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DEVELOPMENT OF A LOGISTIC MODEL FOR ENERGY TRANSITION TO RENEWABLE ENERGY SOURCES WITH ENERGY SECURITY CONSIDERATION

The object of the study is the process of energy transition to renewable energy sources (RES) at the enterprise or regional level, aimed at replacing traditional carbon-based sources of electricity. One of the most problematic issues is the insufficient consideration of energy security factors in existing forecasting models, which leads to risks of electricity shortages, especially under conditions of RES intermittency and geopolitical challenges such as military attacks or import dependence. A literature review showed that existing models do not account for dynamic constraints in the implementation of RES, which limits their practical applicability for ensuring power system resilience.

In the course of the research, numerical modeling methods were used, in particular an adaptation of the logistic growth equation with an integrated dynamic security factor $S_b(t)$. This makes it possible to fill the gaps in existing models with regard to risk assessment and ensuring system stability. The obtained logistic model predicts the energy transition with RES reaching a 68% share in 24 years for a typical region without compromising security. This is due to the fact that the proposed model has such features as the integration of the coefficient of energy transition rate (C_{ETR}) and the dynamic constraint $S_b(t)$, which adapts to changes in demand and reserve. This allows identifying the potential to increase system resilience through the optimal balance of RES and traditional sources during the transition.

As a result, it becomes possible to achieve such indicator values as a 68% share of RES, owing to the model's flexibility to local conditions (variations of ρ, γ, k) and the consideration of worst-case scenarios ($C_{F.min}$). Compared with similar known models, this provides advantages such as adaptability to regional risks, more accurate forecasting of the transition rate, and reduction of blackout probability. This is particularly relevant for vulnerable power systems, both in Ukraine and worldwide.

Keywords: *energy transition, renewable energy sources, modeling, energy security, logistic model, forecasting, resilience, risks.*

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1. Introduction

The transition to renewable energy sources (RES) is an essential part of the global strategy to combat climate change, aimed at reducing CO_2 emissions and enhancing the resilience of power systems. According to the REN21 report [1], the share of RES in the global energy balance increased from 19% in 2010 to more than 28% in 2024, which highlights global trends. Under conditions of growing electricity demand and geopolitical instability associated with dependence on imported fossil fuels, it is important to have effective decision-making tools. For example, blackouts in the United States (Texas, 2021) and in Spain and Portugal (2025) occurred due to RES outages. These situations emphasize the need for adaptive models to ensure energy security.

This study proposes a mathematical model based on the logistic growth equation of the RES share, taking into account such factors as generation intermittency, economic costs, and energy security. The relevance of modeling the energy transition with an emphasis on security is determined by the rapid growth of the RES share and the need for balance in the context of the climate crisis (CO_2 emissions). According to 2025 data, the global energy market faces a "race to overcome constraints" between demand and the supply of clean energy, where the growth of RES, primarily solar and wind energy, must overcome infrastructural barriers [2].

Renewable energy reports of 2025 emphasize that the transition to RES is not an "imposition" or a "trend", but a foundation for resilience and energy security, particularly in the context of achieving net-zero emissions by 2050 [1]. Mathematical models, including system optimization, are necessary to forecast scenarios in which large-scale deployment of decarbonization technologies is key to bridging the gap between plans and the actual state of affairs [3]. In regions with vulnerable infrastructure, models that incorporate security factors help mitigate risks related to energy imports or wartime damage, thereby contributing to enhanced energy security.

Thus, the energy transition to RES is one of the key tasks of global and Ukrainian energy policy. Its successful implementation affects the level of energy security, independence from fossil fuel sources and imports, as well as alignment with global decarbonization trends. Therefore, modeling changes in the share of RES in the energy balance is a relevant tool for forecasting the development of the electricity sector.

Logistic growth models (S-curves) effectively describe the exponential spread of RES, as shown in the analysis of solar and wind energy up to 2030, where they outperform exponential models in forecasting market saturation [4]. Global forecasts, such as the *Energy Outlook 2025*, highlight the growth of RES, primarily solar energy, with a tripling of capacity by 2030 in IEA scenarios [5]. However,

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traditional models often ignore energy security, focusing on economic optimization, as in system models for decarbonization that include input-output scenarios [6].

With regard to energy security in decarbonization, mathematical models are evolving to integrate risks. For instance, models for net-zero systems employ equations to forecast emissions and processes in thermal power generation [7]. Optimization frameworks for power systems account for supply diversification and import reduction, showing how security affects optimal decarbonization pathways. Models for sustainable transition provide mathematical foundations, including simulations for global decarbonization [8]. Recent studies in this field focus on RES use in the energy sector with an emphasis on reducing impacts on climate and ecosystems, while energy security aspects are either absent or downplayed [9, 10].

Research by Ukrainian authors complements global trends, drawing attention to local challenges of RES integration. The analysis of renewable energy development in the "Ukraine Recovery Plan" (2022) [11] includes mathematical models for assessing energy security. However, specific indicators of transition rates are insufficiently considered. Mathematical models of electricity consumption regimes account for the stochastic nature of RES capacity and its impact on power systems without additional external factors [12]. Economic-mathematical models for resource saving and reducing dependence on traditional sources emphasize ecological aspects but are built on simplified operating conditions [13]. Prospects for integrating distributed energy resources into Ukraine's power grid include forecasting models with neural network algorithms. However, when constructing forecasting models, it is necessary to account for current trends in the development of Ukraine's energy sector [14, 15]. Models for ensuring RES generation schedules focus on matching capacity with load schedules of traditional sources. As a rule, such models are simplified and consider only energy-related factors of power system operation [16].

The analysis of the cited sources shows that dynamic constraints incorporating security factors in the growth of RES share are not sufficiently addressed in existing models, particularly in regional contexts. Specifically, in [17] models focus on transition scenarios to 100% RES by 2070 according to economic indicators, but without explicit dynamic "brakes" for energy security when introducing RES into power supply systems. In other words, they do not provide for consideration and limitation of RES implementation rates. Similarly, the emissions trajectory modeling report up to 2050 [18] accounts for greenhouse gases but not for reserve capacity limitations as a security indicator. In [19], the formation of structures is mentioned, but without logistic models with S-shaped factors.

Thus, the unresolved scientific and practical task today is forecasting energy transition scenarios to renewable energy sources with consideration of the energy security criterion.

The aim of the study is to develop a mathematical model for assessing and analyzing the dynamics of RES implementation, which will minimize the risks of electricity shortages and large-scale power outages.

2. Materials and Methods

The object of the study is the process of energy transition to renewable energy sources (RES) at the enterprise or regional level, aimed at replacing traditional carbon-based sources of electricity.

The research hypothesis is that modifying the logistic equation by incorporating an energy security factor will make it possible to forecast the transition to RES while accounting for the risks of electricity shortages. The mathematical model of RES implementation with the simultaneous phasing-out of traditional carbon-based sources for an enterprise or region is based on the logistic growth equation, with energy security introduced as a dynamic constraint. Such a model allows simulating the S-shaped dynamics of the RES share in the energy balance, where growth is limited not only by resources but also by risks of electricity shortages. The model is deterministic, with the possibility of numerical solution, and is designed to forecast the transition rate considering engineering, economic, and regulatory factors.

A typical S-shaped (logistic) growth curve describing the diffusion of new technologies – from slow initial adoption, through rapid growth, to eventual saturation [4] – is shown in Fig. 1. It illustrates the effect of the deployment-rate coefficient on the dynamics of the growth in their share. This curve was used as the basis for constructing the mathematical model, adapting it to the growth rate of the RES share in the energy balance.

In the model, the RES share evolves in a similar manner. This approach is consistent with real-world scenarios of energy transition observed in countries where the share of RES has already exceeded 50%.

A mathematical model is proposed that accounts for the key factors of RES deployment: intermittency of generation, the need for reserve capacity, increasing energy demand, and energy security constraints. The logistic growth curve [4] was chosen as the baseline since it realistically describes the phases of slow start (limited investment and infrastructure), acceleration (straightforward scaling), and deceleration (approaching the maximum share of RES due to existing constraints).

To explain the operation of the mathematical model, Fig. 2 presents a block diagram that reflects the sequence of calculations and the presence of feedback.

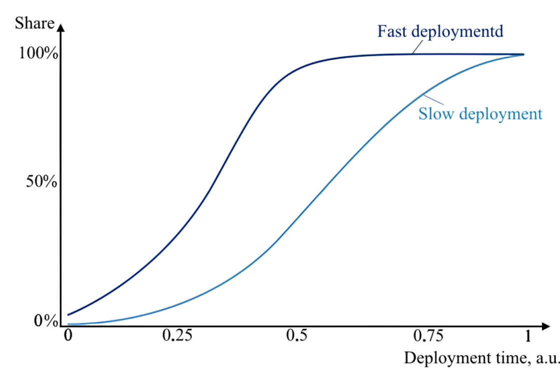

Fig. 1. General view of the dynamics of growth in the share of new technologies during their implementation

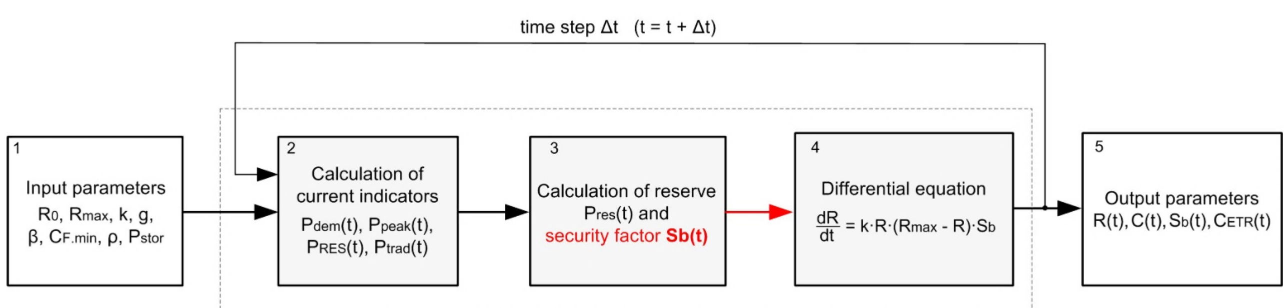

Fig. 2. Structural diagram of the mathematical model for RES deployment

The diagram illustrates the step-by-step computational process of the model over a given time interval. Initially, input parameters are specified, determining the initial conditions and system constraints. At each time step, calculations are performed for the current values of demand, generation, source shares, available reserves, and the energy security factor, which affects the feasible growth rate of the RES share. The new system state is then computed, and the results are used as input data for the next step.

The novelty of the proposed model lies in the integration of the security factor $S_b(t)$, which dynamically adjusts the growth rate, preventing imbalances (generation + reserve ≥ demand). This makes the model applicable for regional scenarios where local risks (for example, in Ukraine – political threats, military actions, and grid constraints) are critical.

As an initial assumption, the model presumes energy balance

$$E_{RES}(t)+E_{trad}(t)=E_{dem}(t), \tag{1}$$

where E_{RES} is the energy generated by RES; E_{trad} is the energy obtained from traditional (carbon-based) sources; E_{dem} is the demand (energy consumption).

It should be noted that equation (1) reflects the overall annual energy balance, where storage systems are not considered as a source, since they redistribute energy over time rather than generate it. Their impact on the system is taken into account further through reserve capacity.

At the same time, the following constraint is adopted: the reserve capacity must be at least 20% of peak demand [20].

The transition from energy to average power (for RES, traditional sources, and demand) is made according to the following expressions:

$$P_{RES}(t)=\frac{E_{RES}(t)}{T},\quad P_{trad}(t)=\frac{E_{trad}(t)}{T},\quad P_{dem}(t)=\frac{E_{dem}(t)}{T}, \tag{2}$$

where T is the number of hours in a year used for converting energy into average power, with a standard approximate value of 8,760 hours/year.

To evaluate the rate of RES deployment, the *Coefficient of Energy Transition Rate* (C_{ETR}) is introduced as an integral indicator.

As an initial condition, it is assumed that $R(0) = R_0$ (the initial share of RES)

$$C_{ETR}(t)=\frac{R(t+\Delta t)-R(t)}{\Delta t}\cdot S_b(t), \tag{3}$$

where Δt is the adopted time step for RES deployment (e. g., 1 year); t is the total time interval of RES deployment (e. g., years); R is the share of RES in the energy balance ($0 \le R \le 1$); S_b is the security factor limiting the growth rate of deployment (0–1)

$$S_b(t)=\min\left(1,\frac{P_{res}(t)}{\rho\cdot P_{peak}(t)}\right), \tag{4}$$

where ρ is the normative coefficient of reserve capacity (15–20% according to the Transmission System Code of Ukraine [20]).

S_b is the key element that makes the model oriented toward energy security. It acts as a "braking factor" for the RES deployment rate, preventing risks of energy shortages or blackouts. This is the security factor at a given moment of time t (in years). Its values range from 0 to 1. If = 1, the system is secure and the share of RES grows at the maximum possible rate. If < 1, the growth slows down to avoid risks.

Using formula (4) to determine the security factor $S_b(t)$, the peak load is calculated as

$$P_{peak}(t)=\beta\cdot P_{dem}(t), \tag{5}$$

where β is the coefficient of margin for peak loads (adopted as $\beta \approx 1.2$). It depends on the region (standard for grids with a 20–50% peak margin).

The available reserve capacity for calculating the security factor $S_b(t)$ is determined by the formula

$$P_{res}(t)=P_{trad}(t)\cdot\gamma+P_{stor}(t)+P_{RES}(t)\cdot C_{F.\min}, \tag{6}$$

where $C_{F.\min}$ is the minimum capacity factor of RES (equal to 0.2–0.5; 0.2 corresponds to the worst-case intermittency scenario); γ is the share of traditional sources available for reserve, i. e., the portion that can be used to ensure system balance during peak loads or shortages caused by RES intermittency (maneuverable capacity); P_{stor} is the storage (accumulation) power of the system.

The power generated by RES and traditional sources is expressed as:

$$P_{RES}(t)=R(t)\cdot P_{dem}(t), \tag{7}$$

$$P_{trad}(t)=C(t)\cdot P_{dem}(t), \tag{8}$$

where $R(t)$ is the share of RES in the energy balance; $C(t)$ is the share of traditional sources in the energy balance; $P_{dem}(t)$ is the total power demand

$$C(t)=1-R(t). \tag{9}$$

Demand growth (exponential)

$$E_{dem}(t)=E_{dem.0}\cdot(1+g)^t, \tag{10}$$

$$P_{dem}(t)=P_{dem.0}\cdot(1+g)^t, \tag{11}$$

where $P_{dem.0}$ is the initial demand; g is the annual demand growth rate (0.01–0.05).

Equation (11) is exponential and describes exponential growth, where demand is multiplied by a constant factor $(1 + g)$ each year (compound interest), creating a curve that accelerates over time (for example, if $g = 0.02$, then growth is 2% relative to the previous value).

The main equation of the mathematical model is the differential equation for the share of RES, expressed as

$$\frac{dR(t)}{dt}=k\cdot R(t)\cdot\left(R_{\max}-R(t)\right)\cdot S_b(t), \tag{12}$$

where k is the growth rate coefficient (0.1–0.5 per year), chosen based on empirical models of RES share growth [21]; $R_{\max}$ is the maximum achievable share of RES (e. g., 0.8 according to [22]).

The input parameters of the model (based on regional or enterprise data) are:

- k – growth rate coefficient (constant);
- $R_{\max}$, R_0 – maximum and initial shares of RES;
- $E_{dem.0}$, g – initial demand and its growth;
- β, $C_{F.\min}$ – peak demand and RES utilization coefficients;
- P_{stor} – storable power (fixed or as a function);
- Δt – time step.

The output parameters of the model are:

- $R(t)$, $C(t)$ – shares of RES and traditional sources;
- $P_{RES}(t)$, $P_{trad}(t)$ – installed capacity from RES and traditional sources;
- $E(t)$, $E_{peak}(t)$ – demand and peak demand;

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– $S_b(t)$, $P_{res}(t)$ – security factor and reserve;
– $C_{ETR}(t)$ – energy transition rate to RES.

As an example, a particular region (oblast [23]) was considered. The initial data and normative coefficients are presented in Table 1. The calculations were performed in Excel according to equations (2)–(12). The obtained graphs of $R(t)$, $C(t)$, $C_{ETR}(t)$, and $S_b(t)$ are shown in Fig. 3–6.

Table 1

Input data

Indicator	Value	
	Variant 1 (Conservative)	Variant 2 (Optimistic)
Annual electricity consumption, $E_{dem.0}$	3424 million kWh	3424 million kWh
Initial RES share, R_0	0.083	0.083
Demand growth coefficient, g	0.02 (2%/year)	0.02 (2%/year)
Final RES share, R_{max}	0.7	0.7
RES growth coefficient, k	0.15	0.3
Peak coefficient, β	1.2	1.2
Normative reserve coefficient, ρ	0.2	0.15
Minimum RES utilization factor, $C_{F.min}$	0.2	0.2
Share of traditional sources available for reserve, γ	0.25	0.1
Storage capacity, P_{stor}	1 MW	1 MW
Time step, Δt	1 year	1 year

Thus, Scenario 1 (conservative) places greater emphasis on security (lower risk of shortages), whereas Scenario 2 (optimistic) represents a faster transition but carries a higher risk if the parameters are not maintained.

3. Results and Discussion

The obtained graphs of the dependencies $R(t)$, $C(t)$, $C_{ETR}(t)$ and $S_b(t)$ are presented in Fig. 3–6.

In the conservative scenario, S_{b1} starts from 1.0 and then decreases (Fig. 6, blue curve). This indicates a significant initial safety margin with its gradual reduction over time. That is, there are high requirements for reserve capacity ($\rho_1 = 0.2$) and a substantial available share of traditional generation for reserve ($\gamma_1 = 0.25$). The reserve power P_{res} is large: almost all energy is generated by traditional sources, and a considerable fraction of this power is allocated to reserve ($\gamma_1 = 0.25$). The required reserve relative to peak load ($\rho \cdot P_{peak}$) is relatively small. Although the coefficient ρ it is multiplied by the initial, lowest peak demand value of the entire period (P_{peak}). As a result, a relatively large number (available reserve) is divided by a relatively small one (required reserve). The ratio is much greater than 1, so S_{b1} is capped at 1.0. The system is "over-secure". Over time, two processes occur simultaneously: (1) the available reserve decreases. The share of traditional sources $C(t)$ falls, and so does the part of the reserve obtained from them ($\gamma_1 \cdot P_{trad}$). The required reserve increases. Total demand $P_{dem}(t)$ grows by 2% annually, along with the peak load $P_{peak}(t)$. RES cannot fully compensate for the decline in reserves.

Thus, the numerator in formula (4) (available reserve) slowly "melts", while the denominator (required reserve) continually increases. Eventually, their ratio drops below 1, and the curve S_{b1} begins to decrease smoothly.

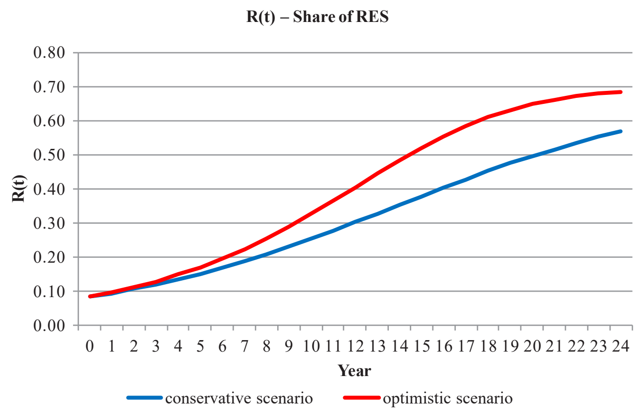

Fig. 3. Growth of RES share over 24 years

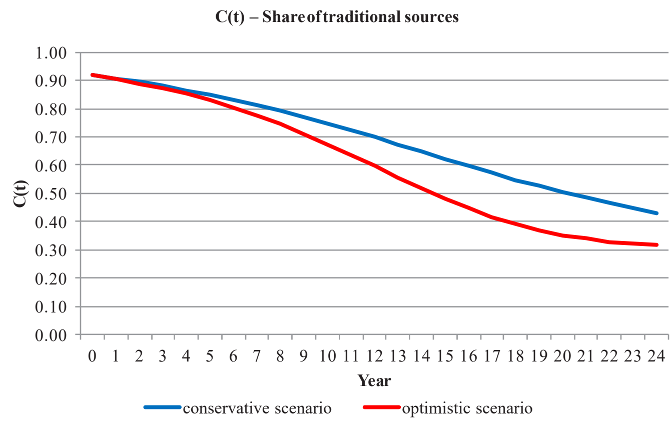

Fig. 4. Decline of traditional sources share over 24 years

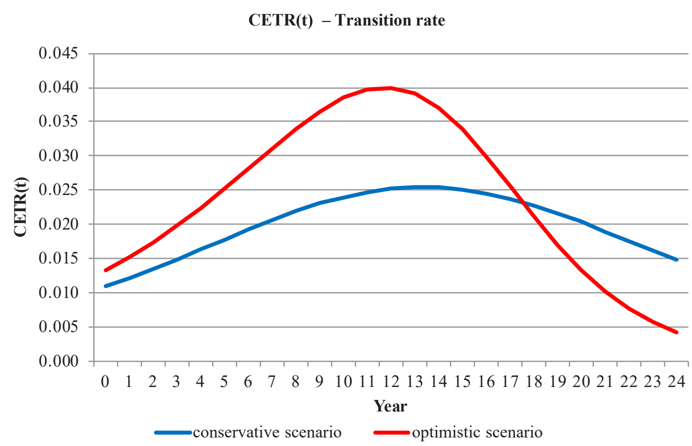

Fig. 5. Change in the Coefficient of Energy Transition Rate (C_{ETR}) over the deployment period

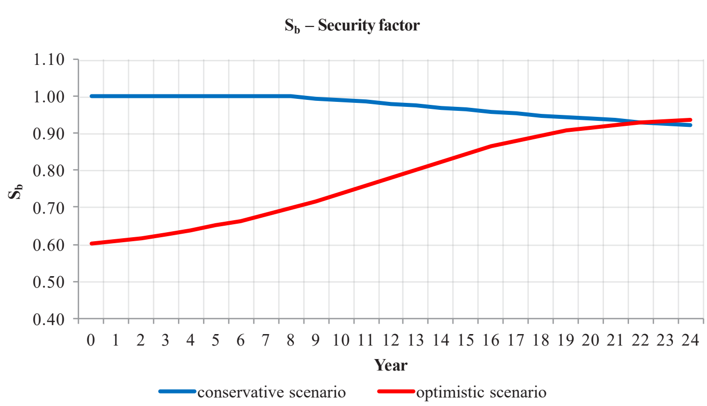

Fig. 6. Change in the security factor over the period of RES deployment

In the accelerated scenario, reserve requirements are lower ($\rho_2 = 0.15$) and reliance on traditional generation is smaller ($\gamma_2 = 0.1$). The red curve (S_{b2}) starts lower (Fig. 6), at 0.6, and grows to 0.93. This indicates higher initial risks but dynamic stabilization over time. The available reserve P_{res} is relatively small, as only a minor share ($\gamma_2 = 0.1$) of traditional generation is allocated to reserve. The contribution from RES at the start is negligible. The required reserve ($\rho \cdot P_{peak}$) is also low, since a small ρ (15%) is multiplied by a low initial demand. In the end, one small number is divided by another, with their ratio less than 1 (≈ 0.6). Thus, the system starts with a lower margin of reliability, and S_{b2} begins from a low level.

The graphs of $R(t)$ (Fig. 3) and $C_{\mathrm{ETR}}(t)$ (Fig. 5) clearly show that the accelerated scenario (red line) pulls ahead from the very beginning. This is because the initial transition rate ($k \cdot S_b \approx 0.18$) is higher than that of the conservative scenario (0.15).

The graphs of $R(t)$ also clearly illustrate the difference between the two pathways of deployment. By year 24, the accelerated scenario reaches nearly 70% RES share, while the conservative one reaches only ~ 56%. More favorable investment conditions (higher k) are a key factor ensuring faster deployment and a higher share of RES over time.

Scenario 1 (stricter security conditions, slower deployment) represents regions (or facilities) with high risks and vulnerable infrastructure. The transition is more stable but slower – the model "does not allow" a rapid leap, so the curve is flatter (lower risk of shortages in the system). Scenario 2 (softer conditions, faster RES deployment) suits stable regions (or facilities) with developed infrastructure and greater resources. The transition is faster and slows down toward the end mainly due to saturation (resource/market limitations, as in the logistic model). These scenarios illustrate the model's sensitivity analysis: the first corresponds to "crisis-prone" regions (or facilities), while the second corresponds to more stable "developed" ones.

To assess the reliability of the proposed model, a comparison was made with actual statistical data [24–28] on the share of RES in Ukraine during 2014–2024. Fig. 7 shows the real data together with modeling results for two scenarios: achieving 35% (conservative scenario) [25] and 70% (optimistic scenario) [26] RES share by 2050.

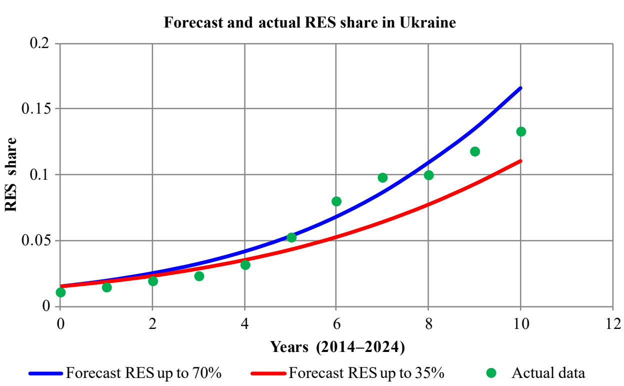

Fig. 7. Comparison of actual and simulated RES share over 11 years

For both scenarios, the following accuracy indicators were calculated for the initial period (2014–2024):

– Mean Absolute Percentage Error (MAPE) – 21.6% (70% RES scenario) and 24.5% (35% RES scenario);

– Root Mean Square Error (RMSE) – 0.0132 (70% scenario) and 0.0183 (35% scenario);

– Coefficient of Determination (R^2) – 0.9 (70% scenario) and 0.812 (35% scenario).

As can be seen, the 70% RES scenario fits better with the dynamics of actual historical data in the initial deployment period. This indicates the potential for faster RES development than foreseen in the conservative scenario.

In further research, to narrow the limitations of the model and refine the results of transition rate modeling, an additional multi-factor model for assessing system efficiency can be applied. This model is based on representing the minimum RES utilization coefficient $C_{F.\min}$ as a target function. This target function for determining the efficiency level of a project involving the deployment of distributed generation sources and other smart technologies is a multi-factor model built on the weighted sum of five key factors and can be integrated into equation (12).

It accounts for the specific features of the energy transition, including grid instability and economic constraints, and has the following form

$$C_{F.\min} = \frac{\sum_{i=1}^{n}(\alpha_i \cdot k_i)}{n} \to 1, \tag{13}$$

where α_1, α_2, α_i are the factors, k_i are the factor coefficients, n is the number of factors.

For example, at $n = 5$

$$C_{F.\min} = \frac{\sum\left[\begin{gathered}(\alpha_{reliability} \cdot k_1)+(\alpha_{savings} \cdot k_2)+(\alpha_{efficiency} \cdot k_3)+ \\ +(\alpha_{RES} \cdot k_4)+(\alpha_{losses} \cdot k_5)\end{gathered}\right]}{5} \to 1, \tag{14}$$

where $\alpha_{reliability} \cdot k_1$ – reliability factor of the power supply system according to established criteria; $\alpha_{savings} \cdot k_2$ – factor of electricity (EE) savings and financial savings from EE purchases; $\alpha_{efficiency} \cdot k_3$ – factor of energy efficiency in EE use; $\alpha_{RES} \cdot k_4$ – factor of RES deployment; $\alpha_{losses} \cdot k_5$ – factor of EE losses in distribution networks.

Next, the specific features of determining the level of power efficiency under the Smart Grid concept are considered. In this approach, factors and their coefficients (weights) are introduced. The arithmetic mean of the sum of factor products should equal or approximate one.

Each factor is described separately depending on specific conditions, using coefficient k, which indicates the significance of a given factor from 0 to 1. A maximum value of the factor corresponds to 1, while its absence corresponds to 0. The factor weights are determined using fuzzy set theory, allowing the most accurate determination of their weights.

The significance of factors is equal in total; however, if at least one factor – previously defined as significant – has no manifestation, it is necessary either to reconsider its significance in the given case or to review measures aimed at improving power supply efficiency.

The levels for determining each factor separately are presented below.

Reliability factor of the power supply system (0, 0.25, 0.5, 0.75, 1):

1) one network electricity supply source;
2) two network electricity supply sources;
3) additional electricity source based on non-renewable energy;
4) additional electricity source based on distributed generation;
5) use of additional electricity storage to further smooth supply schedules (operating modes).

Electricity savings factor and associated financial savings from electricity purchases (0, 0.2, 0.4, 0.6, 0.8, 1):

1) 0%;
2) up to 1% inclusive;
3) from 1 to 5% inclusive;
4) from 5 to 10% inclusive;
5) from 10 to 25% inclusive;
6) over 25%.

Energy efficiency factor of electricity use (0, 0.2, 0.4, 0.6, 0.8, 1):

1) F;
2) E;
3) D;
4) C;
5) B;
6) A.

RES load coverage factor (0, 0.2, 0.4, 0.6, 0.8, 1):
1) no RES deployed;
2) RES covers up to 10% of the load capacity;
3) RES covers up to 25% of the load capacity;
4) RES covers up to 50% of the load capacity;
5) RES covers up to 75% of the load capacity;
6) RES covers up to 100% of the load capacity;
Electricity losses factor in distribution networks (0, 0.25, 0.5, 0.75, 1):
1) maximum electricity losses (over 20%);
2) losses fixed at no less than 16%;
3) losses fixed at no less than 13%;
4) losses fixed at no less than 10%;
5) losses fixed at 7% or lower.

The higher the value of $C_{F.\min}$ and the closer it is to 1, the more it indicates a high level of energy efficiency, reliability, and rationality of RES deployment under a given scenario.

For example, if a system has two network power supply sources ($\alpha_{reliability} \cdot k_1 = 0.25$), 10% electricity savings ($\alpha_{savings} \cdot k_2 = 0.6$), energy efficiency class C ($\alpha_{efficiency} \cdot k_3 = 0.6$), RES load coverage at the level of 25% ($\alpha_{\text{RES}} \cdot k_4 = 0.2$) and network losses of 13% ($\alpha_{\text{losses}} \cdot k_5 = 0.5$), then the indicator $C_{F.\min}$ equals ≈ 0.43.

This value is somewhat higher than the minimum constant value previously adopted ($C_{F.\min} = 0.2$) and indicates the potential to improve the efficiency of RES deployment through reducing network losses, increasing RES load coverage, enhancing the reliability of the power supply system, and lowering costs of electricity and equipment procurement. Such an approach to evaluating the transition to renewable energy sources makes it possible to account for both macroeconomic and micro-level characteristics of the system.

The resulting logistic model forecasts an energy transition with the RES share reaching 68% in 24 years for a typical region without compromising security. This makes it possible to identify the potential for enhancing system resilience through the optimal balance of RES and traditional sources during the transition. Accordingly, the model allows achieving target indicators such as a 68% RES share, owing to its flexibility to local conditions (changes in ρ, γ, k) and consideration of worst-case scenarios ($C_{F.\min}$).

Compared to similar known models, this provides such advantages as adaptability to regional risks, more accurate forecasting of transition rates, and reduced probability of blackouts.

To bring the modeled research results closer to real-world implementation conditions, it is recommended to consider factors that may affect the processes of energy transition in specific contexts. These include the normative reserve coefficient, the share of maneuverable capacity of traditional sources, demand growth, the minimum RES utilization coefficient, availability of economic resources, political risks, reliability of the power supply system, financial savings from electricity and equipment purchases, and network losses.

The practical application of the obtained results is characterized by deployment under the conditions of industrial enterprises, facilities, and energy hubs, both as additional electricity sources and for energy substitution.

The developed model has certain limitations, in particular, it is deterministic and does not fully account for the stochastic nature of RES operation or economic indicators in the transition process, especially when applied to facilities with limited centralized power supply.

A promising direction for further research is to strengthen the resilience of power systems under conditions of sustainable RES deployment.

4. Conclusions

A logistic mathematical model for RES deployment with a dynamic security factor $S_b(t)$, was proposed, which accounts for reserve capacity constraints and peak loads.

An integral indicator of the energy transition rate (C_{ETR}), was introduced, enabling quantitative comparison of scenarios under different regional input parameters.

Numerical modeling for a typical Ukrainian region ($R_0 = 8.3\%$, $R_{\max} = 70\%$, $g = 2\%$) demonstrated that, without balance violations, it is possible to reach ~ 68.4% RES for the accelerated scenario and ~ 56% for the conservative scenario within 24 years.

With an increase in the normative reserve coefficient ρ from 0.15 to 0.2 the RES share $R(t)$ grows more slowly and takes longer to approach the target value. This extends the transition by several years and effectively reduces the pace of the logistic energy transition, demonstrating the sensitivity of transition speed to infrastructural and engineering constraints.

Model validation against data from 2014–2024 indicates its adequacy and shows that the optimistic scenario better reflects the actual growth trend of the RES share and the potential to achieve 70% by 2050 in Ukraine under appropriate policy conditions. The conservative scenario (35% RES) somewhat underestimates the observed dynamics but accounts for economic, political, and technical risks.

The proposed model provides both theoretically and practically significant results for planning and implementing RES deployment. It can be generalized to the enterprise or regional level by adjusting input parameters and thus may serve as a tool for development planning and blackout risk assessment.

Conflict of interest

The authors declare that they have no conflicts of interest regarding this research, including financial, personal, authorship, or other factors that could have influenced the study and its results presented in this article.

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Data availability

This manuscript has no associated data.

Use of artificial intelligence

The authors confirm that no artificial intelligence technologies were used in the preparation of this work.

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