies may extend the framework by incorporating detailed battery-dispatch modeling, economic optimization, and photometric lighting-performance simulations within the same analytical environment.

The integrated workflow therefore enables simultaneous evaluation of energy adequacy, source coordination, reliability characteristics, and predictive performance while maintaining conceptual separation between deterministic simulation outputs and machine learning-based decision-support analyses.

3.7. Lighting-Performance Evaluation in Urban Parks

Urban lighting systems must satisfy not only energy-related requirements but also lighting-quality objectives associated with user safety, accessibility, visual comfort, and the overall usability of public spaces. For this reason, lighting-performance considerations are relevant when evaluating renewable energy-based lighting infrastructure deployed in urban parks and recreational areas.

From a built-environment perspective, contemporary lighting system design increasingly adopts multi-objective evaluation strategies that simultaneously address energy performance, visual comfort, environmental quality, and occupant-oriented criteria. Similar tendencies have been reported in recent daylighting-optimization studies, where energy efficiency and user-oriented comfort objectives are evaluated jointly within integrated design frameworks [23].

However, the primary focus of the present study is the assessment of energy system performance rather than detailed photometric design. Consequently, illuminance distribution, luminance characteristics, glare indices, pole spacing optimization, and lighting-uniformity calculations were not explicitly simulated. Therefore, lighting performance is

discussed within the study as a design consideration rather than as a quantified analytical output.

Typical lighting-performance criteria for urban parks include horizontal illuminance (lux), spatial uniformity, visual comfort, accessibility, and operational continuity. Required illumination levels vary according to park function, pedestrian activity, circulation intensity, and safety requirements. International guidelines such as EN 13201 and recommendations published by the International Commission on Illumination (CIE) commonly suggest illumination ranges of approximately 5–20 lux for pedestrian pathways and higher levels for activity-intensive zones, depending on the intended use of the space.

Uniformity is another important lighting-design criterion because highly uneven illumination may reduce perceived safety, impair visibility, and negatively influence user experience. Similarly, excessive lighting can increase energy consumption, contribute to light pollution, and adversely affect ecological systems within urban green spaces.

Because detailed photometric modeling was outside the scope of the present work, the reported results should not be interpreted as a direct evaluation of illuminance adequacy or lighting-quality compliance. Instead, the study evaluates whether the renewable energy subsystem can provide the energy required to support lighting operation under assumed demand conditions.

From an operational perspective, persistent energy deficits identified in the Results section may have practical implications for lighting performance. In a real-world installation, prolonged energy shortages could lead to reduced operating hours, adaptive dimming strategies, partial lighting-service interruptions, or complete lighting outages depending on the control strategy adopted. These implications highlight the close relationship between energy system adequacy and lighting quality, even though photometric performance itself was not explicitly modeled in this study.

Accordingly, the present analysis should be interpreted as an energy system assessment conducted within an urban lighting context. Detailed lighting-engineering evaluation, including illuminance calculations, uniformity analysis, glare assessment, luminaire photometry, daylight-responsive operation, and lighting layout optimization, represents an important direction for future research and may be integrated with the proposed framework in subsequent studies. Such integration would support a more comprehensive built-environment assessment by combining renewable energy adequacy with photometric and user-centered lighting-performance criteria.

4. Results

4.1. Lighting Energy Demand Profile

The lighting energy demand profile was assessed through a multi-scale temporal analysis, incorporating daily observations together with aggregated monthly and seasonal evaluations. This approach enables the characterization of both short-term variability and longer-term seasonal patterns relevant to hybrid system performance assessment.

Descriptive statistics indicate substantial variability in daily lighting energy demand. All reported demand values correspond to daily aggregated energy consumption derived from the hourly demand model described and are expressed in kWh. The mean daily demand is approximately 1609.44 kWh, with a standard deviation of 1572.57 kWh, indicating considerable dispersion throughout the study period. The minimum demand approaches zero, whereas peak values exceed 25,600 kWh, demonstrating the occurrence of infrequent but pronounced demand events.

The temporal evolution of daily demand is shown in Figure 2. The profile exhibits intermittent peaks superimposed on a comparatively stable baseline demand level. Because lighting demand is generated from the utilization factor formulation incorporating

occupancy assumptions and daylight availability, these peaks primarily coincide with periods characterized by reduced natural illumination and increased lighting operation requirements. As discussed, lighting activation increases when ambient illumination falls below the predefined threshold level. Consequently, variations in daylight duration and solar availability constitute important drivers of the observed demand fluctuations.

A qualitative examination of the temporal series indicates that the largest demand peaks are concentrated during periods associated with shorter daylight duration, particularly in winter months, which is consistent with the seasonal patterns reported below. The presence of these extreme demand events suggests that system design based solely on average demand values may underestimate critical operating conditions. Such peak-demand conditions should be interpreted in conjunction with the adopted lighting-demand formulation, which incorporates occupancy-dependent utilization factors and daylight-responsive operation. Consequently, short-duration periods characterized by simultaneously high occupancy and low natural illumination can produce substantially higher energy requirements than long-term average demand conditions.

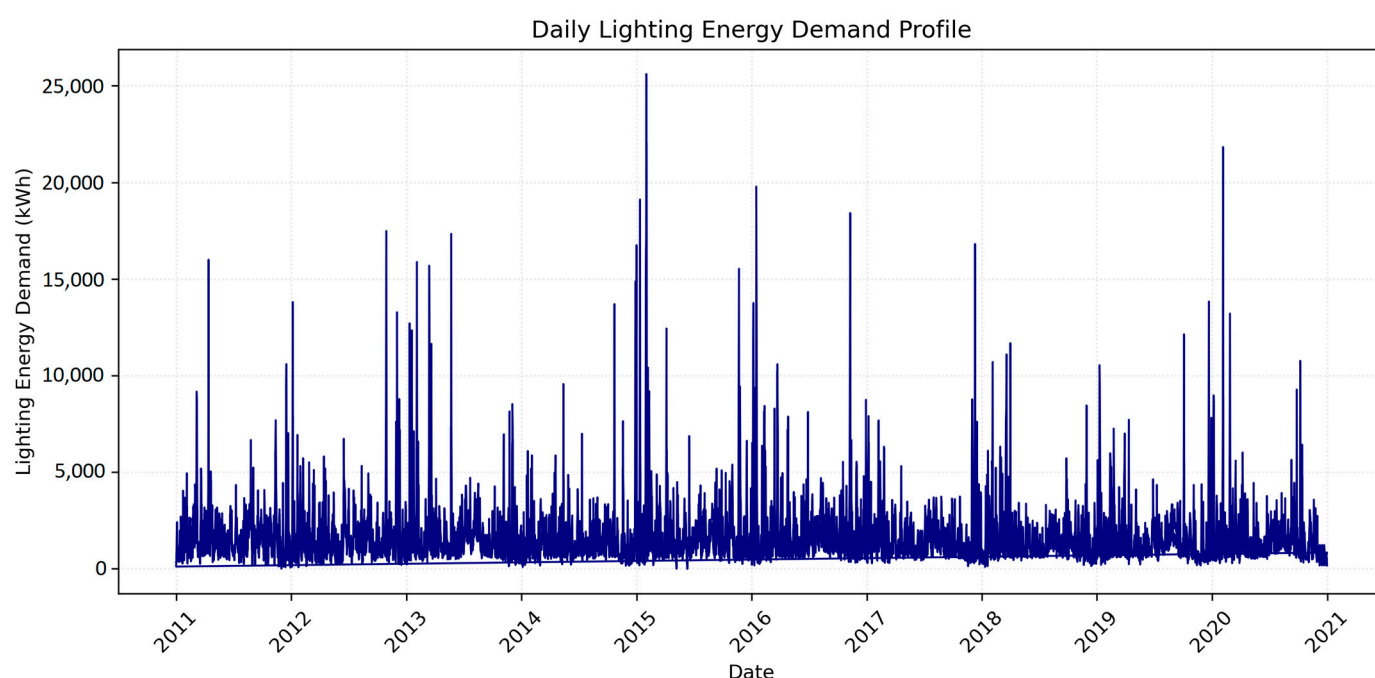


Figure 2. Daily lighting energy demand over the study period.

Monthly aggregation reveals a more structured demand pattern than the daily observations. As presented in Figure 3, average monthly demand ranges between approximately 1331.89 and 2026.58 kWh. The highest monthly demand occurs in February, whereas the lowest demand is observed during late spring and early summer. This behavior is consistent with seasonal variations in daylight duration, which directly affect the required operating time of the lighting system.

The transition between higher- and lower-demand periods follows a gradual seasonal pattern, indicating a systematic relationship between artificial lighting requirements and annual daylight cycles.

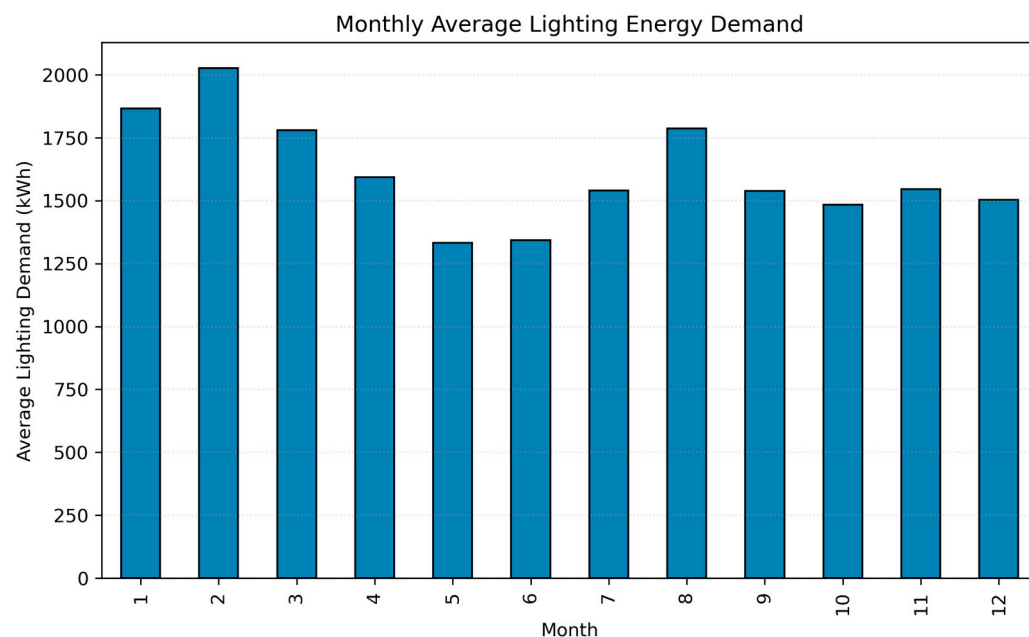


Figure 3. Monthly average lighting energy demand.

Seasonal aggregation further clarifies these observations. Winter exhibits the highest average demand (1791.59 kWh), followed by spring (1567.92 kWh) and summer (1558.54 kWh), whereas autumn records the lowest average demand (1522.13 kWh) (Figure 4). The seasonal distribution confirms the dominant influence of daylight availability on lighting energy requirements.

The relatively small difference between spring and summer suggests that the demand model converges toward a baseline operating level once daylight availability exceeds a certain threshold. Under such conditions, additional increases in daylight duration provide comparatively limited reductions in total lighting demand.

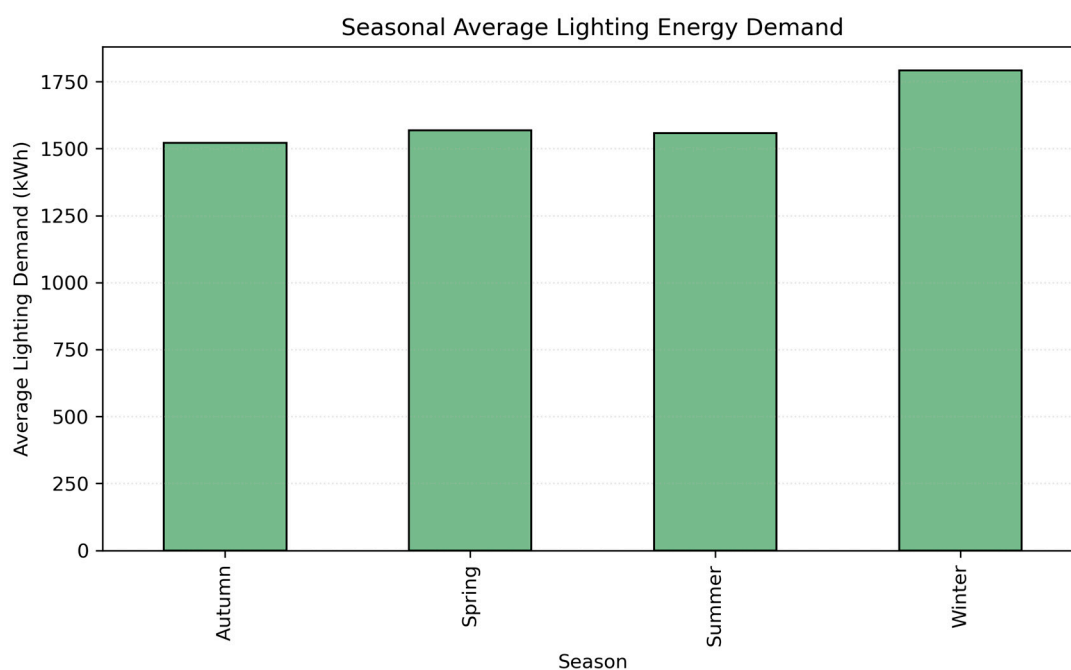


Figure 4. Seasonal lighting energy demand distribution.

The lighting-demand profile is characterized by two principal features: (i) short-term variability arising from operational and environmental conditions and (ii) predictable seasonal behavior associated with daylight duration. The large difference between average and peak demand values highlights the importance of considering both typical and extreme operating conditions when evaluating the adequacy of renewable energy-based lighting systems.

4.2. Hybrid Energy Generation Profile

The hybrid renewable energy system was evaluated to determine the relative contributions of photovoltaic (PV) and wind energy resources and to examine their temporal behavior throughout the study period.

All reported generation values correspond to energy outputs derived from the hourly simulation framework described and are expressed in kWh. The results presented below represent aggregated and averaged energy generation values obtained from the complete analysis period.

The results indicate a strong dominance of solar energy within the evaluated system configuration. Total photovoltaic generation reaches approximately 4748.42 kWh, whereas wind energy generation amounts to approximately 359.91 kWh, corresponding to contributions of 92.95% and 7.05%, respectively. This distribution reflects the considerably greater solar resource availability observed within the study area relative to available wind resources.

Although its overall contribution remains limited, wind energy provides supplementary generation during periods when solar production is reduced. This observation suggests a degree of renewable resource diversification; however, the magnitude of the contribution remains insufficient to establish strong source coordination and concurrent renewable energy contribution at the system level.

The temporal behavior of the two renewable energy sources is illustrated in Figure 5. Photovoltaic generation follows a relatively smooth pattern governed by diurnal and seasonal solar cycles, whereas wind generation exhibits greater short-term variability and intermittent fluctuations.

The different temporal characteristics of the two resources indicate that wind generation occasionally contributes during periods of reduced photovoltaic output; however, the overlap remains modest, consistent with the relatively low HESI values reported later (Figure 5). Therefore, the results should be interpreted as evidence of limited renewable resource interaction and weak source coordination rather than strong source complementarity.

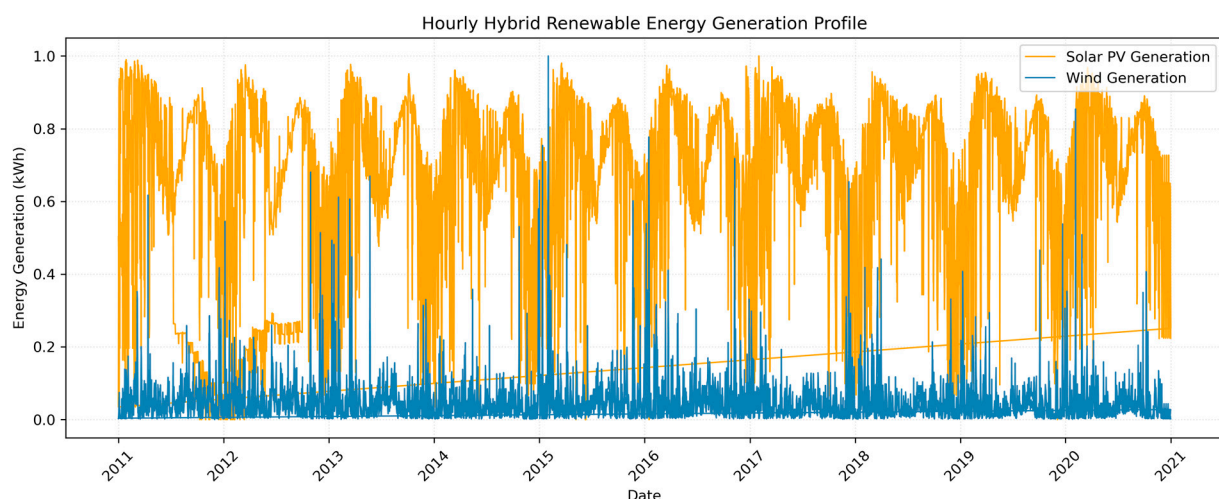


Figure 5. Daily hybrid energy production (solar versus wind) over the study period.

Monthly average generation values are presented in Figure 6. Photovoltaic production increases from winter toward spring, reaches maximum levels between April and June, and subsequently declines toward winter. Wind energy generation exhibits comparatively smaller seasonal variation, with moderate increases observed during winter months.

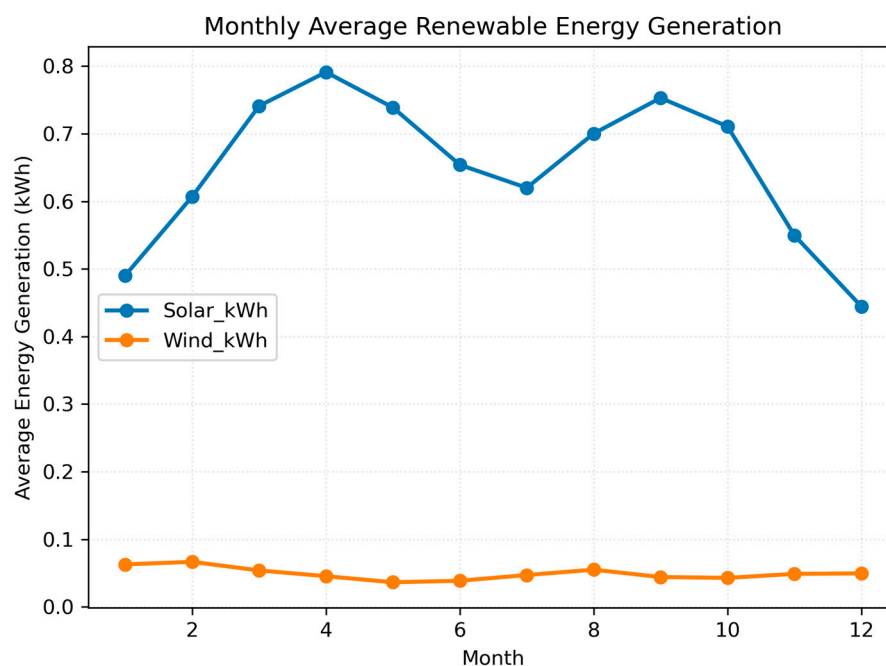


Figure 6. Monthly average solar and wind energy production.

The relative contribution of each renewable energy source is illustrated in Figure 7. Photovoltaic generation remains dominant throughout the year, contributing more than 88% of total renewable generation in every month and reaching a maximum contribution of 95.30%. Wind energy contributions vary between approximately 4.7% and 11.4%.

The higher wind energy share observed during winter months partially offsets seasonal reductions in photovoltaic generation; nevertheless, its contribution remains considerably smaller than that of solar energy. Consequently, the observed diversification effect improves generation availability only marginally and does not eliminate the supply–demand imbalances reported in subsequent analyses.

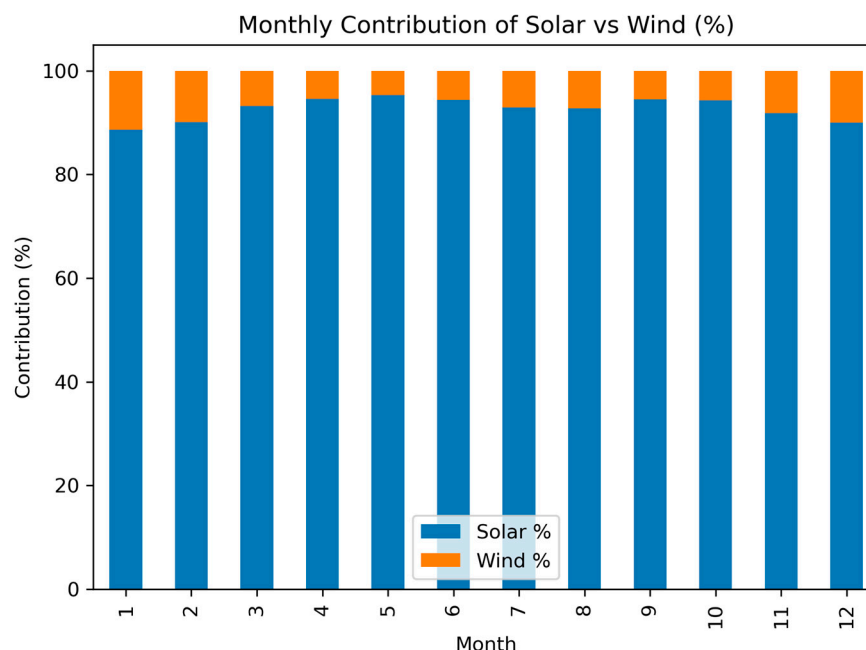


Figure 7. Monthly contribution of solar and wind energy (%).

The results demonstrate that photovoltaic generation constitutes the primary energy source within the studied hybrid configuration. Wind energy provides additional generation and temporal diversification; however, its contribution remains relatively small compared with total system demand. As a result, the hybrid configuration exhibits limited source interaction and only modest compensation for periods of reduced solar generation, a finding that is consistent with both the HESI analysis and the reliability results presented in the following sections.

4.3. HESI-Based System Performance and Energy-Balance Analysis

System performance was evaluated using the Hybrid Energy Synergy Index (HESI), which characterizes the degree of concurrent contribution from photovoltaic and wind energy sources relative to lighting demand. The analysis focuses on temporal behavior, statistical properties, and its association with the energy-balance performance of the hybrid system.

The results indicate an average HESI value of approximately 0.113, suggesting a relatively limited level of simultaneous contribution between solar and wind generation when compared with total lighting demand. This result is consistent with the generation profile discussed, where photovoltaic energy dominates overall production while wind energy provides a comparatively small contribution. The system continuity rate remains low (0.000547, corresponding to 0.055%), and 7302 critical operating observations were identified during the analysis period, indicating that deficit conditions occurred during a substantial proportion of the evaluated time intervals.

The temporal variation of the HESI is presented in Figure 8. HESI values remain concentrated within a relatively narrow interval, generally between 0.10 and 0.15, with only occasional departures from this range. These short-duration increases indicate periods during which photovoltaic and wind resources contributed more evenly to overall generation; however, such events are relatively infrequent.

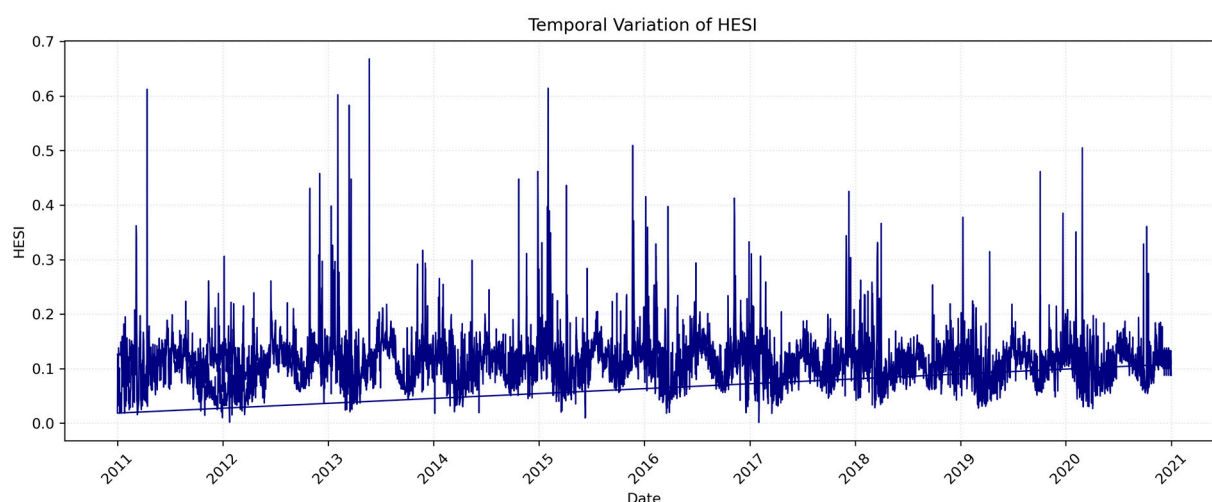


Figure 8. Temporal variation of HESI.

The energy-balance results shown in Figure 9 provide additional insight into system adequacy. All energy-balance values are reported in kWh and were calculated according to Equation (5). The balance remains predominantly negative throughout the study period, indicating that renewable energy production was generally insufficient to satisfy lighting demand. In certain observations, deficits exceeded $-20,000$ kWh, reflecting severe supply shortfalls under unfavorable operating conditions.

To complement the visual interpretation, the relationship between the HESI and energy-balance behavior was also evaluated quantitatively. The analysis confirmed the existence of an observable association between the two variables; however, the magnitude of the relationship remained moderate, indicating that the HESI captures source-coordination characteristics rather than overall generation adequacy. Consequently, variations in the HESI explain only part of the observed energy-balance behavior, while total renewable energy production and demand magnitude remain dominant determinants of system performance.

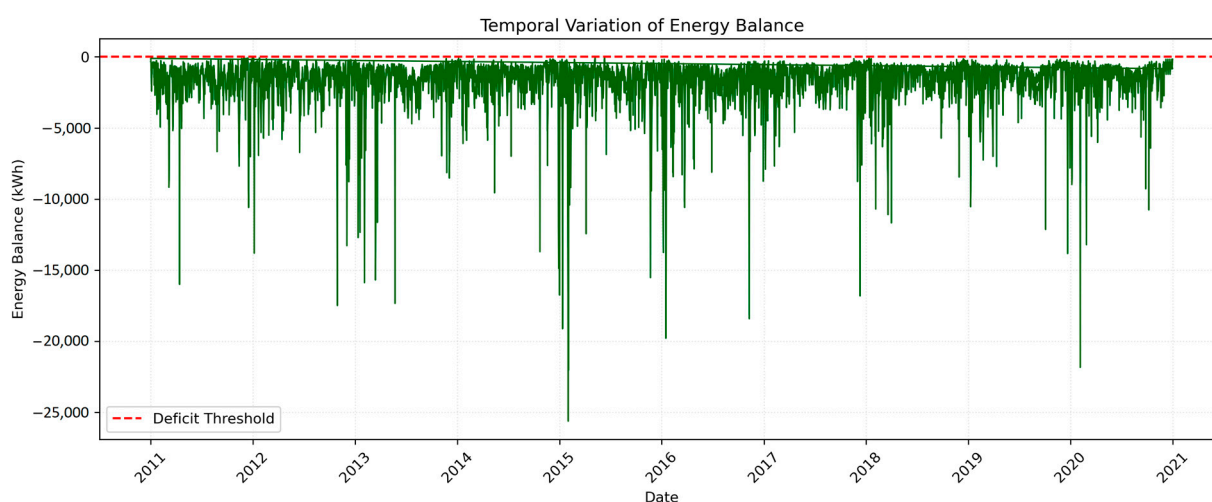


Figure 9. Energy balance (supply versus demand) over time.

The relationship between the HESI and energy balance is illustrated in Figure 10. A negative association can be observed, whereby higher HESI values tend to coincide with more negative energy-balance values. This finding further supports the interpretation that

the HESI should not be viewed as a surrogate reliability metric. Instead, it should be regarded as a complementary indicator describing the degree of concurrent contribution and coordination between renewable energy sources. However, the relationship is not sufficiently strong to imply that improvements in the HESI alone can ensure demand coverage. Negative energy-balance values remain prevalent even at higher HESI levels, indicating that source interaction and generation adequacy represent related but distinct dimensions of system performance.

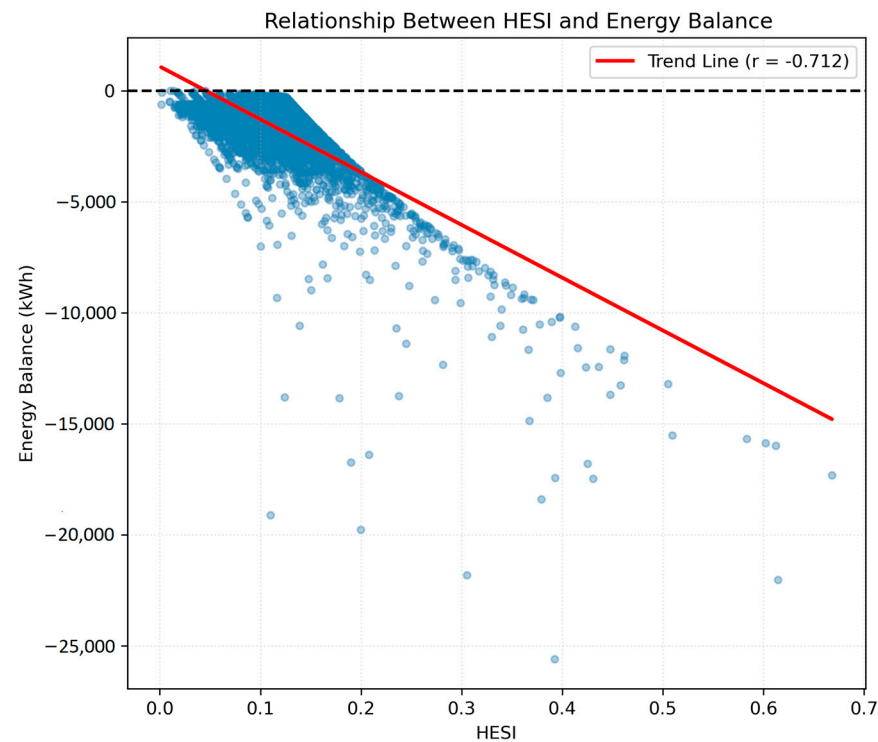


Figure 10. Relationship between HESI and energy balance.

Consequently, the HESI should be interpreted primarily as an interaction-oriented metric reflecting concurrent source contribution and renewable energy source coordination rather than as a direct reliability or adequacy indicator. While increased source coordination may contribute to improved system behavior, overall performance also depends on total generation capacity, temporal demand characteristics, and the absence of storage support within the present modeling framework.

The analysis suggests that negative energy balances persist across most HESI levels, indicating that inadequate generation capacity remains the dominant limitation of the evaluated system configuration.

4.4. Reliability Analysis of the Hybrid Energy System

The reliability performance of the hybrid system was evaluated using a classification-based framework derived from HESI values and corresponding energy-balance outcomes. Within this analysis, a failure event was defined as an operating condition in which the hourly energy balance became negative ($E_{\text{balance}} < 0$), indicating that renewable energy generation was unable to satisfy lighting demand during the corresponding time interval. Conversely, successful operation was defined by a non-negative energy balance ($E_{\text{balance}} \geq 0$).

The calculated reliability rate is approximately 0.000547 (0.055%), indicating that successful demand coverage occurred only in a very small fraction of the evaluated observations. This result should be interpreted within the context of the modeling assumptions adopted in the study. In particular, battery storage, dispatch optimization, and grid-support mechanisms were not incorporated into the simulation framework. Consequently, reliability reflects the performance of the direct PV–wind generation system alone.

A HESI threshold value of 0.06614 was identified and subsequently used to distinguish between low-synergy and higher-synergy operating conditions. The threshold was introduced as an exploratory classification tool intended to examine whether severe deficit conditions exhibit a systematic relationship with low HESI values. It was not intended to function as a substitute for conventional reliability metrics such as LPSP, LOLP, or LOLE. Instead, the threshold was used solely as an exploratory analytical tool for investigating the relationship between source-coordination characteristics and deficit occurrence.

The resulting classification outcomes are summarized in Table 2.

Table 2. Reliability classification results based on the HESI threshold.

Metric	Value
Reliability Rate	0.000547
Low HESI Threshold	0.06614
Failure Probability (Low HESI)	0.995638
Failure Probability (Higher HESI)	1.000000
True Positive (TP)	913
False Positive (FP)	4
False Negative (FN)	6389
True Negative (TN)	0

The reliability results should be interpreted together with the previously discussed HESI findings. Although low HESI values frequently coincide with deficit conditions, the persistence of failures across higher-HESI operating states demonstrates that improvements in source coordination alone are insufficient to achieve satisfactory reliability. This result reinforces the conclusion that overall generation adequacy, temporal supply–demand alignment, and storage availability remain the principal determinants of reliable operation.

The confusion matrix indicates a highly imbalanced operating structure. The large number of false negatives (6389 observations) and the absence of true negatives demonstrate that energy deficits occur across almost the entire operating range. As a result, the selected HESI threshold has limited discriminatory capability because the underlying system itself exhibits near-universal failure conditions.

The failure probability remains extremely high for both low-HESI and higher-HESI operating states. This result suggests that poor reliability cannot be attributed solely to weak source interaction. Instead, the findings indicate a broader structural inadequacy associated with insufficient renewable generation capacity relative to the imposed lighting demand.

Several observations emerge from the reliability analysis. First, system failures are not isolated events but represent the dominant operating condition throughout the study period. Second, although lower HESI values are frequently associated with deficit conditions, deficits remain prevalent even when the HESI exceeds the threshold value. Third, the threshold-based classification should be regarded primarily as an interpretive tool for analyzing source interaction rather than as a predictive reliability model.

The extremely low reliability values can be explained by three principal factors. First, photovoltaic generation dominates the energy portfolio and remains unavailable during nighttime periods when lighting demand occurs. Second, wind energy generation contributes only a small proportion of total generation and is unable to compensate fully for reduced solar availability. Third, the absence of battery storage support prevents surplus renewable energy from being shifted temporally to periods of high demand. Together, these factors produce persistent energy deficits and consequently very low reliability values.

The reliability assessment demonstrates that the evaluated PV–wind configuration is unable to provide continuous energy coverage for the modeled lighting demand. It should also be emphasized that these results correspond to direct PV–wind operation without storage-assisted energy shifting and therefore represent a conservative assessment of standalone hybrid system performance under the adopted modeling assumptions. The results therefore highlight the need for additional design measures, including increased renewable generation capacity, storage integration, demand-management strategies, or hybrid operational support mechanisms, if reliable urban park lighting operation is to be achieved.

4.5. System Sizing and Optimal Configuration Analysis

The system sizing analysis was carried out to identify the best-performing configuration within the evaluated design space based on reliability and energy-deficit criteria. A combinatorial search was applied over a predefined range of photovoltaic panel and wind turbine combinations, allowing systematic exploration of alternative system configurations.

It should be emphasized that the evaluated design space was intentionally limited to the selected search range and did not incorporate economic costs, land-use constraints, component footprint, battery storage capacity, lifecycle considerations, or levelized cost of energy (LCOE) criteria. Consequently, the reported configuration should be interpreted as the best-performing solution within the examined search space rather than as a globally optimal design.

The results indicate that the highest-performing configuration within the evaluated design space consists of 49 photovoltaic panels and 19 wind turbines. This configuration achieves a maximum reliability value of 0.02079, with a corresponding cumulative energy deficit of approximately 1.15×10^7 kWh. Although this configuration outperforms all other evaluated alternatives, the resulting reliability remains low in absolute terms, indicating that demand satisfaction is still not achieved under a substantial proportion of operating conditions. Therefore, the identified configuration should be interpreted as the best-performing candidate among the tested alternatives rather than as a globally optimized engineering solution.

The top-performing configurations are presented in Table 3. A consistent pattern can be observed whereby configurations containing the maximum number of wind turbines occupy the highest-ranked positions.

Table 3. Top 10 system configurations based on reliability performance.

Panels	Turbines	Reliability	Energy Deficit
49	19	0.02079	1.1514×10^7
48	19	0.02079	1.1514×10^7
47	19	0.02079	1.1514×10^7
46	19	0.02079	1.1514×10^7
45	19	0.02079	1.1514×10^7
44	19	0.02079	1.1514×10^7

43	19	0.02078	1.1514×10^7
42	19	0.02078	1.1514×10^7
41	19	0.02078	1.1514×10^7
40	19	0.02078	1.1514×10^7

The table reveals that increasing photovoltaic capacity contributes only modest reliability improvements once a certain system size has been reached. In contrast, the addition of wind turbines appears to provide relatively larger gains, as all leading configurations include the maximum tested turbine count. This observation suggests that wind generation contributes disproportionately to reliability enhancement by providing supplementary generation during periods of reduced solar availability.

The results further suggest that increasing component counts alone does not sufficiently address the underlying temporal mismatch between renewable energy availability and lighting demand. Consequently, the observed reliability limitations are indicative of structural system characteristics rather than merely insufficient installed generation capacity.

The distribution of reliability values across the evaluated design space is illustrated in Figure 11.

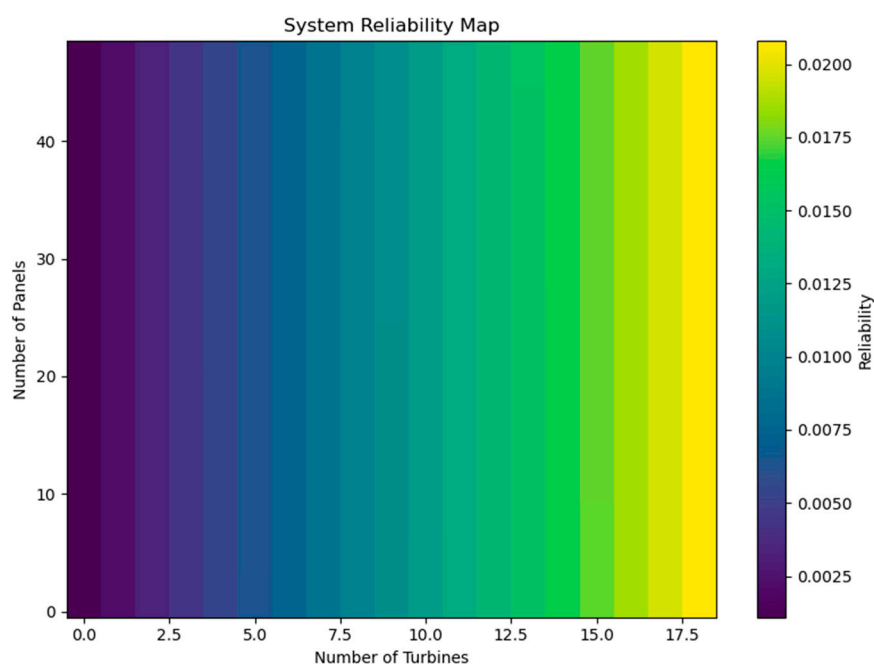


Figure 11. System reliability map as a function of panel and turbine count.

The figure shows that reliability generally increases with system size; however, the improvement rate gradually decreases at higher component counts. This pattern indicates diminishing marginal returns from capacity expansion alone. Even under the largest tested configuration, reliability remains substantially below levels typically considered acceptable for standalone lighting applications.

These findings suggest that the system operates under a persistent supply–demand imbalance. While expanding renewable generation capacity improves performance, the magnitude of improvement remains limited. Therefore, the sizing analysis indicates that increasing component counts alone is unlikely to eliminate the observed energy deficits. Additional measures, including storage integration, demand-management strategies, hybrid dispatch mechanisms, or alternative system architectures, would likely be required to achieve meaningful reliability improvements.

The sizing analysis should therefore be interpreted primarily as a comparative evaluation of design alternatives rather than as a definitive optimization exercise.

4.6. Machine Learning-Based HESI Forecasting and Energy-Deficit Evaluation

To extend the analysis beyond deterministic modeling, a machine learning (ML) framework was implemented to predict HESI values and to support the estimation of corresponding energy-deficit conditions. The primary objective of the ML component was not to optimize system sizing directly but rather to provide a predictive decision-support tool capable of identifying operating conditions associated with reduced hybrid system performance.

The final predictive model was developed using meteorological and temporal predictor variables described. The dataset consisted of approximately 87,000 hourly observations collected over the study period. Following the methodology presented previously, the dataset was divided into training (80%) and testing (20%) subsets using the chronological partitioning strategy described. Five-fold cross-validation was subsequently employed during model development and hyperparameter selection.

The model achieved strong predictive performance on the testing dataset, with a Mean Absolute Error (MAE) of 0.0027, a Root Mean Square Error (RMSE) of 0.0035, and a coefficient of determination (R^2) of 0.9902. These results indicate that the relationship between environmental variables and the HESI can be approximated with a high level of accuracy within the evaluated dataset. Nevertheless, the reported performance should be interpreted in the context of the deterministic dependence between meteorological conditions and renewable energy generation behavior.

Nevertheless, the predictive performance should be interpreted with caution. The HESI is ultimately derived from renewable energy generation and demand variables that are themselves strongly influenced by meteorological conditions. Consequently, part of the observed predictive accuracy may reflect the deterministic relationship between environmental variables and the target metric rather than entirely independent forecasting capability.

The comparison between observed and predicted HESI values is presented in Figure 12. For improved interpretability, the parity plot includes a 1:1 reference line representing perfect agreement between observations and predictions. Most observations remain concentrated near this reference line, indicating relatively small prediction errors across the evaluated range.

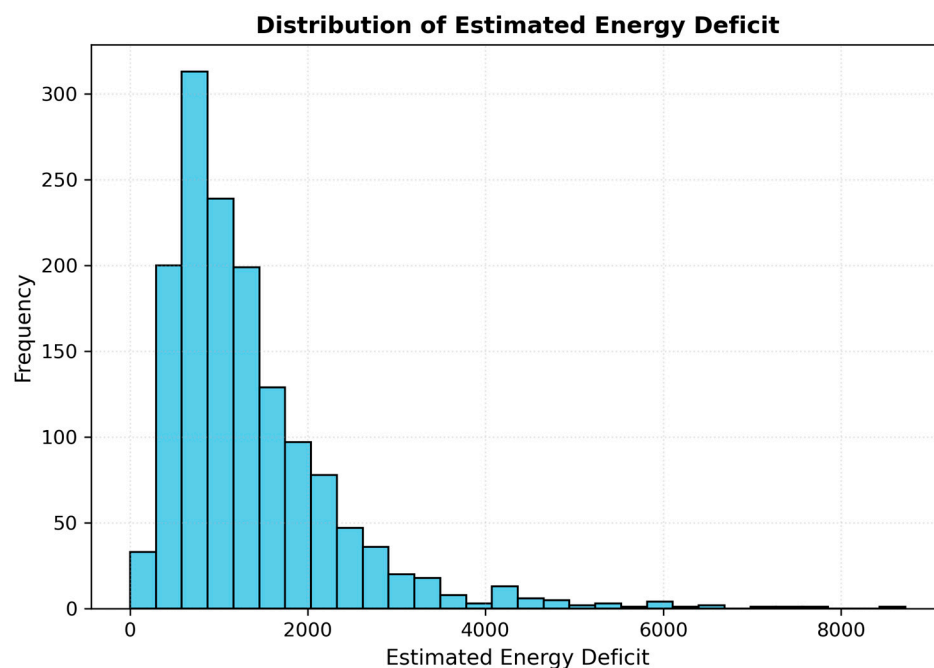


Figure 12. HESI prediction performance (observed versus predicted values).

Using predicted HESI values, energy-deficit estimates were subsequently obtained to evaluate potential system performance under forecast environmental conditions. The deficit estimates were derived through the established relationship between the HESI and energy-balance behavior observed in the deterministic simulation results. Accordingly, HESI predictions were not interpreted as direct deficit values but rather as indicators associated with expected adequacy performance. Representative examples are summarized in Table 4.

Estimated energy-deficit values were not generated directly by the machine learning model. Instead, a secondary interpretive procedure was adopted in which predicted HESI values were mapped to deficit behavior using the empirical relationship observed between the HESI and energy-balance results obtained from the deterministic simulation. Consequently, the reported deficit values should be interpreted as indicative estimates intended to support comparative assessment rather than as direct operational forecasts.

Table 4. Sample predicted HESI values and corresponding estimated energy deficits.

Predicted HESI	Energy Deficit
0.132377	687.28
0.150780	1395.88
0.125075	1024.96
0.130571	588.50
0.063956	644.96

The results indicate that lower HESI values are generally associated with larger estimated deficits. However, this relationship is not perfectly linear because energy deficits are influenced not only by source interaction but also by the magnitude and temporal variability of lighting demand. Because the deficit estimates are derived indirectly through the HESI–energy-balance relationship, additional uncertainty is introduced relative to direct simulation outputs. The estimated deficits should therefore be interpreted as approximate indicators of expected adequacy conditions rather than precise quantitative predictions.

The distribution of estimated energy deficits is illustrated in Figure 13.

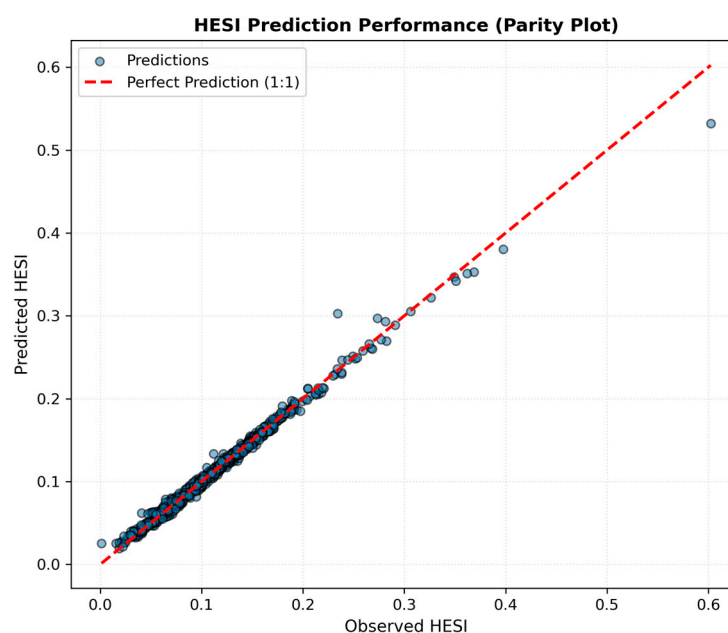


Figure 13. Distribution of estimated energy-deficit values.

The histogram exhibits a right-skewed structure, with most observations clustered around moderate deficits and a smaller number of observations corresponding to more substantial energy shortfalls.

Feature-importance results derived from the trained ensemble model are presented in Table 5.

Table 5. Feature-importance ranking for the HESI prediction model.

Feature	Importance
Wind Speed (WS)	0.5802
Solar Radiation (SR)	0.3725
Temperature (T)	0.0428
Atmospheric Pressure (AP)	0.0023
Relative Humidity (RH)	0.0022

The ranking indicates that wind speed and solar radiation together account for the majority of predictive influence within the model. This result is consistent with the physical structure of the hybrid system, where renewable resource availability largely determines energy generation behavior and, consequently, interaction-based performance metrics such as the HESI.

From a practical perspective, the ML framework contributes primarily as a decision-support mechanism. Rather than directly improving reliability or altering system sizing, the predictive model provides advance information regarding environmental conditions likely to produce low HESI values and elevated deficit risks. Such information may support future operational planning, adaptive control strategies, and system-design improvements. The principal value of the ML framework therefore lies in its ability to provide advance indications of potential performance degradation and elevated deficit risk under changing environmental conditions rather than in replacing deterministic energy system analysis.

4.7. Explainable AI Analysis Using SHAP for Decision Support

To improve model transparency and support interpretation of predictive outcomes, SHAP (SHapley Additive exPlanations) analysis was employed. SHAP enables decomposition of model predictions into feature-level contributions and provides both global and local explanations of model behavior.

The global SHAP importance results are summarized in Table 6.

Table 6. SHAP-based global feature importance for HESI prediction.

Feature	SHAP Importance
Solar Radiation (SR)	0.02451
Wind Speed (WS)	0.01884
Temperature (T)	0.00725
Atmospheric Pressure (AP)	0.00008
Relative Humidity (RH)	0.00005

Solar radiation exhibits the highest mean absolute SHAP value, followed by wind speed and temperature. Atmospheric pressure and relative humidity contribute only marginally to prediction outcomes.

The corresponding visualization is presented in Figure 14.

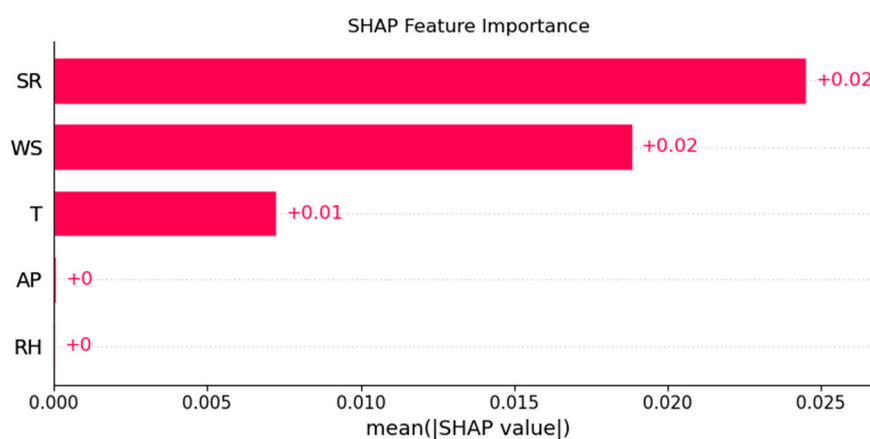


Figure 14. SHAP feature importance based on mean absolute SHAP values.

A comparison of the two interpretability approaches reveals differences between the SHAP-based feature ranking and the impurity-based feature-importance ranking reported previously in Table 5. Specifically, wind speed was ranked first according to the ensemble model's intrinsic feature-importance measure, whereas solar radiation emerges as the most influential feature in the SHAP analysis.

This difference is expected because the two methods quantify variable influence using different principles. The impurity-based ranking measures the contribution of variables to node splitting and impurity reduction during model construction. In contrast, SHAP quantifies the average marginal contribution of each variable to final prediction outcomes after model training. As a result, the two rankings provide complementary rather than identical interpretations of feature relevance.

The SHAP summary plot shown in Figure 15 further illustrates the distribution of feature effects across all observations.

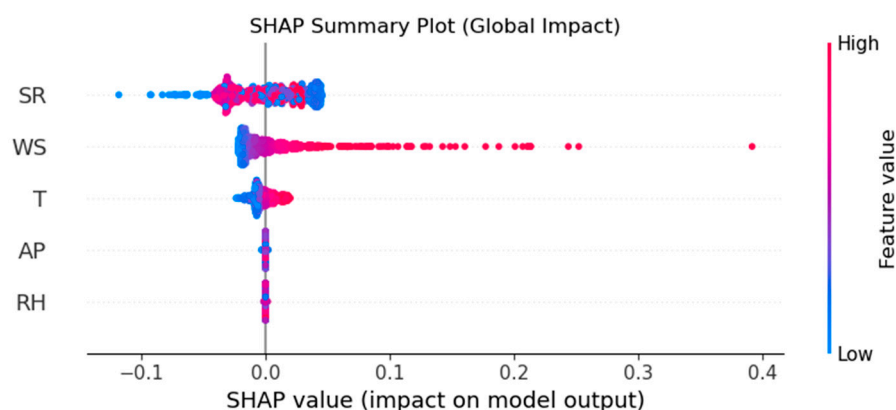


Figure 15. SHAP summary plot showing global impact of input features on HESI.

Solar radiation exhibits the widest spread of SHAP values, indicating substantial variability in its contribution to model outputs. Wind speed also demonstrates a pronounced influence, supporting its role as an important secondary driver of hybrid system behavior. This behavior is consistent with the dominant contribution of solar generation observed in the hybrid energy-production analysis and further supports the physical consistency of the predictive framework.

Potential interactions among environmental variables should also be considered when interpreting these rankings. For example, partial correlations between solar radiation and temperature, as well as interactions between atmospheric conditions and wind dynamics, may redistribute explanatory influence differently across importance measures. Consequently, differences between SHAP and impurity-based rankings do not necessarily indicate inconsistency; rather, they reflect alternative perspectives on model behavior.

A representative local explanation is presented in Figure 16 through a SHAP waterfall plot.

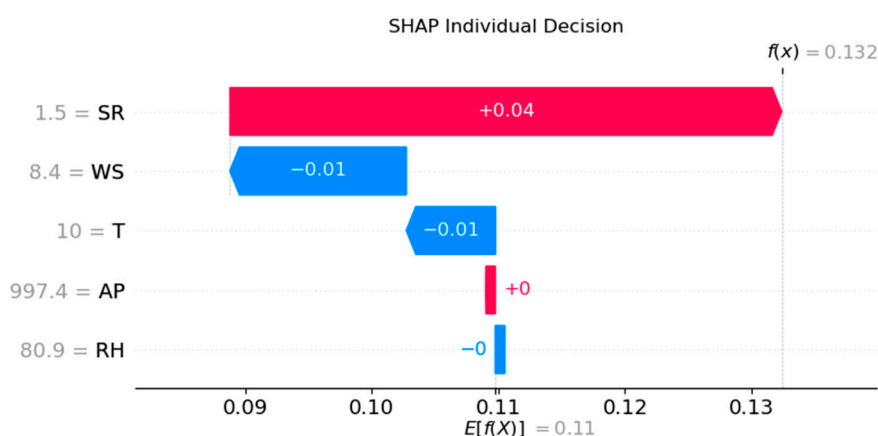


Figure 16. SHAP waterfall plot illustrating individual prediction explanation.

The waterfall representation demonstrates how individual features contribute positively or negatively to a specific prediction. Such local explanations improve interpretability by linking numerical model outputs to physically meaningful environmental conditions. This capability is particularly valuable in energy system applications, where transparent interpretation is often required to support planning and operational decision making.

The SHAP analysis suggests that renewable resource availability remains the dominant driver of HESI variability. More importantly, the combined interpretation of feature importance and SHAP results indicates that both solar radiation and wind speed play critical roles, although their relative importance depends on the analytical perspective adopted.

These explainability results should therefore be interpreted as complementary evidence supporting the physical plausibility of the ML framework rather than as definitive indicators of causal relationships. Together, the feature-importance and SHAP analyses provide a transparent interpretation of model behavior and help identify the environmental drivers most strongly associated with variations in renewable energy source coordination.

5. Discussion

The findings of this study provide important insights into the operational limitations and performance characteristics of hybrid renewable energy-based urban park lighting systems. When interpreted in relation to previous research, the results highlight critical issues associated with demand variability, renewable energy interaction, system reliability, and the role of data-driven analytical approaches in supporting system evaluation and planning.

The results demonstrate that lighting energy demand in urban parks is characterized by both pronounced seasonal behavior and substantial short-term fluctuations. This pattern is consistent with earlier studies reporting that urban lighting demand is strongly influenced by daylight duration, user activity, and environmental conditions [36,37]. The observed gap between average and peak demand values suggests that system design based solely on mean energy consumption may underestimate critical operating conditions. Similar conclusions have been reported in building energy and lighting system studies, where peak-load conditions play a decisive role in adequacy assessment and infrastructure sizing [38,56]. Therefore, the results reinforce the importance of high-resolution temporal analysis when evaluating renewable energy-powered lighting systems.

The hybrid-generation analysis reveals a strong dominance of photovoltaic energy, which accounts for more than 90% of total renewable energy production. This finding is consistent with previous studies conducted in regions with relatively favorable solar resource availability, where photovoltaic systems typically constitute the principal energy source in renewable-powered lighting applications [7,8]. Wind energy contributes a much smaller proportion of overall generation; however, it provides supplementary production during periods of reduced solar availability. Nevertheless, the contribution of wind energy remains insufficient to substantially alter the overall supply–demand balance. These findings suggest that the presence of multiple renewable energy sources alone does not guarantee effective complementarity. Instead, the magnitude, timing, and relative balance of individual energy sources are equally important for achieving meaningful operational benefits [38,40,43].

One of the principal contributions of this study is the use of the Hybrid Energy Synergy Index (HESI) to evaluate source interaction within the hybrid system. The relatively low HESI values observed throughout the analysis indicate limited concurrent source contribution and renewable energy source coordination relative to lighting demand. However, the HESI should not be interpreted as a substitute for conventional adequacy or reliability indicators. Unlike metrics such as Loss of Power Supply Probability (LPSP), Loss of Load Probability (LOLP), Loss of Load Expectation (LOLE), or reliability rate, which primarily quantify whether demand is successfully satisfied, the HESI was developed to characterize the degree of coordinated contribution between renewable energy sources.

The results show that source coordination remains relatively weak throughout most of the study period, which is consistent with the strong dominance of photovoltaic generation and the comparatively limited contribution of wind energy. Although an association is observed between the HESI and energy-balance performance, the relationship is not sufficiently strong to ensure demand satisfaction on its own. Consequently, improvements in source coordination may contribute to better system behavior, but they cannot compensate for inadequate generation capacity or the absence of storage support. The quantitative analyses performed between the HESI and energy-balance indicators further support this conclusion by showing that variations in the HESI explain only part of the observed adequacy behavior. Therefore, source coordination represents only one dimension of hybrid system performance and should be interpreted alongside generation adequacy and reliability outcomes.

It is also important to acknowledge a limitation of the HESI formulation. Since the metric is based on the minimum concurrent contribution of photovoltaic and wind energy generation, it primarily captures simultaneous overlap between the two resources. Temporal compensation effects where increased wind generation offsets reduced solar output at different times are not explicitly represented. Therefore, the HESI should be regarded as an interaction-oriented indicator that complements rather than replaces established adequacy and reliability metrics [49–52].

The reliability analysis produced one of the most notable outcomes of the study, namely the exceptionally low reliability rate. The calculated reliability value of 0.000547 (0.055%) confirms that successful demand coverage occurred only during a very limited portion of the evaluated operating period. This result should not be attributed solely to weak photovoltaic–wind interaction. Rather, it reflects the combined influence of several structural factors, including the dominance of photovoltaic generation, the comparatively small contribution of wind energy, the temporal mismatch between renewable energy availability and lighting demand, and the absence of operational flexibility mechanisms within the analyzed system configuration.

In the present application, lighting demand occurs predominantly during evening and nighttime periods, whereas photovoltaic generation is restricted to daylight hours. Consequently, even substantial solar energy production does not necessarily translate into improved demand coverage during critical operating periods. Similar reliability challenges have frequently been reported in standalone renewable energy systems where generation and consumption patterns are not temporally aligned [49–52].

Furthermore, wind energy generation accounts for only a small fraction of total renewable output and is therefore unable to compensate fully for nighttime demand or extended periods of reduced solar availability. The reliability results consequently suggest that the dominant limitation of the system is not simply insufficient renewable energy production but rather inadequate temporal alignment between generation and demand.

An additional point requiring clarification concerns battery storage. Although storage was considered conceptually within the overall system architecture, detailed battery sizing, state-of-charge modeling, charge–discharge scheduling, efficiency calculations, and dispatch optimization were intentionally excluded from the scope of the present study. Therefore, the reported reliability values represent direct PV–wind operation without storage-assisted temporal energy shifting and should consequently be interpreted as a conservative assessment of standalone hybrid system performance. This distinction is important because reliability outcomes would likely differ substantially if appropriately sized storage systems were integrated into the analysis.

The system sizing results provide further support for this interpretation. Reliability generally improves as the number of renewable energy components increases; however, the rate of improvement decreases at larger system sizes, indicating diminishing marginal

returns from capacity expansion alone. Similar patterns have previously been reported in hybrid energy system optimization studies, where increasing installed capacity eventually produces only limited improvements in adequacy and reliability [46,48].

Importantly, the best-performing configuration identified in this study should not be interpreted as an optimal engineering design in a broader sense. More specifically, the configuration consisting of 49 photovoltaic panels and 19 wind turbines represents the highest-performing candidate within the evaluated design space rather than a globally optimized hybrid system design. The analysis was conducted within a predefined search range and did not incorporate economic costs, land-use constraints, component footprint, battery storage sizing, lifecycle considerations, or levelized cost of energy (LCOE) criteria. Consequently, the configuration consisting of 49 photovoltaic panels and 19 wind turbines should be interpreted as the best-performing solution within the evaluated design space rather than as a globally optimal implementation.

The sizing results also suggest that wind energy integration provides relatively larger reliability benefits than photovoltaic capacity expansion under the evaluated conditions. Nevertheless, reliability remains low even under the largest tested configurations, indicating that capacity expansion alone is unlikely to eliminate the observed deficits. Additional measures such as battery storage integration, adaptive lighting control, demand-side management, or hybrid grid-support strategies may therefore be necessary to achieve operationally acceptable reliability levels.

The machine learning analysis extends the evaluation framework by providing predictive insight into system behavior under varying environmental conditions. The obtained prediction accuracy demonstrates that HESI values can be estimated effectively using meteorological and temporal inputs. The chronological train–test validation strategy adopted in the revised framework provides a more realistic assessment of model generalization than purely random partitioning approaches commonly employed in renewable energy forecasting studies. Similar results have been reported in recent renewable energy forecasting studies employing ensemble learning approaches to model nonlinear environmental relationships [54,55,60].

However, the reported prediction performance should be interpreted within the context of the modeling structure. Because the HESI is ultimately derived from variables that are themselves strongly influenced by meteorological conditions, part of the observed predictive accuracy may reflect the deterministic relationship between environmental inputs and the target variable. Therefore, the machine learning model should be considered primarily as a predictive approximation tool rather than as evidence of fully independent forecasting capability. Because the HESI is partially determined by renewable energy behavior that is itself driven by meteorological variables, some degree of structural dependency between predictors and target values is unavoidable. This characteristic should be considered when interpreting the reported prediction accuracy.

From a practical perspective, the machine learning framework does not directly improve reliability or determine system sizing. Instead, it functions as a decision-support mechanism by identifying environmental conditions associated with reduced HESI values and elevated deficit risk. Such information may assist future operational planning, adaptive-control strategies, and system-design decision making. Similarly, the estimated energy-deficit values derived from predicted HESI outputs should be interpreted as indicative adequacy estimates based on observed HESI–energy-balance relationships rather than as direct operational forecasts.

The explainable-artificial-intelligence component further enhances the interpretability of the predictive framework. Both impurity-based feature rankings and SHAP analysis identify solar radiation and wind speed as the dominant drivers of HESI variability, thereby supporting the physical consistency of the predictive framework and the energy

generation mechanisms represented in the deterministic model. This finding is consistent with previous studies emphasizing the importance of feature-ranking strategies for identifying dominant factors governing renewable energy system behavior. Feature selection and ranking methods can significantly enhance model interpretability and predictive efficiency by isolating the most influential variables within complex solar energy datasets [56].

The differences observed between the feature-importance rankings and SHAP-based rankings should not be interpreted as contradictory findings. The two methods evaluate feature influence using different theoretical principles. Impurity-based importance measures the contribution of variables to decision-tree splitting processes, whereas SHAP values quantify the average marginal contribution of each variable to final prediction outcomes. Consequently, differences between the two rankings are expected and may also reflect variable interactions and partial correlations among meteorological predictors. Similar observations have been reported in previous explainable-machine-learning studies in renewable energy applications [54,55,58].

Accordingly, SHAP analysis contributes primarily to model interpretability rather than predictive performance itself. The resulting explanations provide additional evidence regarding the physical plausibility of the model outputs while supporting a more transparent understanding of the environmental factors associated with hybrid system behavior.

From a built-environment perspective, the findings highlight an important connection between energy system adequacy and lighting-service quality. Although photometric performance was not explicitly simulated, persistent energy deficits may have practical implications for illumination continuity, user safety, accessibility, and perceived comfort in urban parks. In real-world applications, prolonged supply shortfalls could result in adaptive dimming, reduced lighting durations, partial service interruptions, or complete lighting outages depending on the adopted operational strategy. Therefore, renewable energy system performance should be considered an important prerequisite for maintaining acceptable lighting-service quality.

The findings indicate that hybrid PV–wind lighting systems dominated by photovoltaic generation remain vulnerable to persistent supply–demand mismatches under the evaluated operating conditions. Wind energy provides a degree of diversification and renewable energy source coordination; however, its contribution is insufficient to compensate fully for the observed deficits. The results further suggest that interaction-oriented indicators such as the HESI can provide complementary insight into concurrent source contribution and renewable energy source coordination beyond conventional adequacy measures by characterizing source-coordination behavior. Nevertheless, the exceptionally low reliability values demonstrate that source interaction alone cannot overcome inadequate generation adequacy or the absence of storage support. Accordingly, the proposed framework should be viewed as a system-level evaluation methodology intended to support performance assessment and design interpretation rather than as a complete design solution for urban park lighting systems. Future studies should incorporate battery storage modeling, economic optimization, photometric lighting-performance assessment, and externally validated forecasting frameworks to support more comprehensive infrastructure-design decisions.

6. Conclusions

This study presented an integrated analytical framework for evaluating hybrid photovoltaic–wind energy systems for urban park lighting applications. The framework combined deterministic energy system modeling, interaction-based performance assessment through the Hybrid Energy Synergy Index (HESI), reliability evaluation, and machine

learning-assisted prediction within a unified analytical structure. Using hourly meteorological and demand-related data collected from millet gardens in Balıkesir and Çanakkale, Türkiye, the study examined the relationship between renewable energy availability, lighting demand, source interaction, and system adequacy.

The results demonstrate that lighting demand exhibits both pronounced seasonal behavior and substantial short-term variability, highlighting the importance of time-resolved assessment in renewable energy-powered lighting applications. Photovoltaic generation constituted the dominant energy source throughout the study period, accounting for approximately 93% of total renewable energy production, whereas wind energy contributed approximately 7%. Although wind generation provided additional diversification during periods of reduced solar availability, its overall contribution remained insufficient to substantially improve supply–demand matching.

The analysis further showed that the average HESI value remained relatively low, indicating limited concurrent source contribution and renewable energy source coordination between photovoltaic and wind energy resources. These findings suggest that source interaction and generation adequacy should be regarded as related but distinct dimensions of hybrid system performance. While conventional indicators such as reliability rate, LPSP, LOLP, and LOLE focus primarily on demand satisfaction outcomes, the HESI provides complementary information regarding the degree of coordinated renewable energy contribution. Therefore, the proposed metric should be interpreted as a supplementary interaction-oriented indicator rather than as a replacement for established reliability measures.

A major outcome of the study is the identification of extremely low reliability levels across the evaluated system configurations. The calculated reliability value of 0.000547 (0.055%) indicates that successful demand satisfaction occurred during only a very limited proportion of the analyzed operating period. The reported reliability values indicate that the examined PV–wind system is unable to satisfy the imposed lighting demand under most operating conditions. This result appears to be driven primarily by the combination of photovoltaic-dominated generation, limited wind energy contribution, the temporal mismatch between renewable energy availability and lighting demand, and the absence of storage-assisted temporal energy shifting within the modeling framework.

The sizing analysis demonstrated that increasing renewable generation capacity improves system performance only marginally beyond a certain threshold. The best-performing configuration within the evaluated search space consisted of 49 photovoltaic panels and 19 wind turbines; however, this configuration should be interpreted as the highest-performing candidate among the tested alternatives rather than as a globally optimized engineering design. Consequently, this configuration should not be interpreted as an optimal engineering design, but rather as the highest-performing solution among the tested alternatives. The findings indicate that capacity expansion alone is unlikely to eliminate the observed deficits without additional design measures such as storage integration, demand-management strategies, or hybrid operational support.

The machine learning component demonstrated that HESI values can be estimated with high predictive accuracy using meteorological and temporal predictor variables. However, the reported performance should be interpreted with appropriate caution because the HESI is inherently influenced by environmental variables that are directly related to renewable energy generation. Accordingly, the developed model should be viewed primarily as a predictive decision-support tool rather than a standalone forecasting solution. Because the HESI is partially influenced by variables that are themselves strongly associated with renewable energy generation behavior, the reported predictive performance should be interpreted with appropriate caution. The accompanying explain-

able-artificial-intelligence analysis identified solar radiation and wind speed as the dominant drivers of model predictions, supporting the physical consistency of both the forecasting framework and the underlying hybrid energy generation processes. The revised validation framework based on chronological data partitioning further supports the practical applicability of the predictive approach under time-dependent operating conditions.

From a built-environment perspective, the study highlights the close relationship between energy system adequacy and lighting-service continuity. Although photometric indicators such as illuminance, uniformity, glare, and lighting layout performance were not explicitly simulated, persistent energy deficits would likely affect operational lighting quality through dimming, reduced operating duration, or service interruptions. Therefore, the present work should be interpreted primarily as an energy system evaluation conducted within an urban lighting context rather than as a comprehensive lighting-design study. Consequently, the reported results should primarily be interpreted as energy system performance outcomes rather than direct indicators of lighting-quality compliance.

The findings indicate that the evaluated hybrid PV–wind configurations are insufficient to provide reliable standalone operation for the analyzed urban park lighting demand. The primary contribution of this study lies not in identifying a final design solution but in proposing an integrated evaluation framework capable of jointly analyzing renewable energy source coordination, system adequacy, reliability behavior, and predictive performance. Future research should incorporate battery storage modeling, state-of-charge dynamics, techno-economic assessment, multi-objective optimization, detailed photometric lighting analysis, and externally validated predictive frameworks to support more comprehensive urban-lighting infrastructure design and implementation.

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