A SCALABLE WEB-BASED TOOL FOR WIND AND SOLAR ENERGY POTENTIAL ASSESSMENT AND GENERATION FORECASTING

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Abstract. Ukraine's energy sector is undergoing rapid transformation due to both the need to restore generation capacity following large-scale infrastructure damage and the accelerated transition to renewable energy sources (RES). Accurate forecasting of electricity production from solar and wind power plants is a key factor for balancing the energy system and reducing investment risks associated with the development of distributed generation. This paper presents GreenPowerAtlas — a software-information platform that integrates long-term satellite climatic datasets from NASA POWER with short-term weather forecasts from Open Meteo. The system implements advanced forecasting algorithms, including statistical models (ARIMA), neural networks (LSTM), and stochastic wind speed distributions (Weibull, Gamma). This ensures both long-term potential assessment and short-term generation forecasting. The architecture of GreenPowerAtlas provides scalability, high performance, and secure user access, while interactive visualization tools support decision-making for investors, engineers, and energy network operators. The platform has been successfully tested on real projects in Ukraine, particularly in assessing the solar energy potential of the Novyi Rozdil Industrial Park, confirming its practical value and readiness for large-scale implementation.

Keywords: Energy Forecasting, Renewable Energy Sources, Solar Generation, Wind Generation, ARIMA Models, LSTM Neural Networks, Stochastic Wind Modelling, NASA POWER Satellite Data, Meteorological Forecasts, Distributed Generation, Energy Analytics

1. Introduction

In recent years, Ukraine has lost a significant portion of its generation capacity: according to industry experts, more than 42% of electricity generation facilities have been destroyed or occupied, including almost 87% of coal-fired thermal power plants. Renewable generation assets have also been damaged or lost — more than 3.9 GW of solar and wind power plants are unavailable for operation. Such losses have seriously undermined the country's energy security and increased dependence on electricity imports from the EU, which cannot fully compensate for capacity shortages during peak consumption periods [1].

Against this background, the development of distributed generation based on renewable energy sources (RES) is gaining special importance. In 2024 alone, more than 944 MW of new distributed generation facilities — mostly solar — were commissioned in Ukraine, though only part of this capacity has been fully connected to the grid. Long-term projections suggest that by 2030, the installed renewable generation capacity may reach 9.2 GW, accounting for about 12–15% of the national energy mix. Alongside the development of storage technologies and flexible gas-engine units, this will form the foundation for restoring system stability and balance. However, the growing share of RES brings major challenges, primarily related to generation variability and the need for accurate forecasting of electricity production [1].

Existing international tools for RES potential assessment and forecasting — such as PVGIS (Photovoltaic Geographical Information System), Meteonorm, and RETScreen — play a role in preliminary planning but have limitations for application in Ukraine. They often lack sufficient spatial resolution, do not integrate real-time weather forecasts, and are mainly focused on techno-economic evaluation rather than accurate short- and medium-term forecasting. Global climate databases such as NASA POWER provide long-term satellite datasets but lack local adaptation and integration with current forecasts. This creates a gap between the needs of the Ukrainian energy sector and the available analytical tools [2-4].

To address these challenges, the Institute of General Energy of the NAS of Ukraine developed the GreenPowerAtlas — a modern web platform for analysing and forecasting solar and wind power generation. The system integrates NASA POWER's long-term satellite data with short-term Open Meteo forecasts, supports interactive visualisation and analytics, and implements advanced forecasting algorithms ranging from classical statistical models (ARIMA) to deep neural networks (LSTM). Its purpose is to help investors, engineers, and energy operators plan and balance distributed generation during Ukraine's energy recovery [5].

2. Review of Existing Solutions and Scientific Approaches

Accurate forecasting of renewable electricity production is critical for maintaining grid stability and integrating new solar and wind facilities. Over the past decades, numerous tools and methods have been developed, but most face limitations that hinder their use in Ukrainian conditions (Table 1) [5-7].

Among the most widespread international platforms for RES assessment are PVGIS, Meteonorm, and RETScreen Expert. PVGIS provides long-term climatic series and potential generation estimates for given locations, but its data have insufficient spatial resolution for Ukraine and lack short-term weather forecast integration. Meteonorm, a commercial product, generates climate series for any location but focuses mainly on long-term averages and lacks real-time meteorological API integration. RETScreen Expert is widely used for techno-economic evaluation of energy and efficiency projects, offering strong investment analysis features but limited short-term forecasting capabilities.

The NASA POWER service provides free access to long-term satellite climate datasets — including solar irradiation, wind speed and direction, temperature, and humidity — but lacks local adaptation for Ukraine and does not include short-term forecasts necessary for operational management. Conversely, Open Meteo offers high-resolution, hourly forecasts with easy API access but lacks the deep historical data needed for strategic planning [7-9].

Recent literature (2020–2024) shows growing interest in hybrid approaches combining statistical and machine learning models for renewable forecasting. Classical methods such as AR, ARMA, and ARIMA remain popular for their simplicity but have limited accuracy under rapidly changing weather conditions. Machine learning approaches (SVR, Random Forest, XGBoost) and recurrent neural networks such as LSTM demonstrate improved accuracy for non-linear temporal dynamics. Hybrid models like ARIMA-LSTM capture both seasonal and short-term variations effectively.

For wind potential assessment, stochastic models of wind speed distributions — particularly Weibull, Gamma, and lognormal — remain standard. Combining these with satellite data (e.g., NASA POWER) improves accuracy, though local calibration remains necessary. Increasingly, integrated systems are being developed that merge long-term statistics with real-time forecast data [10-12].

In summary, most tools address separate tasks: long-term planning, short-term forecasting, or techno-economic analysis. Ukrainian energy needs an integrated system combining multi-year satellite data, current weather forecasts, scalable architecture, and intuitive visualisation — which is the niche that GreenPowerAtlas aims to fill [4, 9].

Table 1. Comparison of key international solutions for forecasting energy production from renewable energy sources (RES)

System	Data sources	Temporal resolution	Short-term forecasting capability	Wind energy support	Visualization & interactivity	Local adaptation for Ukraine
PVGIS	Satellite climate series (JRC/EC)	Daily / monthly	No	Limited (primarily solar)	Online maps and charts	Low (general European data)
Meteonorm	Global database of climate stations	Monthly	No	Partial	Graphical interface	No adaptation
RETScreen Expert	NASA, climate archives	Daily	No	Yes	Analytical dashboards	Limited
NASA POWER	Satellite climate data	Daily / monthly	No	Yes	API without interactive interface	Low
Open Meteo	NWP forecast models	Hourly	Yes	Yes	API	None
GreenPowerAtlas	NASA POWER + Open Meteo + local stations	Hourly and multi-year	Yes (ARIMA, LSTM)	Yes	Interactive map, charts, export	High (adapted to regions of Ukraine)

3. Architecture and Software Implementation

The GreenPowerAtlas software and information complex has been conceived as a state-of-the-art web platform with a modular and scalable architecture, engineered to process and analyze vast volumes of meteorological and energy data efficiently. The fundamental design philosophy was to unite a flexible client–server architecture with high-performance data storage systems and advanced visualization tools — providing users with intuitive access to sophisticated analytics without compromising system responsiveness [2, 9].

Structurally, the platform is organized into three principal layers: the user interface (frontend), the application server (backend), and the data storage and processing subsystem (Fig. 1). This separation ensures scalability and resilience under heavy computational loads, which is critical when dealing with multi-decadal hourly datasets and simultaneous access from numerous users.

At the user interface level, the system employs the Vue.js framework, offering interactive work with cartographic layers, analytical widgets, and dynamic graphics. The interface enables users to select geographic regions, define temporal ranges, and visualize data through interactive maps, time-series plots, box plots, and histograms. Owing to its adaptive design, the platform provides equal usability across desktop and mobile environments. In addition, data export features to CSV, Excel, and PDF formats facilitate subsequent analysis and integration with other analytical systems.

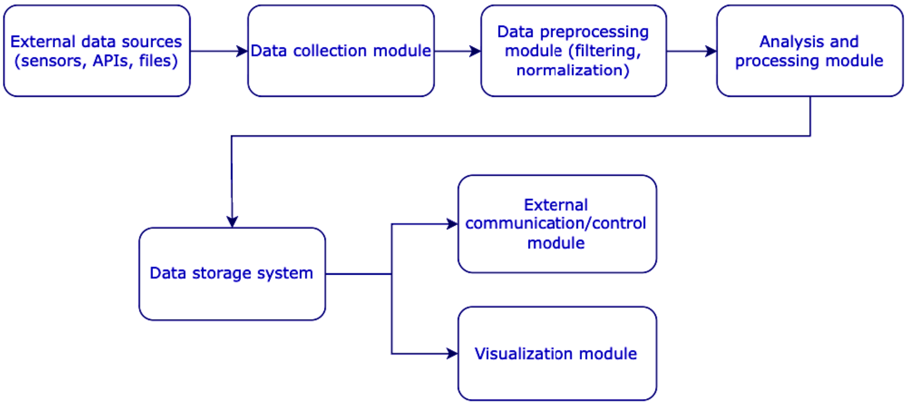

Fig. 1 Architecture of the GreenPowerAtlas software suite

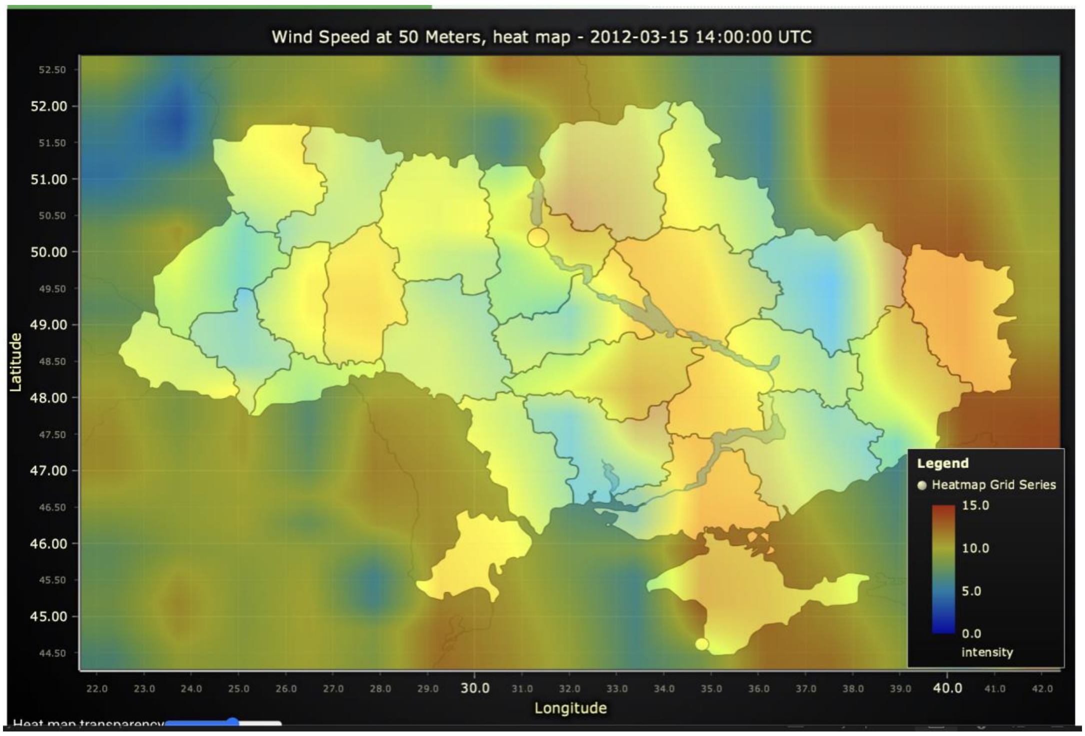

Fig. 2 *Web application interface: interactive map and dynamic charts*

The backend is implemented using Laravel (PHP) with a REST API architecture, which allows for fast scaling and seamless integration of external services. Heavy user requests are processed asynchronously, minimizing latency when interacting with large datasets. Caching mechanisms based on Redis significantly accelerate the system's performance by reducing redundant computations for repeated queries.

The data storage layer combines two database management systems — PostgreSQL and ClickHouse. PostgreSQL stores user configurations, analytical results, and auxiliary metadata, while ClickHouse is optimized for handling massive hourly climate datasets. Its column-oriented storage and analytical query optimization ensure exceptional performance and enable near-instantaneous access to historical meteorological records. This hybrid architecture successfully merges transactional flexibility with analytical speed.

Data security constitutes a separate design priority. The platform employs HTTPS encryption with the AES-256 algorithm, two-factor authentication, and protection against SQL injection attacks. Role-based access control allows the system to handle sensitive research and corporate datasets with precision and confidentiality.

Architecturally, GreenPowerAtlas supports horizontal scaling: additional servers can be deployed for load balancing and data storage expansion without significant changes to the source code. This capability is essential in the context of continuously growing climate and forecast datasets and the expanding user base. Furthermore, the system adheres to the principles of Big Data analytics and is designed for future integration with machine learning platforms to enable automated forecast updates.

Finally, the platform's interface provides broad capabilities for cartographic visualization. Users can explore maps of average annual wind speed, solar irradiance, temperature, and other climatic parameters, overlay analytical layers, and compare scenarios interactively (Fig. 2). Dynamic charts make it possible to evaluate temporal variations, analyze seasonal dynamics, and export the resulting datasets for energy-system modeling.

4. Mathematical and Algorithmic Forecasting Methods

Forecasting renewable energy production requires integrating historical climate series, adaptive forecasting data, and models that account for both seasonal and short-term variations. GreenPowerAtlas implements a multi-layered approach combining statistical and machine learning methods.

Data preprocessing ensures data quality and consistency. NASA POWER and Open Meteo datasets undergo normalization, missing-value handling, anomaly detection, and interpolation to align temporal resolutions (e.g., converting daily NASA data to hourly using Open Meteo corrections) [11, 13-15].

For short-term forecasting (hourly/daily), the ARIMA model is used:

$$y_t = c + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \theta_1 \varepsilon_{t-1} + \\ + \cdots + \theta_q \varepsilon_{t-q} + \varepsilon_t,$$

where p is the autoregressive order, q is the moving average order, and ε_t represents white noise. While ARIMA captures seasonal patterns, its accuracy decreases under rapidly shifting weather conditions.

To model complex, non-linear temporal dependencies, LSTM neural networks are applied. LSTM networks retain long-term dependencies through memory gates (input, output, forget), mitigating vanishing gradient issues typical of recurrent networks. They are particularly effective for wind generation forecasting, where sudden wind changes occur.

Stochastic Wind Potential Modeling

Wind speed distribution is modeled using probability density functions, most commonly the Weibull distribution:

$$f(v) = \frac{k}{c}\left(\frac{v}{c}\right)^{k-1} e^{-(v/c)^k},$$

where v is wind speed, k the shape parameter (turbulence), and k the scale parameter (mean wind speed). This helps estimate the capacity factor and optimize turbine height.

Model accuracy is evaluated using metrics such as MAPE, RMSE, and the coefficient of determination (R^2). Combining ARIMA with LSTM improves short-term forecast accuracy compared to standalone methods [16-17, 19].

To represent the statistical spread and detect outliers in the data, the box-and-whisker plot (or simply, the box plot) was employed (Fig. 3). This visualization method is particularly effective in energy analytics, as it concisely displays the variability and asymmetry of wind speeds, solar irradiance, or other meteorological variables across time intervals. Unlike a simple mean–standard deviation analysis, a box plot highlights medians, quartiles, and outliers, providing deeper insight into distribution shape and data stability [18-19].

Let $X = \{x_1, x_2, \ldots, x_n\}$ be the ordered dataset.

The median (Q_2) divides the dataset into two equal halves:

$$Q_2 = \begin{cases} x_{\frac{n+1}{2}}, & if\ n\ is\ odd \\ \dfrac{x_{\frac{n}{2}} + x_{\frac{n}{2}+1}}{2}, & if\ n\ is\ even \end{cases}.$$

The first (Q_1) and third quartiles (Q_3) represent the 25th and 75th percentiles respectively, marking the boundaries of the central 50% of values:

$$Q_1 = x_{(n+1)\cdot 0.25}, Q_3 = x_{(n+1)\cdot 0.75}.$$

The interquartile range (IQR) expresses the spread of the middle half of the dataset:

$$IQR = Q_3 - Q_1.$$

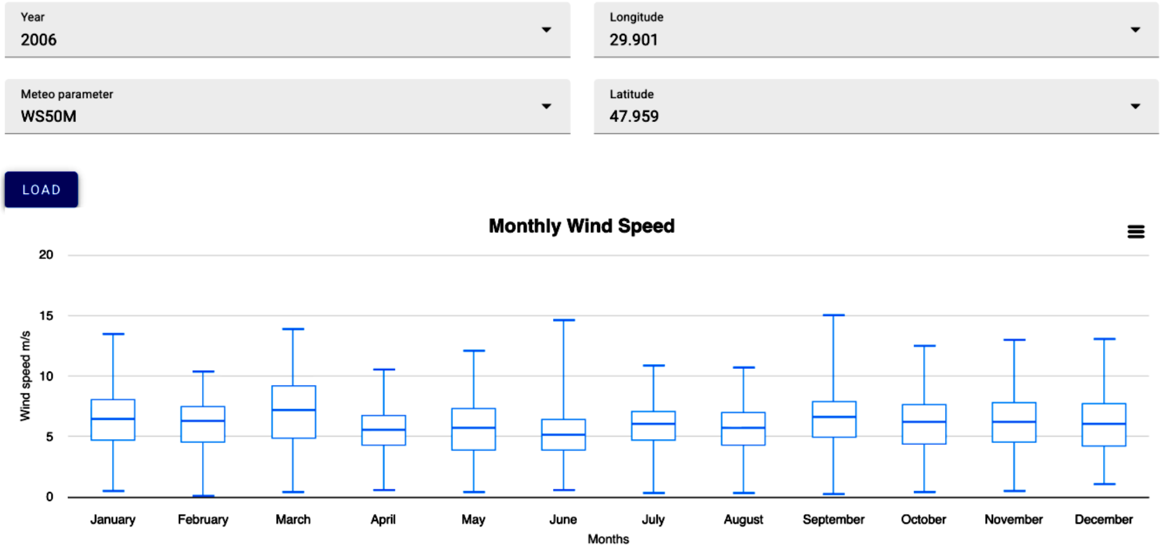

Fig. 3 *Distribution of monthly wind speed at a height of 50 m for 2006 at coordinates 47.959° N, 29.901° E. The chart shows the median, interquartile range, and minimum/maximum observations for each month.*

The whiskers extend to the most extreme values within 1.5 IQR of the quartiles, defining the non-outlier range:

$$L = Q_1 - 1.5 \times IQR, U = Q_3 + 1.5 \times IQR.$$

Values outside $[L, U]$are considered outliers, often plotted as individual points. These outliers are crucial in renewable energy analysis since they may correspond to extreme meteorological conditions — such as sudden wind gusts or high-irradiance peaks — which can significantly affect generation forecasts [20-22].

Overall, box plots provide an intuitive means of comparing data distributions between time periods, locations, or datasets. Within GreenPowerAtlas, this method enhances visual interpretation of wind and solar variability, helping analysts quickly assess data reliability and detect anomalies before applying forecasting models.

5. Applications and Results

The GreenPowerAtlas platform has been thoroughly validated using real-world datasets, proving its versatility and efficiency across numerous renewable energy applications in Ukraine. The validation process combined multi-decade climatic series with short-term meteorological forecasts, providing a comprehensive assessment of model accuracy, integration quality, and computational performance. Over two decades of NASA POWER wind speed data and Open Meteo forecasts were processed to produce detailed wind potential maps. By applying Weibull and Gamma probability distributions, the system calculated average wind speeds and capacity factors at various turbine hub heights. These results enabled the creation of interactive maps displaying both annual and seasonal variations, which help identify regions with the highest wind energy potential and optimize the configuration of wind farms for maximum efficiency.

In the field of solar energy, GreenPowerAtlas generates high-resolution solar irradiance maps that identify the most promising areas for photovoltaic development. Comparative analyses revealed considerable discrepancies between officially reported climatic norms and modern satellite observations, emphasizing the system's ability to provide more accurate and region-specific assessments. Such refined data prove invaluable for investors, project developers, and engineers who seek to minimize uncertainty in production estimates and improve the financial viability of solar projects.

The platform's technological foundation ensures exceptional performance. Integration of the ClickHouse database allows near-instantaneous querying of tens of millions of hourly meteorological records, while interactive regional maps are generated in less than 200 milliseconds. This responsiveness demonstrates the platform's readiness not only for academic and research use but also for continuous operation in industrial and governmental contexts. Additionally, GreenPowerAtlas accommodates external datasets and local meteorological sensors, extending its capacity for customized forecasting and high-precision analysis.

A notable example of the platform's application is the feasibility study of the Novyi Rozdil Industrial Park, where GreenPowerAtlas was employed to determine optimal wind turbine placement and hub height configurations. Using over twenty years of wind data, refined through current meteorological forecasts, the system produced accurate capacity factor estimates and identified the most efficient project design scenarios. This methodological integration of long-term statistics and short-term forecasts significantly reduces investment risks by combining spatial visualization with analytical modeling, ensuring well-founded decision-making during the early stages of renewable energy development.

Beyond technical modeling, the platform plays a critical role in enhancing grid stability and balancing by providing high-resolution generation forecasts that assist operators of distributed energy systems. It supports integration with SCADA and dispatch management systems, supplying reliable analytical data for real-time operations. Moreover, GreenPowerAtlas serves as a valuable educational and research environment, offering opportunities for experimenting with extensive climate datasets, developing innovative forecasting algorithms, and simulating distributed generation scenarios.

Platform embodies both a scientific research instrument and a practical engineering solution, bridging the gap between theoretical analysis and practical application. By uniting big data analytics, visualization, and scalable computation, it advances Ukraine's transition toward renewable energy independence and technological resilience.

6. Conclusions

The developed GreenPowerAtlas platform addresses a critical challenge for Ukraine's energy sector — accurate and flexible forecasting of renewable electricity production. By integrating NASA POWER's long-term satellite datasets with Open Meteo's short-term forecasts and leveraging advanced algorithms (ARIMA, LSTM, stochastic models), it provides a powerful analytical tool for multiple time horizons.

Practical applications, such as the Novyi Rozdil Industrial Park assessment, demonstrated real-world usability. The platform reduces investment risk, improves grid stability, and enhances decision-making for renewable development.

Future work will focus on deeper integration of machine learning algorithms, local sensor networks, and GHG emission analytics to evaluate the carbon footprint of renewable projects. Thus, GreenPowerAtlas represents both a scientifically sound and commercially viable product that strengthens Ukraine's renewable energy potential and energy independence.

Gratitude

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Conflict of Interest

The authors state that there are no financial or other potential conflicts regarding this work.

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