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INTELLIGENT FORECASTING OF RENEWABLE GENERATION FOR DEFICIT REDUCTION AND GRID STABILITY

The increasing penetration of variable renewable energy sources creates new challenges for regional power systems characterized by structural electricity deficits and dependence on external power transfers. This paper develops an intelligent forecasting framework for wind and solar power generation aimed at supporting power balance assessment and grid stability analysis in the Almaty region of Kazakhstan. The proposed approach combines historical meteorological data, renewable generation profiles, and machine-learning algorithms to forecast variable renewable energy output under different operating conditions. Forecasting models based on time-series analysis and machine-learning techniques are evaluated using standard accuracy indicators, including RMSE, MAE, and MAPE. The forecasted renewable generation is further integrated into a regional power balance assessment to estimate its potential contribution to reducing electricity deficit and supporting operational planning. The results demonstrate that intelligent forecasting can improve the predictability of renewable generation, reduce uncertainty in dispatch decisions, and provide a data-driven basis for renewable energy integration in deficit-prone power systems. The study contributes to the development of practical forecasting tools for emerging power systems with growing shares of renewable energy.

Keywords: intelligent forecasting, Renewable energy forecasting, variable renewable energy, wind power forecasting, machine learning, artificial intelligence.

Introduction

The rapid expansion of variable renewable energy sources is changing the operational logic of modern power systems. Wind and solar generation are no longer marginal technologies added at the edge of the grid; in many countries, they are becoming central components of generation adequacy, investment planning, and power system security. However, their technical value depends not only on installed capacity, but also on the ability of system operators to anticipate their output with sufficient accuracy. Unlike conventional thermal units, wind and solar power plants are governed by meteorological variability, which introduces uncertainty into generation scheduling, reserve allocation, voltage control, and transmission planning [1; 2]. This challenge is particularly important for power systems where renewable energy development is occurring in parallel with structural regional imbalances. Kazakhstan represents such a case. The national power system remains strongly dependent on thermal generation, while renewable energy is growing steadily. By the end of 2024, Kazakhstan had 157 renewable energy facilities with a total installed capacity of 3,038.6 MW, including 1,525.7 MW of wind power plants, 1,216.6 MW of solar power plants, 295.2 MW of small hydropower plants, and 1.1 MW of bioelectric power plants. Renewable generation reached 7.55 billion kWh in 2024, corresponding to 6.4 % of total electricity production [3]. Although this share remains modest compared with long-term decarbonization targets, the increasing penetration of weather-dependent generation already requires more advanced tools for forecasting and operational planning.

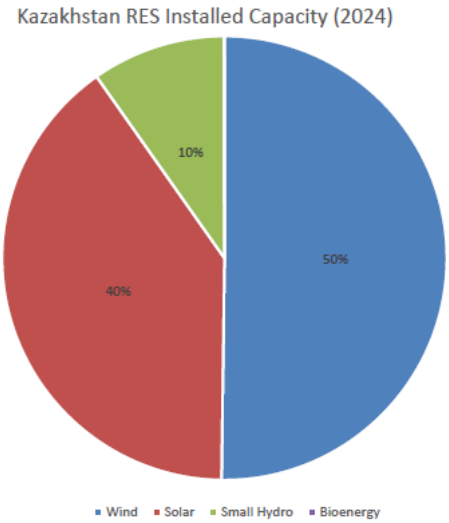


Figure1 – RES Installed Capacity [3]

The regional dimension of this problem is essential. Kazakhstan's electricity system is characterized by a spatial mismatch between generation and consumption. Large conventional power plants are concentrated mainly in the northern part of the country, while the southern regions experience increasing electricity demand and dependence on power transfers. In 2024, national electricity consumption increased by 4.3 % and reached 119,995.5 million kWh, while electricity consumption in the Southern zone increased by 5.6 % compared with 2023 [3]. In 2025, this trend continued: total electricity consumption reached 124,606.5 million kWh, and the Southern zone accounted for 30,641.0 million kWh, or 24.6 % of national consumption [4]. These figures indicate that the southern part of the system is not merely a passive load area, but a structurally important region for future adequacy and flexibility planning.

Almaty region is one of the most relevant examples of this transition. The region combines growing electricity demand, proximity to major load centers, and significant renewable energy potential. As of 2025, Almaty region had 23 operating renewable energy facilities with a combined installed capacity of 328.1 MW, including 8 hydropower plants with 25.78 MW, 9 wind power plants with 142 MW, and 6 solar power plants with 160.365 MW [5]. This resource base creates an opportunity to reduce regional dependence on external electricity supply. At the same time, the variability of wind speed, solar irradiation, cloud cover,

ambient temperature, and seasonal demand patterns makes renewable generation difficult to use as a firm planning resource without reliable forecasting.

For this reason, renewable energy forecasting should be treated not as an auxiliary data-processing task, but as a core element of power system operation and planning. Accurate forecasting of wind and solar generation improves day-ahead scheduling, reduces balancing costs, supports reserve management, and helps system operators evaluate possible deviations between load and renewable output. Recent studies show that machine-learning-based forecasting models can capture nonlinear relationships between meteorological variables and renewable power output more effectively than purely linear statistical methods, especially when historical generation data, weather variables, and temporal features are jointly considered [6]. Nevertheless, many forecasting studies remain focused on model accuracy alone and do not sufficiently connect forecasting results with regional power balance, import dependency, and grid stability indicators.

This paper addresses this gap by developing an intelligent forecasting based on random forest method with framework for wind and solar power generation in the Almaty region of Kazakhstan. The proposed approach combines meteorological data, historical renewable generation profiles, and machine-learning techniques to forecast variable renewable energy output.

Materials and methods

Research design

This study develops an intelligent forecasting framework for estimating variable renewable energy generation in the Almaty region of Kazakhstan and linking the forecasted output to regional power balance assessment. The methodological design follows the logic that renewable energy forecasting should not be treated only as a statistical prediction problem, but as an operational tool for power system planning. In a deficit-prone region, the practical value of a forecast is determined by its ability to reduce uncertainty in dispatch, reserve planning, import dependency, and grid stability evaluation.

The proposed framework consists of four main stages. First, meteorological, renewable generation, and power system data are collected and harmonized. Second, statistical and machine-learning forecasting models are developed for wind generation. Third, the forecasting performance is evaluated using standard accuracy indicators. Finally, the predicted renewable generation is incorporated into a regional power balance model to assess the contribution of wind and solar power to deficit reduction.

Study area and power system context

The Almaty region was selected as the case study because it combines three important characteristics: growing electricity demand, limited local generation

capacity, and significant potential for wind power development. These conditions make the region a suitable test case for evaluating the operational role of renewable energy forecasting in a structurally constrained power system.

Unlike regions with abundant conventional generation, the Almaty region depends partly on electricity transfers from other parts of the national power system. Therefore, the integration of variable renewable energy sources must be assessed not only in terms of installed capacity, but also in terms of hourly availability, seasonal variability, forecast uncertainty, and their effect on the regional power balance. This is particularly relevant for wind generation, whose output depends strongly on meteorological conditions and cannot be dispatched in the same way as conventional thermal units [7; 8; 9; 10].

Mathematical model for solar generation:

$$P_{PV,t} = \eta_{PV} * A_{PV} * G_{,t} * [1 - \beta(T_{cell,t} - T_{ref,t})] \quad (1)$$

where:

$P_{PV,t}$ – the power of the solar station at time t,
η_{PV} – efficiency of photovoltaic modules
A_{PV} – area of PV modules
$G_{,t}$ – solar irradiation
β – temperature coefficient
$T_{cell,t}$– PV panel temperature
T_{ref} – temperature

For wind generation:

$$P_{W,t} = \begin{cases} 0, & v_t < v_{ci} \\ P_r \dfrac{v_t^3 - v_{ci}^3}{v_r^3 - v_{ci}^3}, & v_{ci} < v_t < v_r \\ P_r, & v_r < v_t < v_{co} \\ 0, & v_t < v_{co} \end{cases} \quad (2)$$

where:

v_t – wind speed,
v_{ci} – cut-in speed
v_r – rated speed
v_{co} – cut out speed
P_r – nominal power of wind turbine

Random forest method

The Random Forest method [11] was applied as a machine-learning approach for forecasting wind power generation based on historical meteorological and operational data. Wind power generation is highly dependent on meteorological

conditions and shows a nonlinear relationship with wind speed, wind direction, air density, temperature, and atmospheric pressure.

The accuracy of the model was assessed using statistical error indicators such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2). These indicators allow evaluation of how closely the predicted values correspond to the actual measured wind power generation.

$$\text{RMSE}=\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i-\hat{y}_i)^2} \quad (3)$$

$$\text{MAE}=\frac{1}{n}\sum_{i=1}^{n}(y_i-\hat{y}_i)^2 \quad (4)$$

$$\text{MAX}=max|y_i-\hat{y}_i| \quad (5)$$

$$R^2=1-\frac{\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}{\sum_{i=1}^{n}(y_i-\bar{y})^2} \quad (6)$$

where n=1,2,…n; -actual values; $\hat{y}_i$ – predicted values, n-number of validation

In this study, the Random Forest method is used to forecast wind power output because it can effectively capture nonlinear dependencies between input variables and generated power without requiring strict assumptions about the statistical distribution of the data.

$$P_{W.t}^{forecast}=f_{RF}\left(v_t,d_t,T_t,p_t,H_t,P_{w,t-1}\right) \quad (7)$$

Random forest based wind power forecasting model

The proposed model is a data-driven framework for forecasting wind power generation under variable meteorological conditions. It combines time-series weather data, historical renewable generation, Random Forest regression, scenario generation, and power system analysis.

At the input stage, the model uses wind speed, wind direction, temperature, humidity, atmospheric pressure, and previous wind and solar generation values. These variables are preprocessed through data cleaning, missing value treatment, outlier detection, normalization, and train-test splitting.

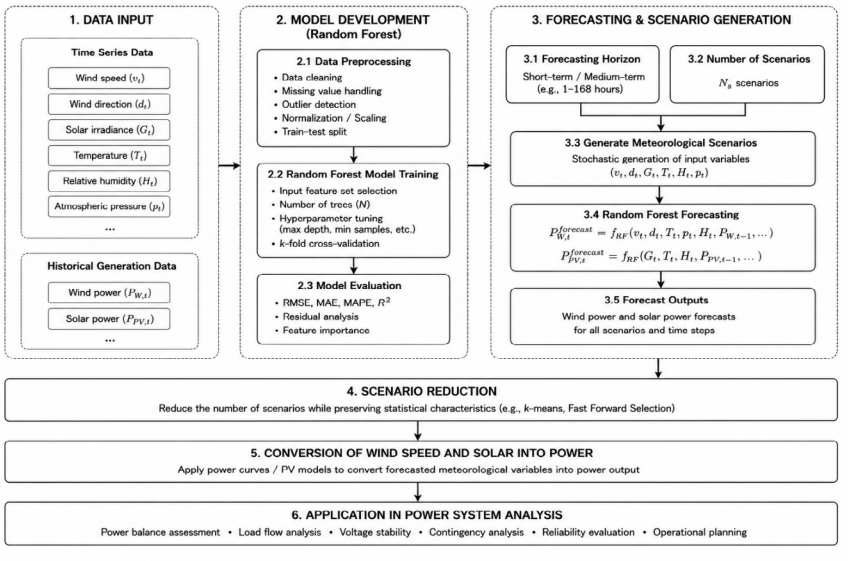


Figure 2 – Overall model

The figure shows multiple regression trees. Each tree learns a different relationship between meteorological variables and renewable power output. The final forecast is obtained by averaging the outputs of all trees, which improves robustness and reduces overfitting.

Results and discussion

To understand the objective patterns underlying the process of formation and development of personal and professional competencies of social workers through advanced training courses, it is necessary to clearly understand their model [12; 13].

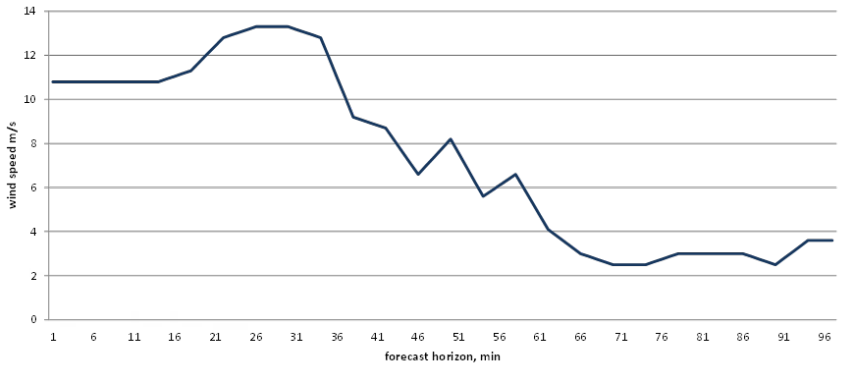


Figure 3 – Historical wind speed [14]

At previous research the wind speed forecast was investigated by Auto-regressive moving average method (ARMA) in [14].

Using the same historical data, we apply random forest method in order to evaluate the accuracy of this method.

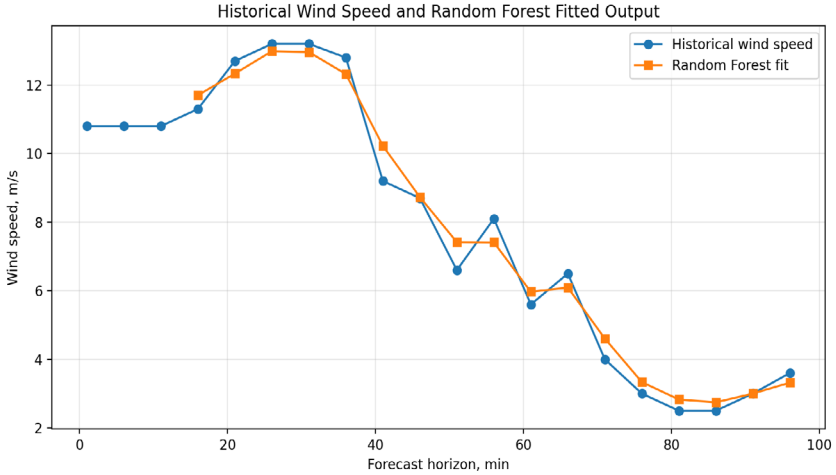


Figure 4 – Prediction using random forest method

The Random Forest model reproduces the main dynamics of the historical wind-speed profile with reasonable accuracy. The model captures the initial stable

wind regime, the increase to the peak value of about 13 m/s, the subsequent rapid decline, and the low-wind period near the end of the forecast horizon. Minor deviations appear during sharp local fluctuations, which is expected for an ensemble model that tends to smooth short-term variability.

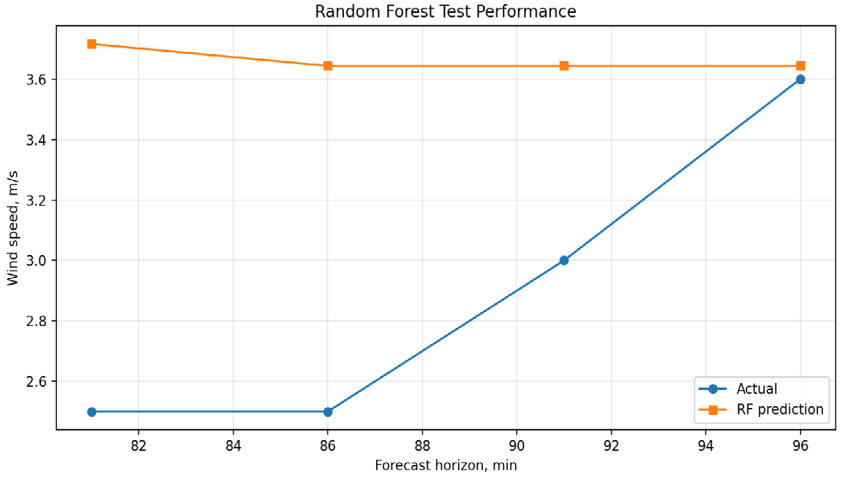


Figure 5 – Random forest test performance

The Figure-5 show that the Random Forest model captures the general low-wind regime but overestimates the actual wind speed during the final forecast interval. While the observed values increase from about 2.5 to 3.6 m/s, the model prediction remains nearly constant at around 3.6–3.7 m/s. This indicates that the model smooths short-term variations and is less sensitive to rapid changes when only a limited historical dataset is used. From a power-system perspective, such overestimation is important because it may lead to an optimistic assessment of available wind generation.

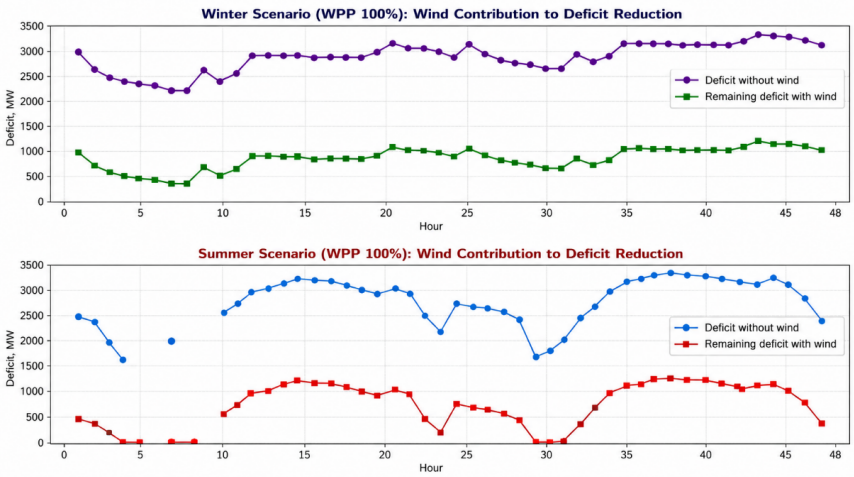


Figure 6 – Wind contribution to deficit reduction

The graphs compare the regional electricity deficit before and after the integration of wind power under the 100 % WPP scenario for winter and summer operating conditions. In the winter scenario, the deficit without wind remains high throughout the analyzed 48-hour period, generally ranging between 2,500 and 3,300 MW. After wind generation is included, the remaining deficit decreases substantially, mostly to the range of 500–1,200 MW. This indicates that wind power provides a significant contribution to deficit reduction, although it does not fully eliminate the winter deficit. In the summer scenario, the impact of wind power is even more visible. The deficit without wind varies strongly over time and reaches more than 3,000 MW during several hours. With wind generation included, the remaining deficit is sharply reduced and, in some hours, approaches zero. This shows that wind power can cover a considerable part of the regional shortage during favorable operating conditions.

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Conclusions

The analysis of the generation scenarios demonstrates that wind power has a substantial and quantifiable impact on the regional power balance of the Almaty

region. Across both winter and summer operating conditions, higher wind power penetration consistently reduces the remaining supply deficit and improves the balance between local generation and regional demand.

In the winter case, the system remains structurally constrained even under high wind availability. When WPP output increases from 20 % to 100 %, the average remaining deficit decreases from approximately 1517 MW to 942 MW. This corresponds to an average deficit reduction of about 68 %. The result is technically significant: wind generation materially improves adequacy, but it does not fully close the winter supply gap. This reflects the combined effect of high seasonal demand, limited dispatchable local generation, and the variability of renewable output.

The summer case shows a similar but slightly more favorable pattern. The average remaining deficit declines from approximately 1342 MW under the 20 % WPP scenario to about 845 MW under the 100 % WPP scenario. The average deficit reduction reaches approximately 65 %. In several hours, the remaining deficit approaches zero, indicating that wind power can temporarily provide a major contribution to regional self-sufficiency when weather conditions are favorable.

From a power engineering perspective, the results lead to an important conclusion: wind power is not merely an additional energy source, but a strategic resource for reducing regional import dependency and improving operational adequacy. However, the persistence of a residual deficit under all scenarios confirms that wind generation alone cannot guarantee full supply security. Its variability requires complementary flexibility resources, including battery energy storage, fast-ramping conventional generation, demand-side response, reserve capacity, and accurate short-term forecasting.

Therefore, the integration of wind power in the Almaty region should be planned as part of a coordinated system strategy rather than as an isolated capacity expansion measure. The most reliable pathway is the combined deployment of wind generation, storage, forecasting tools, and grid reinforcement. Such an approach would allow renewable energy to contribute not only to decarbonization, but also to regional adequacy, operational reliability, and long-term energy security.

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ЖЭК ӨНДІРІСІН ИНТЕЛЛЕКТУАЛДЫ БОЛЖАУ АРҚЫЛЫ ТАПШЫЛЫҚТЫ АЗАЙТЫП ЭЛЕКТР ЖҮЙЕСІНІҢ ТҰРАҚТЫЛЫҒЫН АРТТЫРУ

Айнымалы жаңартылатын энергия көздерінің үлесінің артуы құрылымдық электр энергиясы тапшылығымен және сыртқы электр энергиясы ағындарына тәуелділігімен сипатталатын өңірлік энергетикалық жүйелер үшін жаңа сын-қатерлер туындатады. Бұл мақалада Қазақстанның Алматы өңірі мысалында қуат балансын бағалауды және электр желісінің тұрақтылығын талдауды қолдауға бағытталған жел және күн электр энергиясын өндіруді интеллектуалды болжау әдістемесі әзірленеді. Ұсынылған тәсіл әртүрлі жұмыс режимдерінде айнымалы жаңартылатын энергия көздерінен өндірілетін электр энергиясын болжау үшін тарихи метеорологиялық деректерді, жаңартылатын энергия өндіру профильдерін және машиналық оқыту алгоритмдерін біріктіреді. Уақыттық қатарларды талдау және машиналық оқыту әдістеріне негізделген болжау модельдері RMSE, MAE және MAPE сияқты стандартты дәлдік көрсеткіштері арқылы бағаланады. Бұдан әрі болжанған жаңартылатын энергия өндірісі өңірлік қуат балансына біріктіріліп, оның электр энергиясы тапшылығын төмендетуге және операциялық жоспарлауды қолдауға қосатын ықтимал үлесі

бағаланады. Нәтижелер интеллектуалды болжау жаңартылатын энергия өндірісінің болжамдылығын арттырып, диспетчерлік шешімдердегі белгісіздікті азайтып, электр энергиясы тапшылығы бар энергетикалық жүйелерде жаңартылатын энергия көздерін интеграциялау үшін деректерге негізделген әдістемелік негіз қалыптастыратынын көрсетеді. Зерттеу жаңартылатын энергия үлесі артып келе жатқан дәстүрлі энергетикалық жүйелер үшін қолданбалы болжау құралдарын дамытуға үлес қосады.

Кілтті сөздер: интеллектуалды болжау, жаңартылатын энергияны пайдалануды болжау, айнымалы жаңартылатын энергия, жел энергиясын пайдалануды болжау, Машиналық оқыту, жасанды интеллект.

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ИНТЕЛЛЕКТУАЛЬНОЕ ПРОГНОЗИРОВАНИЕ ВИЭ ДЛЯ СНИЖЕНИЯ ДЕФИЦИТА И УСТОЙЧИВОСТИ ЭНЕРГОСИСТЕМЫ

Растущее распространение различных возобновляемых источников энергии создает новые проблемы для региональных энергосистем, характеризующихся структурным дефицитом электроэнергии и зависимостью от внешних поставок электроэнергии. В данном документе разрабатывается интеллектуальная система прогнозирования для ветровой и солнечной энергетики, направленная на поддержку оценки энергетического баланса и анализа стабильности энергосистемы в Алматинском регионе Казахстана. Предлагаемый подход объединяет исторические метеорологические данные, профили возобновляемой генерации и алгоритмы машинного обучения для прогнозирования выработки энергии из возобновляемых источников в различных условиях эксплуатации. Модели прогнозирования, основанные на анализе

временных рядов и методах машинного обучения, оцениваются с использованием стандартных показателей точности, включая RMSE, MAE и MAPE. Прогнозируемая возобновляемая генерация дополнительно интегрируется в оценку регионального энергетического баланса для оценки ее потенциального вклада в сокращение дефицита электроэнергии и поддержку оперативного планирования. Результаты показывают, что интеллектуальное прогнозирование может повысить предсказуемость возобновляемой генерации, снизить неопределенность при принятии диспетчерских решений и обеспечить основу для интеграции возобновляемых источников энергии в энергосистемы, подверженные дефициту энергии. Исследование способствует разработке практических инструментов прогнозирования для развивающихся энергосистем с растущей долей возобновляемых источников энергии.

Ключевые слова: интеллектуальное прогнозирование, прогнозирование использования возобновляемых источников энергии, переменная возобновляемая энергия, прогнозирование использования энергии ветра, машинное обучение, искусственный интеллект.

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