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Methodology for Assessing the Technical Potential of Solar Energy Based on Artificial Intelligence Technologies and Simulation-Modeling Tools

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Abstract

The integration of renewable energy sources (RES) into energy systems is becoming increasingly widespread around the world, driven by various factors, the most relevant of which is the high environmental friendliness of these types of energy resources and the possibility of creating stable generation systems that are independent of the economic and geopolitical situation. The large-scale involvement of green energy leads to the creation of distributed energy networks that combine several different methods of generation, each with its own characteristics. As a result, the issues of data collection and processing necessary for optimizing the operation of such energy systems are becoming increasingly relevant. The first stage of renewable energy integration involves building models to assess theoretical potential, allowing the feasibility of using a particular type of resource in specific geographical conditions to be determined. The second stage of assessment involves determining the technical potential, which allows the actual energy values that can be obtained by the consumer to be determined. The paper discusses a method for assessing the technical potential of solar energy using the example of a private consumer's energy system. For this purpose, a generator circuit with load models was implemented in the SimInTech dynamic simulation environment, accepting various sets of parameters as input, which were obtained using an intelligent information search procedure and intelligent forecasting methods. This approach makes it possible to forecast the amount of incoming solar insolation in the short term, whose values are then fed into the simulation model, allowing the forecast values of the technical potential of solar energy for the energy system configuration under consideration to be determined. The implementation of such a hybrid assessment system allows not only the technical potential of RES to be determined based on historical datasets but also provides the opportunity to obtain forecast values for energy production volumes. This allows for flexible configuration of the parameters of the elements used, which makes it possible to scale the solution to the specific configuration of the energy system in use. The proposed solution can be used as one of the elements of distributed energy systems with RES, where the concept of demand distribution and management plays an important role. Its implementation is impossible without predictive models.

Keywords: renewable energy; intelligent methods; energy systems; potential assessment; technical potential; simulation modeling



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1. Introduction

The development of society, the phenomenon of widespread industrialization and automation of production leads to a large-scale increase in power consumption, which cannot always be met using traditional energy sources [1], making the supply of electricity to consumers one of the most challenging tasks of the twenty-first century [2]. In addition to the ever-increasing demand for electricity, the global community faces various contingencies, such as pandemics or unstable geopolitical situations, leading to a high level of concern for a number of states seeking to increase their own energy independence and, in general, to achieve greater efficiency in their own energy systems [3,4]. Despite all measures taken, currently a significant number of people living in rural areas still remain without access to a stable energy network, using small generating substations and generators for private households [5,6].

One of the important results of the process of world globalization is the emergence of high interdependence in different sectors of the economy, which has contributed to the growth of socio-economic development [7], the introduction of new innovations and the formation of new consumer trends [8,9], in which an important place is given to environmental issues that play a dominant role in decision-making. Since the energy sector is closely related to all sectors of the economy [10,11], it receives the most attention, attracting new investments that allow the introduction of new approaches in energy conversion [12] and utilization through the implementation of more environmentally friendly modes of transportation [13,14], thereby reducing the detrimental impact on the environment. One of these approaches is the use of renewable energy conversion technologies (Figure 1); i.e., solar [15], wind [16], tidal energy [17], bioenergy [18] and small hydropower [19], the use of which allows a significant reduction in greenhouse gases, including carbon dioxide, and the vast areas of distribution of these resources allow the realization of energy systems in various regions that are difficult to access, ensuring greater energy independence and stability of the operated systems. All these aspects lead to the fact that during the last years there has been an annual growth of interest in renewable energy sources, which is confirmed both by the volume of publications on this topic [20–22] and by the increasing percentage of green energy in the total share of energy generation in the world market (Figure 2) [23,24]. Table 1 presents the main advantages and disadvantages of renewable energy.

Table 1. Some advantages and disadvantages of RES.

Source of Energy	Advantages	Disadvantages
Geothermal	Potentially unlimited source of energy.	Development cost can be expensive.
Bio	Cheap to construct; waste products can be utilized.	Can potentially cause greenhouse gases.
Hydro	No standby losses; relatively inexpensive; abundant sources.	Costly to build a dam; possibility of causing flood; water availability is highly uncertain.
Solar	No air/water pollution; infinite potential of energy.	Manufacturing costs of PV panels are costly; storage/backup is mandatory; dependent on sunlight.
Wind	No air/water pollution; free source of energy; wind farms are relatively inexpensive.	Requires constant stream of air and large space; significant visual impact on the landscape.

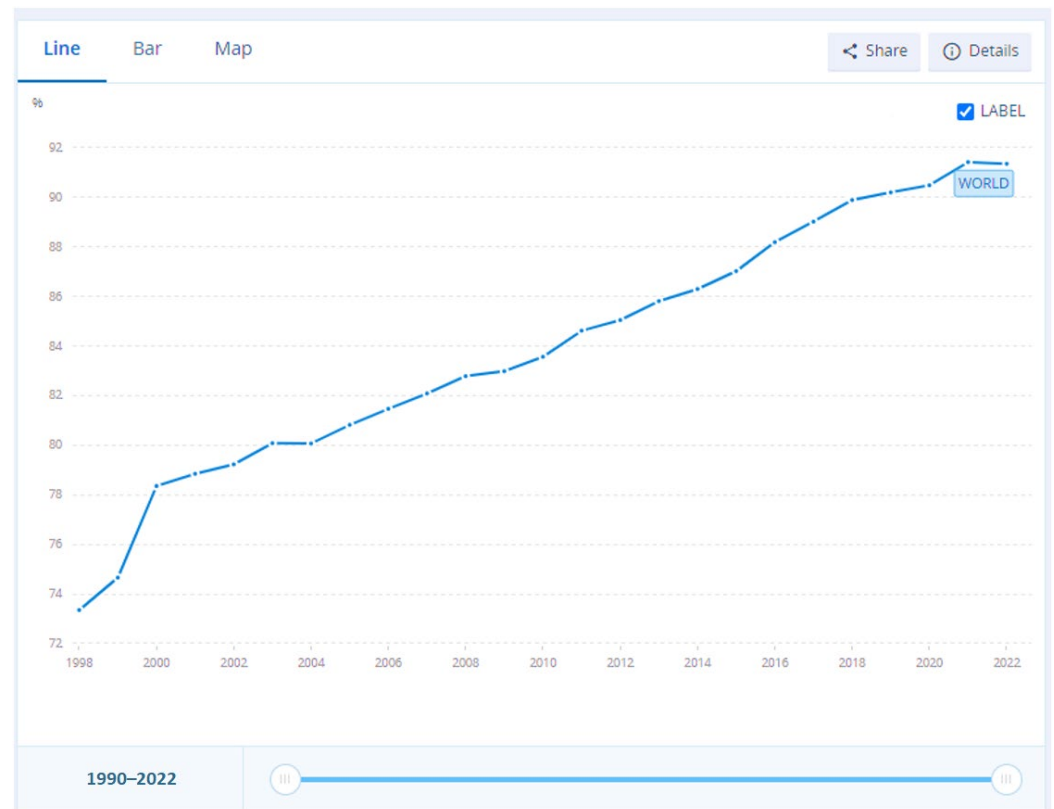


Figure 1. Access to electricity (% of population).

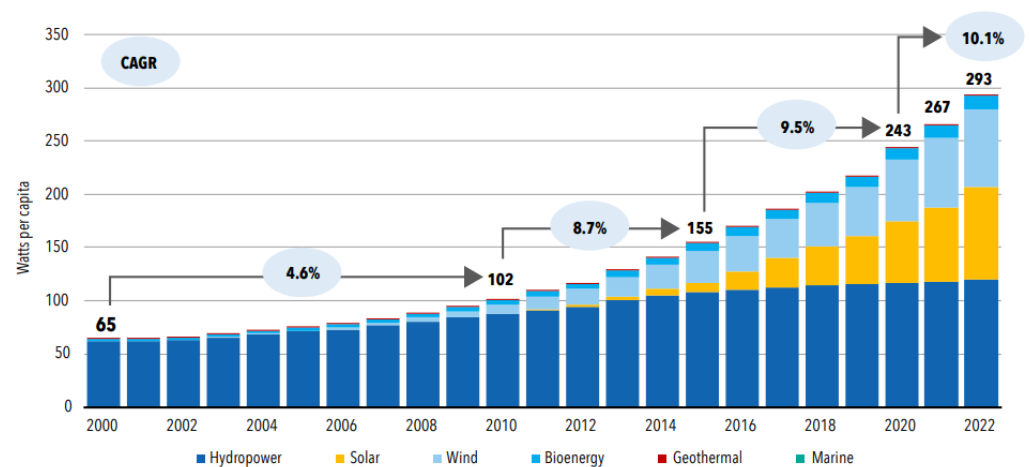


Figure 2. Global installed renewable energy generating capacity per capita, 2000–22.

However, despite all the advantages of renewable energy, there are a number of difficulties associated with its successful integration into energy systems, among which we can highlight the most important aspect—the variable nature of the supply of these types of resources [25], which creates the need to organize distributed energy networks and energy hubs to meet demand in times of unstable generation, and the organization of effective management systems of such distributed systems [26]. The general approach to the implementation of successful integration of renewable energy sources is presented in Figure 3 [27].

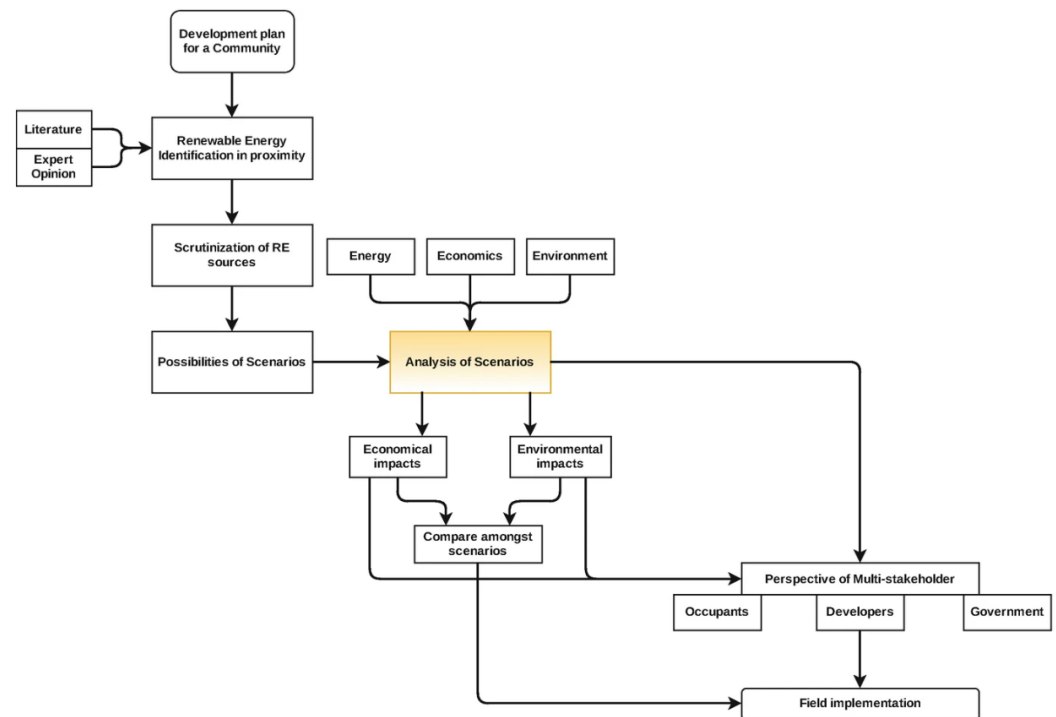


Figure 3. Basic strategy implementation for renewable energy integration.

Various approaches are used to solve such problems [28], based on assessing potential, modeling energy supply and forecasting production and generation volumes. The use of such practices makes it possible to assess the most suitable locations for energy infrastructure, determine the potential amount of energy supplied and generated using specific converters and make forecasts with different time intervals to optimize energy system management processes.

In this regard, the paper considers a hybrid approach for assessing and forecasting the technical potential of solar energy, based on the use of simulation modeling, for which an energy system model was implemented that allows for the specific characteristics of energy converters and artificial intelligence technologies used to implement the procedure for forecasting the incoming level of solar radiation, the results of which are further used as input data for the technical potential assessment model.

2. Main Approaches for Assessing the Theoretical Potential of RES

The use of renewable energy sources allows us not only to achieve the goals of low-carbon energy realization, but also to provide residents of areas with few traditional resources with the possibility of using electrification, thus reducing the costs of logistics costs, conducting power lines, allowing full utilization of the potential of locally available resources, further stimulating the economic development of the region [29]. Depending on the existing situation, three main directions of RES integration can be chosen:

- Integration of separate conversion technology [30]—applied to provide energy to isolated areas and private energy consumers, for which the following types of energy can be used:
 - Solar photovoltaic systems, which are the most affordable and easy to implement, but are not able to generate energy during dark hours [31];
 - Systems based on wind energy [32];
 - Systems based on biogas/biomass gasifier, the application of which show high efficiency in remote forest and agricultural areas [33];

- Micro-hydro power (MHP) systems, which are best suited for remote mountainous areas with many small rivers and streams [34].
- Realization of an aggregated integration technology, which involves the use of multiple sources of “green energy”, which allows us to achieve greater sustainability of the energy system with a large volume of coverage of potential demand. As a result, the concept of Integrated Renewable Energy System (IRES) [35,36] was developed, which is the most suitable for off-grid energy generation from RES, an example of which is presented in Figure 4.
- Integration of RES into already existing energy systems to reduce the amount of energy generation from hydrocarbon resources, resulting in so-called distributed energy systems, combining several different generation sources [37], the list of which is presented in Figure 5:

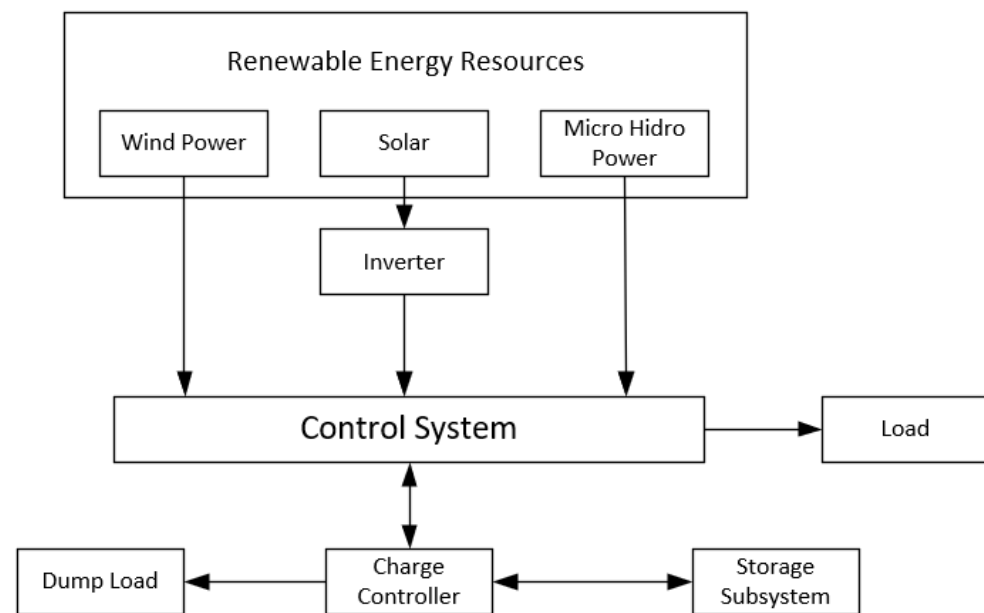


Figure 4. Schematic of wind–solar–MHP based integrated system.

With this variety of conversion methods, generation technologies allow us to create different configurations of energy systems, to meet the stated requirements and to achieve the necessary results in the operation of the system. However, the initial step in the development of renewable energy systems is the evaluation of the gross or theoretical potential of the type of energy of interest [38], which is necessary to estimate the amount of incoming energy, allowing us to determine the most suitable locations for the placement of energy plants, as well as to determine the most relevant types of energy resource.

Each type of energy resource has its own specialized methods for assessing its energy potential. The toolkit of such approaches is most widely developed for solar and wind energy, as these types of renewable energy are currently the most widespread and account for the largest percentage of energy generation compared to other types of RES. In the case of solar energy, one of the key parameters in assessing the theoretical potential is solar radiation (insolation), the amount of which directly affects the total amount of generation [39].

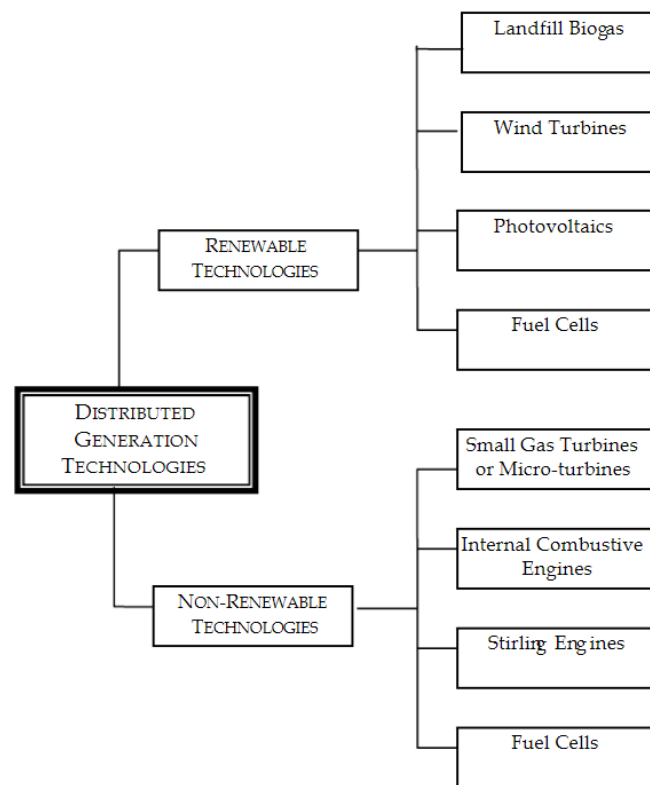


Figure 5. Distributed Generation technologies for power generation.

In general, models for solar energy estimation can be divided into the following groups [40]: mathematical models (linear and nonlinear empirical models) and models based on artificial intelligence and data mining techniques. Such approaches are aimed at modeling the amount of solar energy inflow and are usually used on the following groups of parameters [41]:

- Geographical, such as latitude and longitude, altitude and albedo;
- Geometric, which takes into account the position of the transforming elements in space;
- Physical parameters, which take into account factors such as dust and dispersion of air molecules;
- Meteorological parameters such as temperature, precipitation, humidity, cloud cover, etc.

As a result, it is possible to define the following classification [42] of models for assessing the theoretical solar energy potential, presented in Figure 6.

A general classification of forecasting methods is presented in Figure 7. The use of forecasting methods, most often based on intelligent methods, allows not only to assess the theoretical potential of energy resources in the studied area, but also to determine the amount of energy received within a specific forecasting horizon, thereby allowing the prospects for energy generation to be assessed. This can be used to make correct decisions when determining the power balance, which is particularly relevant when using distributed systems [43] with variable levels of demand from end users.

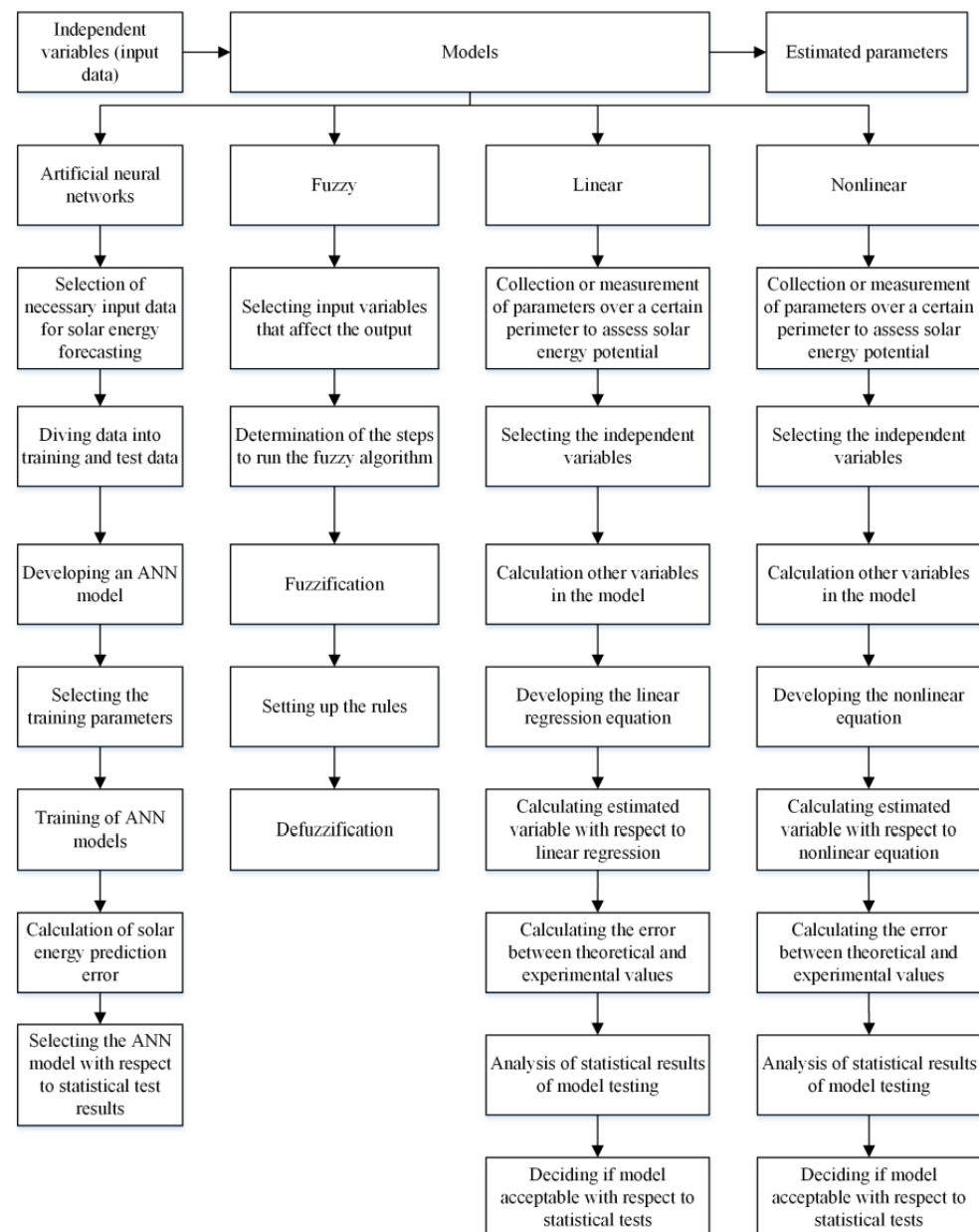


Figure 6. Block diagrams of models for estimating global solar radiation.

The methods considered for assessing and forecasting renewable energy sources allow for an evaluation of the theoretical potential of energy resources, but they do not take into account the conversion technologies used, thereby preventing an assessment of the technical potential, the significance of which is reflected in actual energy production volumes. In order to assess the technical potential, it is necessary to use either data from real energy installations, which can serve as a basis for building intelligent models for assessing and forecasting energy production volumes, or to use a comprehensive approach based first on forecasting the necessary parameters [44] (climatic), after which this data can be used in models that take into account the specific characteristics of energy facilities.

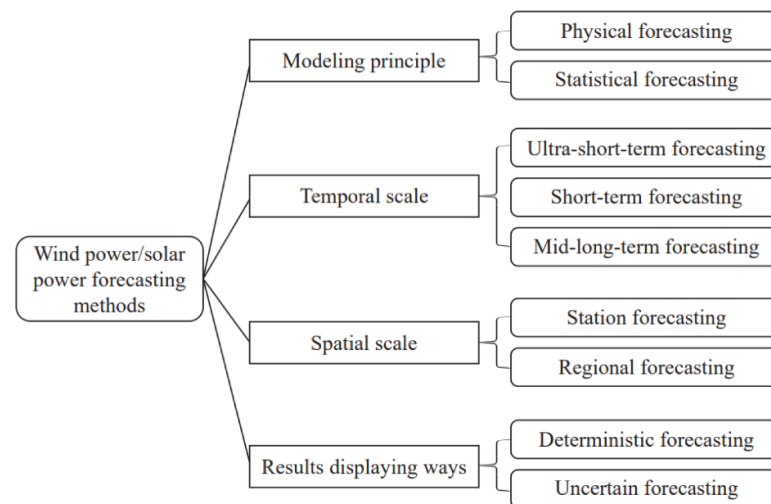


Figure 7. Classification of methods for predicting solar energy.

3. Assessment of Technical Potential of RES

The assessment of the gross potential (theoretical) will allow us to determine the most favorable locations for the location of power plants, but it is not sufficient for the full design of an energy system, the configuration of which strongly depends not only on the availability of resources, but also on the efficiency of conversion elements and economic costs [45]. Analyzing the most convenient ways to design such energy systems, a study [46] divided technical and economic factors, defining six different types of renewable energy potential:

- Theoretical potential—this is the simplest potential, for the assessment of which only natural and climatic factors are taken into account;
- Geographical potential is the second highest level in this list, which depends on the constraints of geographical areas (i.e., land use);
- Technical potential is obtained through geographical potential, which is limited by conversion efficiency (technical constraints);
- Techno-economic potential is obtained through technologies that are technically feasible and economical;
- Economic potential is technical potential in terms of economic competitiveness;
- Market potential is the total amount of renewable energy that applies to the market, taking into account energy demand, costs and government incentives for renewable energy and barriers.

Technical potential is the theoretical annual electricity production if power plants were deployed in all suitable areas based on the prevailing state of technology. It can also be defined as part of the real potential of an energy resource, which is a subset of the economic potential that takes into account social and environmental factors that may limit technology deployment, such as high initial costs that may deter investment [47]. In this way, it can be understood that the technical potential allows us to determine the theoretical amount of energy to be produced with specific energy conversion technologies based on a predetermined energy system configuration [48,49].

In the following study we will only focus on the aspect of technical potential definition, which will determine the amount of energy produced for the considered energy system configuration under specific geographical conditions, and the main types of green energy potential are presented in Figure 8.

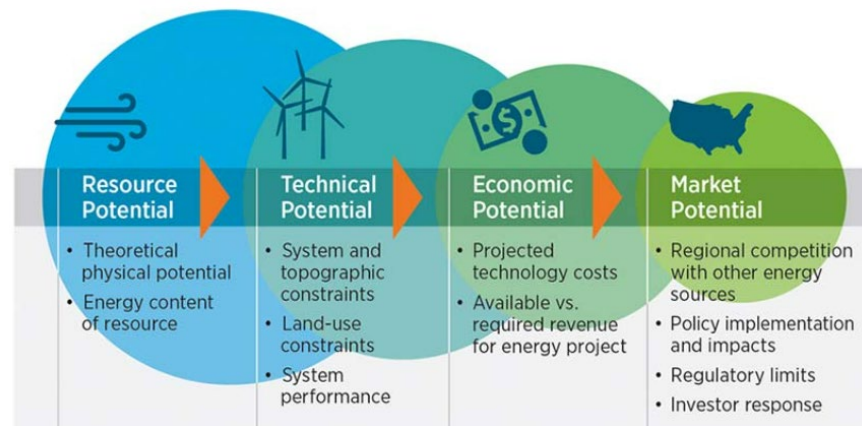


Figure 8. Types of renewable energy generation potential.

When determining the technical potential of the involved energy source, one of the important factors is the realization of the possibility to take into account the efficiency of the converter used and the specific technology, which will make it possible to obtain generation volumes using similar technological solutions. One of the possible ways to estimate the technical potential is to use large datasets, the processing of which is carried out using machine learning methods and artificial intelligence technologies. A similar approach was used by the authors of the study [50], who, using clustering methods, first assessed the theoretical potential for different regions, and then, by adding additional sets of parameters (such as installed capacity, voltage levels and type of conversion technology used), produced an estimation of the possible generation volumes and potentially possible substitution of conventional power generation.

In the study [51], the authors investigated ways to assess the technical potential of solar energy using such technology as concentrating solar power (CSP), for which they conducted a comprehensive analysis of the features and characteristics of such converters, determined the necessary requirements for the location of such installations, which allowed us to determine only suitable locations for placement of all potential points identified in the calculation of the theoretical potential of solar energy. After all these actions, a typical example of such a converter was selected, which is the most suitable for the realized requirements and then the calculation of generation volumes for each of the considered regions and states was made. The undoubted advantage of this approach is its relative simplicity, as there is no need to build complex models that require real data on the operation of such energy facilities, which allows the solution to be applied to any region on the basis of statistical data. However, this approach cannot be characterized by high accuracy because it is not able to reflect all technical aspects of the converter, which can negatively affect the design of small autonomous energy systems.

At the moment, there is no clearly defined general methodology that could allow the assessment of the technical potential of renewable energy [52]. Over the years, groups of researchers have proposed a variety of approaches to this task: the use of GIS-based decision support systems [53], other researchers use geospatial data, green resource distribution maps and available calculators to calculate the efficiency of implementing such energy solutions [54], while others take into account current land use and develop specific scenarios [55]. There are also a number of different tools to assess both the theoretical and technical potential of RES [56], but most of them have a rather limited functionality, not allowing the selection of the necessary energy system configurations or not allowing the assessment of some areas due to limited spatial resolution [57].

Considering various approaches and methodologies to the assessment of theoretical potential, the following approach applicable to all major types of RES can be proposed (Figure 9).

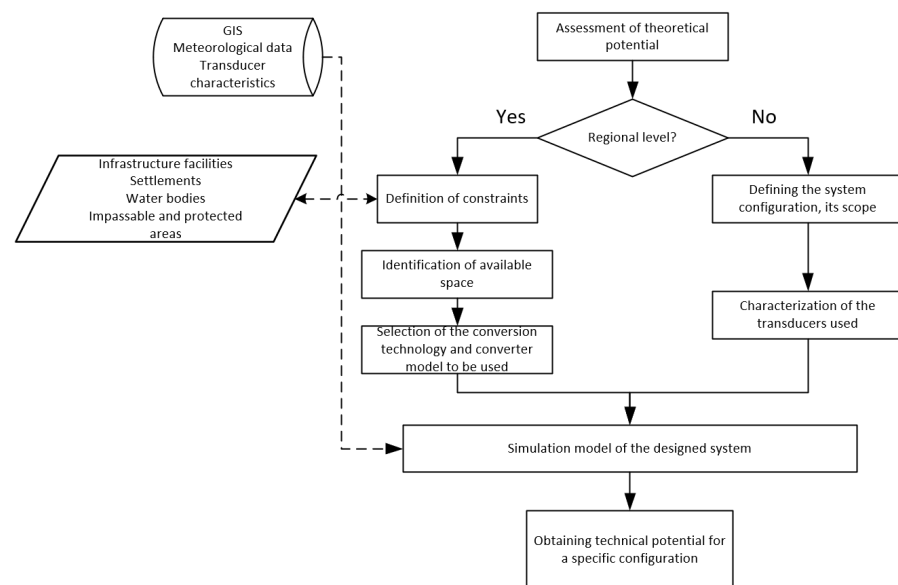


Figure 9. Simulation-based approach to assessing the technical potential of renewable energy sources.

The proposed approach involves the use of flexible simulation-modeling tools, whose functionality allows for the highly accurate recreation of the type of real energy converter under consideration, enabling the consideration of important technical characteristics that determine the amount of energy generated.

However, if we are talking not only about assessing technical potential, but also about forecasting it in the short term, then the general approach based on the use of artificial intelligence technologies and a simulation model of the system can be represented as shown in Figure 10.

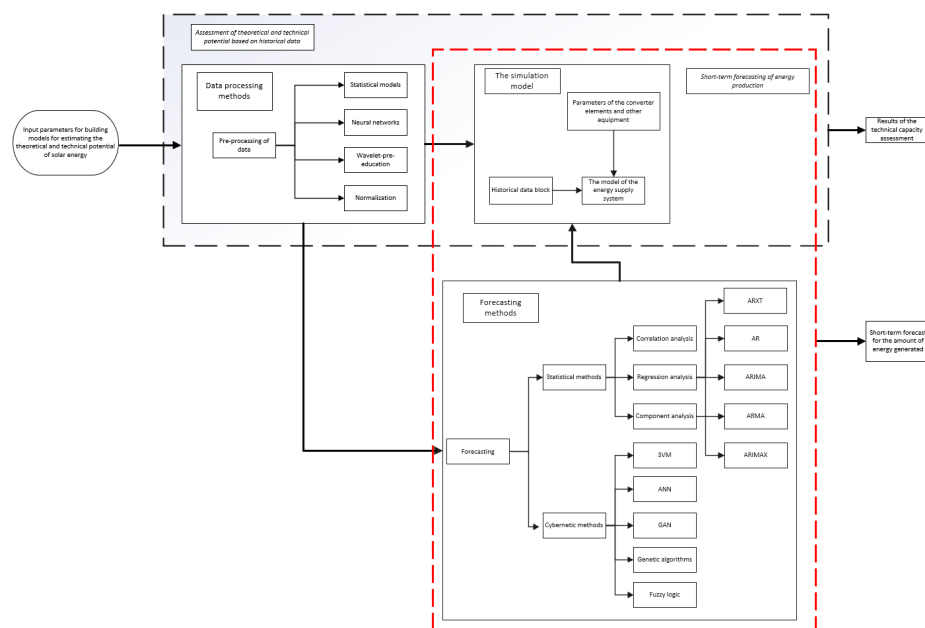


Figure 10. Approach to assessing and forecasting the technical potential of renewable energy sources based on the use of artificial intelligence methods and a physical object model.

4. Use of Simulation-Modeling Tools for RES Assessment

Modern simulation tools provide a wide range of capabilities used in modeling real technical systems [58]. Each of them has its own features and functionality, allowing, among other things, to make models of energy systems with the integration of renewable sources, which allows not only to study the features of the behavior of the simulated system, but also to estimate the resulting volumes of energy generation. One of the most common tools for creating simulation models is the MATLAB/SIMULINK R2024b environment [59], which has been used to study various configurations of wind turbines [60,61], systems based on solar panels [62] and small hydropower systems [63]. However, in addition to such a tool as MATLAB R2024b, there are many other solutions, one of which is the SimInTech dynamic simulation environment [64,65], which was originally developed for modeling complex technical systems, for example, energy and electromechanical. SimInTech has extensive built-in libraries containing ready-made, verified components, including photovoltaic panel modules—standard models with detailed volt-ampere characteristics that consider dependence on solar insolation and ambient temperature. The second reason for choosing the SimInTech environment is that the basic version can be provided to researchers on request, without purchasing additional licenses, unlike MATLAB/Simulink and its various expansion packs (such as Simscape Electrical/SimPowerSystems), which require an additional license and are more difficult to configure for specific physical processes.

To apply the models and obtain relevant results, it is necessary to use sets of real input data for each of the simulated energy sources located in the geographical area under study. Some of the values can be obtained using open data sources such as PVGIS [66] (this is how data on temperature, solar radiation and wind speed were obtained). Other data can be obtained through the use of autonomous measuring complexes [67] and information from actual functioning energy generation facilities (in particular, small hydroelectric power plants).

When assessing the potential of solar energy using solar panels, one of the important parameters is the temperature of the panel in operation, whose dependence on the ambient temperature can be determined from the following expression [68,69]:

$$T_{pi} = T_{air} + \frac{E_i}{800} \cdot (T_{not} - 20 \text{ }^{\circ}\text{C}), \quad (1)$$

where T_{pi} —solar panel surface temperature, $^{\circ}\text{C}$; E_i —incoming solar radiation; T_{air} —ambient temperature at the calculation point, $^{\circ}\text{C}$; and T_{not} —normal operating temperature of the solar panel, $^{\circ}\text{C}$.

To build the model, a monocrystalline solar panel YSM-100 [70] was used, the normal operating temperature of which is $45 \text{ }^{\circ}\text{C}$. In order to determine the amount of generated energy taking into account the efficiency of the converter used, the following expression was used [71]:

$$P = I_{gtc} \cdot F \cdot \eta \cdot (1 - k_t \cdot (T_{pi} - 25)), \quad (2)$$

where P —solar power plant capacity, W; I_{gtc} —total solar radiation, W/m^2 ; F —area of solar panels, m^2 ; η —efficiency of photovoltaic converters; k_t —temperature coefficient of variation in photovoltaic panel efficiency, relative units; and T_{pi} —solar panel surface temperature, $^{\circ}\text{C}$.

Using the available technical characteristics of the panel, it is possible to determine some coefficients, as a result of which expression 2 will take the following form:

$$P = I_{gtc} \cdot 0.5092 \cdot 0.1964 \cdot (1 - 0.0045 \cdot (T_{pi} - 25)). \quad (3)$$

Using expression 3, it is possible to realize a user block for calculating the generated power to the input of which real data such as ambient temperature and the amount of solar radiation are fed. The scheme of realization of the solar energy potential estimation module is presented in Figure 11.

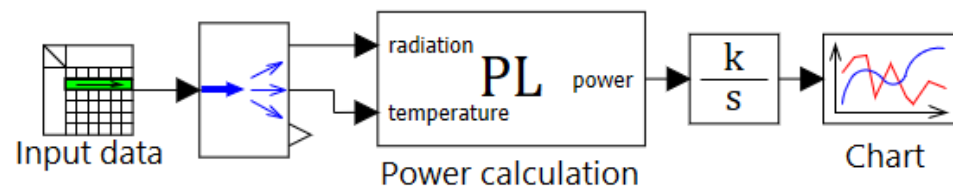


Figure 11. Structure diagram of the solar energy potential assessment module.

The result of the calculation is presented as a graph in Figure 12. Unfortunately, the used environment does not allow us to realize the output of values for several intervals, so for displaying the theoretical power of energy generation the integrator block was additionally used, which allows us to output the total amount of energy at the current moment considering the previously generated volume.

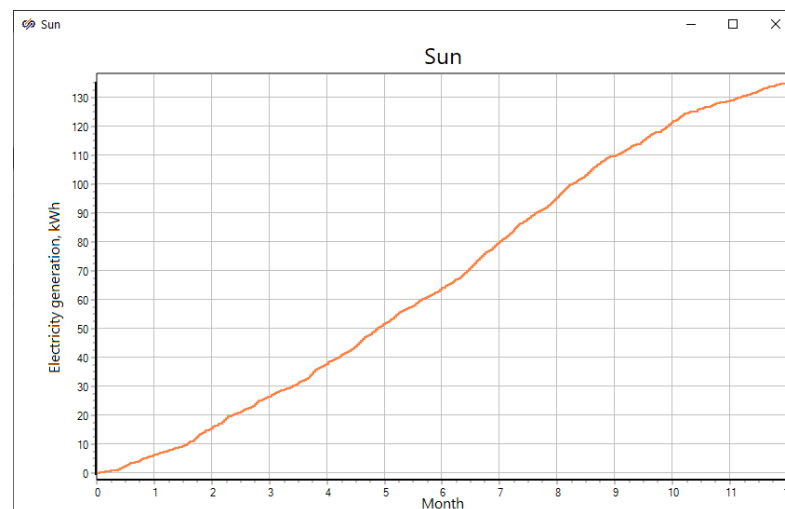


Figure 12. Chart of energy generation per year.

The realization of such a model does not allow us to consider all technical aspects of the inverter used, so to increase the accuracy of the assessment of the technical potential of solar energy, the scheme was realized using a functional block of the photovoltaic panel, which allows for a more accurate adjustment, as well as using a load model and an inverter that converts DC voltage into AC voltage. The functional diagram of the PV module is shown in Figure 13.

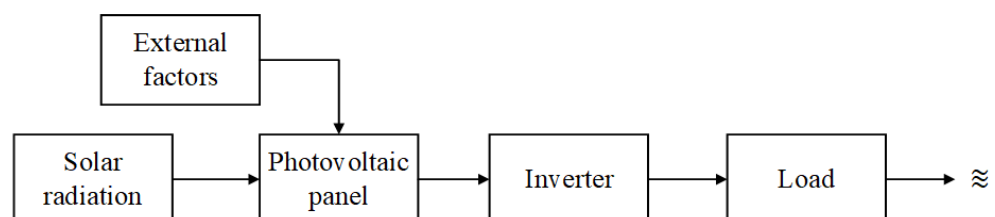


Figure 13. Functional diagram of the photovoltaic module.

Based on Figure 13, the simulation model shown in Figure 14 was implemented, which includes a typical solar panel module, an inverter and a load model simulating a consumer.

current is 3.65 A, the voltage is 19.1 V (zone 3, Figure 17). The percentage of inverter losses is ~6.3%.

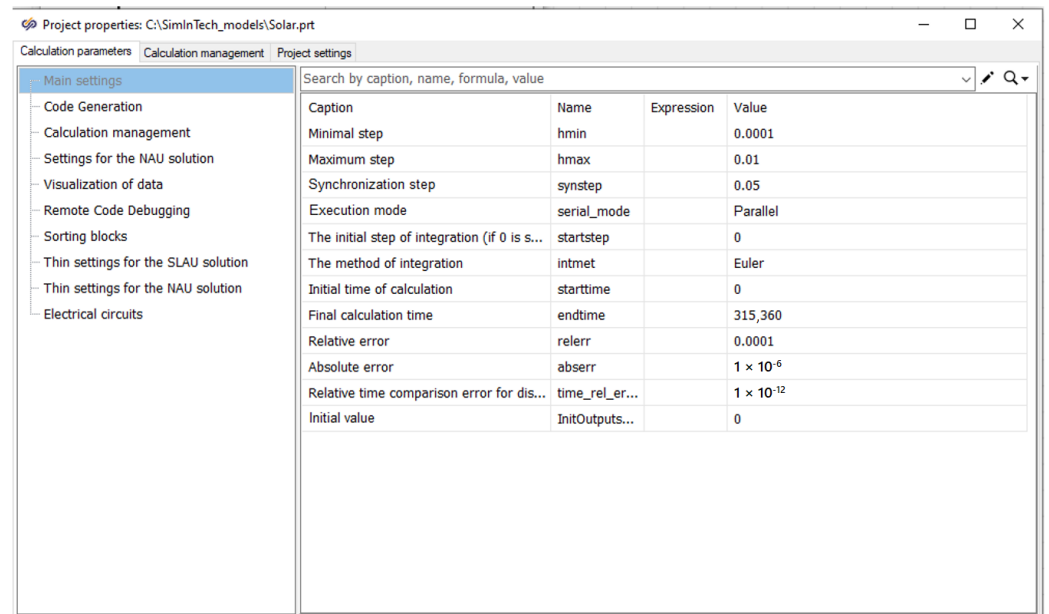


Figure 16. Parameters of the modeling process.

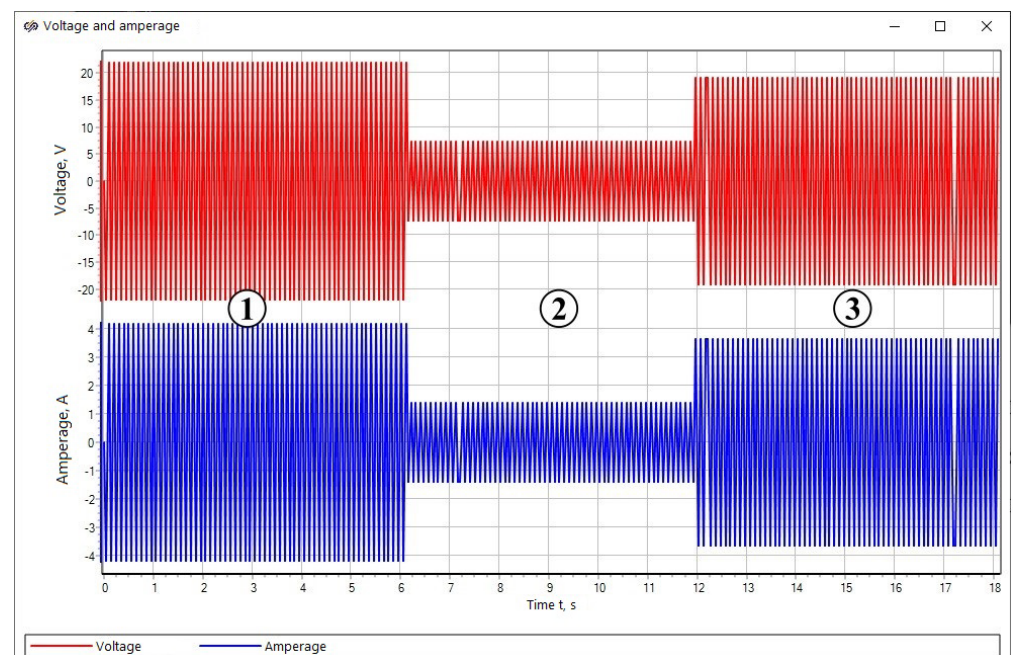


Figure 17. Chart of voltage and amperage produced by the solar panel under different operating conditions.

Based on the results, the power at different levels of solar radiation was determined: the power of the photovoltaic installation at solar radiation of 1000 W/m^2 is 91.7 W, and at 800 W/m^2 —69.69 W, which, taking into account the losses on the inverter, is close to the values specified in the technical documentation of the inverter.

The next stage was to run the model with a real set of input values with an interval of one year to determine the amount of energy generation, the result of which is shown in Figure 18.

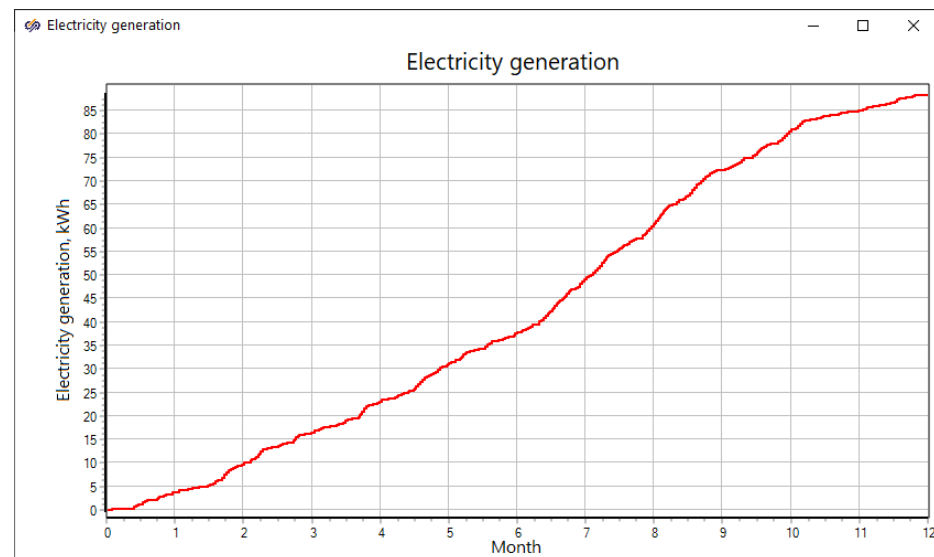


Figure 18. Electricity generation by photovoltaic panel per year.

It can be seen that, compared to the results obtained during the first model test (Figure 12), there was a drop in generation from 135 kWh per year to 87.5 kWh. This reduction is due to the finer tuning of the model and the inclusion of additional technical parameters of the converter beyond just temperature and efficiency.

5. Forecasting the Technical Potential of Solar Energy Based on Data from an Intelligent Model

As the input data for the energy system simulation model includes solar radiation data, it is necessary to obtain forecast values for solar insolation in order to carry out the technical potential forecasting procedure, which requires the use of some approach for forecasting it. As mentioned above, there are many different approaches to solar energy forecasting, the most relevant and accurate of which is the use of artificial intelligence algorithms [42,72]. However, to estimate solar insolation (solar radiation), it is best to use models that cope well with time series, nonlinearities and incomplete data [73]. Among the best methods that have demonstrated high accuracy and stability in predicting solar insolation in practice are: Long Short-Term Memory (LSTM) [74,75], Convolutional Neural Networks (CNN) [76,77], Gradient Boosting Models (XGBoost, LightGBM, CatBoost) [78], Support Vector Regression (SVR) [79], Hybrid Models (LSTM + CNN, ANN + GA, etc.) [80,81] and Physics-Informed Neural Networks (PINNs) [82,83]. This set of approaches allows us to work well with forecasting tasks not only for solar energy, but also for other types of renewable energy. Within this set of approaches, the authors chose the LSTM architecture for several reasons. LSTMs are specifically designed to process sequential data and have the ability to remember long-term dependencies, which is critically important when taking into account daily and seasonal cycles and weather trends (e.g., gradual cloud thickening). Other analogs have their advantages, but CNNs are good at identifying local patterns but do not “remember” long-term dynamics without the help of other models, GBM/XGBoost work with tabular features but do not preserve the temporal structure without additional transformations (lags, rolling statistics), SVR is linear and weak over long time intervals, while Hybrid and PINNs are accurate but difficult to implement and train. Figure 19 shows the structure of an LSTM architecture cell.

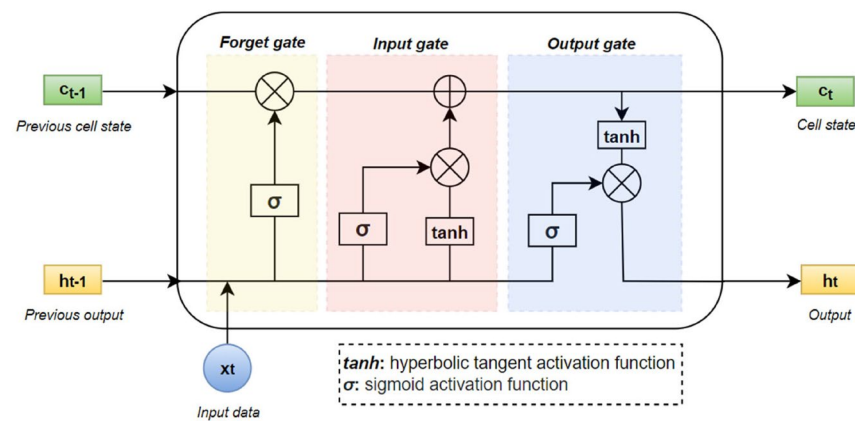


Figure 19. The LSTM structure [75].

In an earlier paper [74], the authors already discussed the issue of choosing an architecture for predicting solar energy, where as a result of comparison with other architectures of intelligent models, it was determined that using the LSTM model is the most optimal, allowing for sufficient accuracy over the short-term forecasting horizon, for which there are several definitions of duration, one of which is given in Table 2 [84,85].

Table 2. Description of forecasting horizons.

Horizon	Time
Very short-term forecast	Ahead by 1 min to several minutes
Short-term forecast	Ahead by 1 h or several hours to 1 day or 1 week
Medium-term forecast	Ahead by 1 month to 1 year
Long-term forecast	Ahead by 1–10 years

Another important parameter when choosing a model is the training time [86] and the demands on computing resources, which can be critical for field research. Thus, the LSTM shows excellent quality indicators [75], although it is slightly inferior in accuracy compared to other hybrid models.

A dataset from open sources was used to train the network, specifically the NSRDB (National Solar Radiation Database) [87]—an open platform developed by the US National Renewable Energy Laboratory (NREL) designed to provide highly accurate meteorological data related to solar radiation. The database contains data on global, direct and diffuse solar radiation, as well as weather parameters (temperature, cloud cover, humidity, wind speed, etc.) with high spatial (up to 4 km) and temporal (hourly and 30 min) resolution, an example of which is shown in Figure 20.

A dataset for 2021–2022 was used to train the model for one of the observation stations with coordinates (48°07′48.0″ N 122°46′48.0″ W, United States, Washington, Jefferson County). The dataset under consideration has a large number of parameters, not all of which were used to train the model. In Figure 20, several example objects in the locality of the specified coordinates are marked in different colors (green, yellow, and blue). The choice of the NASA’s Prediction of Worldwide Energy Resources (POWER) database and, in particular, the NSRDB (National Solar Radiation Database) data source was determined by some key factors, including the ability to access long-term, homogeneous and verified data on solar insolation with global coverage, the availability and completeness of meteorological parameters, long-term temporal rows, which has a positive effect on the learning efficiency of the model used. Since the proposed methodology is general, the choice of location coordinates is determined by the possibility of extracting the necessary dataset and their further verification. This is not always possible when using regional databases, which are

characterized either by limited sampling or by the inability to obtain data in the public domain or even on request.

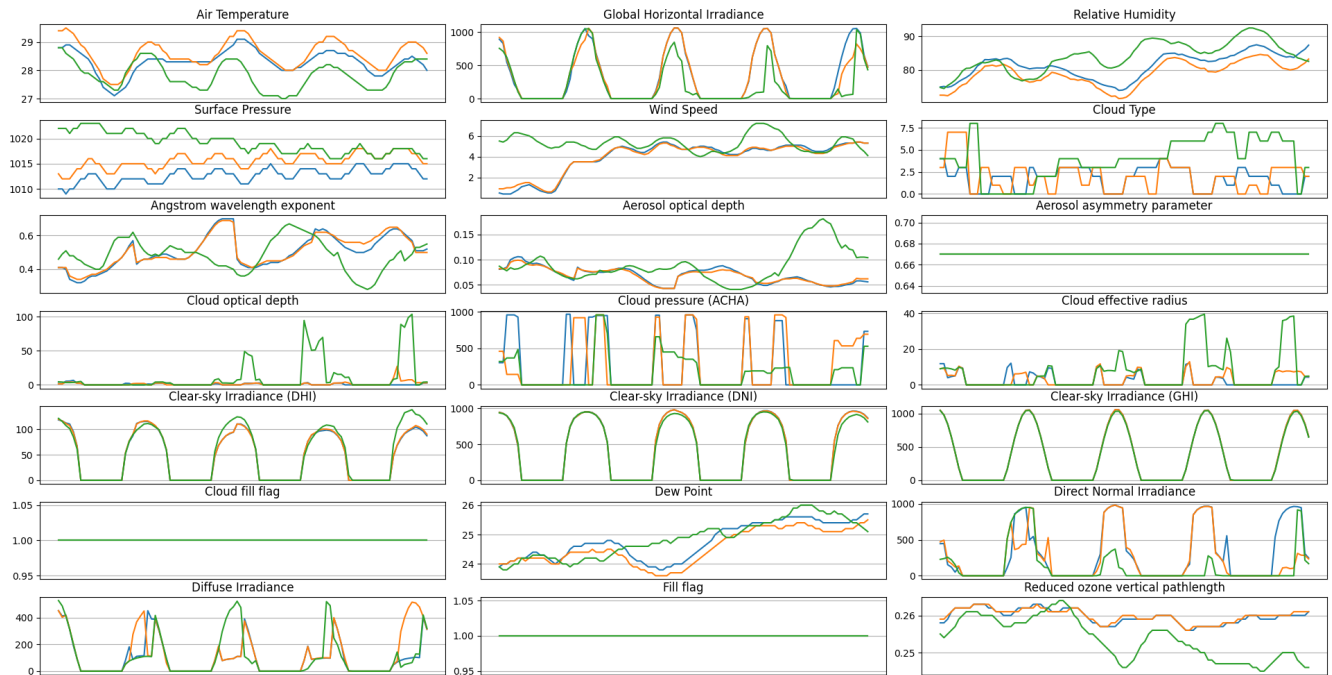


Figure 20. Example data from the NSRDB dataset.

The main parameters were defined as historical values of solar radiation in the form of a time series, air temperature and humidity values. The first stage of model construction was the data preprocessing process, which allows avoiding the presence of peak and non-stationary elements in the original dataset (outliers) that adversely affect the effectiveness of using a model trained on such data. Therefore, data preprocessing methods are used to save, eliminate missing values and scale functions. At this stage, an exponential smoothing procedure [88–90] was used to suppress short-term noise inherent in solar insolation values, which can change dramatically due to clouds, atmospheric dust, etc. As a result, despite its noise resistance, the LSTM model still suffers from sharp fluctuations, especially with a small training sample size [91], after which the data is fed as features to the implemented model.

ConvLSTM is a modified version of the LSTM network for efficient processing of sequential data having a spatial or spatiotemporal structure [92]. The parameters for a similar architecture are calculated as follows:

$$\begin{cases} i_t = \sigma(W_i * x_t + W_i * h_{t-1} + W_i \circ C_{t-i} + b_i) \\ f_t = \sigma(W_f * x_t + W_f * h_{t-1} + W_f \circ C_{t-i} + b_f) \\ C_t = f_t \circ C_{t-i} + i_t \circ \tanh(W_C * x_t + W_C * h_{t-1} + b_C) \\ o_t = \sigma(W_o * x_t + W_o * h_{t-1} + W_o \circ C_{t-i} + b_o) \\ h_t = o_t \circ \tanh(C_t) \end{cases} \quad (4)$$

Here, the asterisk (*) symbol indicates the convolution operation. The key difference between ConvLSTM and LSTM methods is their handling of input and recurrent connections. The ConvLSTM model processes them using convolutions, while the LSTM model processes them using fully connected layers. Figure 21 shows the architecture of the LSTM model used, adapted to spatial data from the NSRDB dataset.

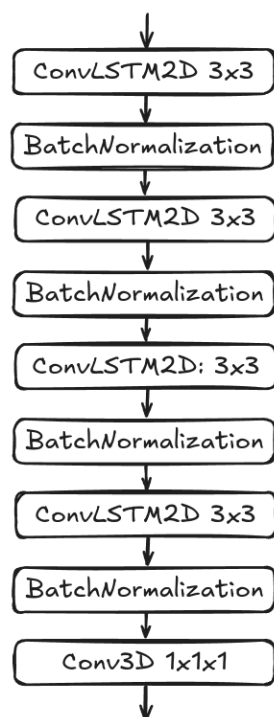


Figure 21. Architecture of the neural network used.

The model processes data in 4D tensor format (time steps, height, width, features) and predicts subsequent time steps for all grid points. The model parameters are shown in Table 3.

Table 3. Model characteristics.

Parameter	Values	Description
Input tensor	SEQ_OUT_LEN, GRID_SIZE_H, GRID_SIZE_W, N_IN_FEATURES	SEQ_IN_LEN: the number of hours of forecast data (8760 measurements) GRID_SIZE_H, GRID_SIZE_W: the size of the spatial grid (32 grid cells, 32 grid cells) N_IN_FEATURES—input attributes: air temperature, cloud type, relative humidity, solar zenith angle, surface pressure, total precipitable water
	SEQ_OUT_LEN, GRID_SIZE_H, GRID_SIZE_W, N_OUT_FEATURES	SEQ_OUT_LEN: the number of hours of forecast data (135 measurements). GRID_SIZE_H, GRID_SIZE_W: the size of the spatial grid (32 grid cells, 32 grid cells) N_OUT_FEATURES—ghi output attribute
Model Layers	ConvLSTM2D	- Convolution in space (3×3 core) and time - Saves the size of the space at all stages - Returns a sequence of time steps
	BatchNormalization	Improves learning stability - Core size: 1 × 1 × 1 - linear activation
	The final layer	- Does not change the dimensions of space and time

Figure 22 shows the result of the forecast.

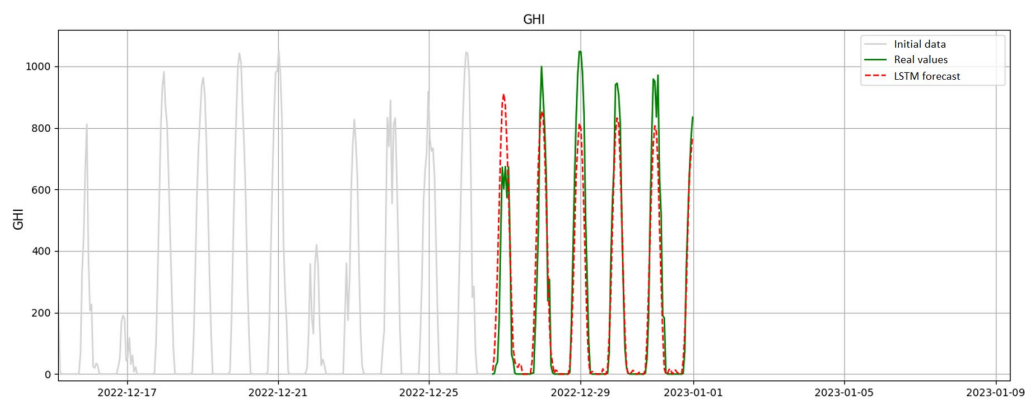


Figure 22. Results of forecasting using the LSTM model.

Various metrics can be used to evaluate the model [93], one of which is MSE, which can be determined using the loss function [94]. During training, the following values were obtained: for the test sample, the loss function took a value of 0.079 (0.0079), and for the validation sample, the loss function was 0.248 (0.0248). Additionally, the following metrics were used:

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (X_{\text{pred}} - X_{\text{means}})^2}, \quad (5)$$

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^n |X_{\text{pred}} - X_{\text{means}}|, \quad (6)$$

$$R^2 = \frac{\sum_i (\hat{y}_i - \bar{y}_i)^2}{\sum_i (y_i - \bar{y}_i)^2}. \quad (7)$$

The assessment of the accuracy of solar radiation level forecasting using a recurrent neural network of the LSTM type demonstrated the following metric values: $\text{RMSE} = 77.4$, $\text{MAE} = 42.3$ and coefficient of determination $R^2 = 0.824$, which indicates a high degree of correspondence between the forecast values and the actual data. Low error values (MAE and RMSE) indicate that the model deviates from actual observations by an average of tens of watts per square meter, which is an acceptable level of accuracy for short-term solar radiation forecasting tasks. At the same time, the value of $R^2 = 0.824$ demonstrates that the model explains more than 82% of the dispersion of the initial data, which allows us to discuss the reliability of forecasts and sufficient stability of the algorithm to fluctuations in input parameters.

The following equipment was used for training: AMD Ryzen 9 5950X 16-Core Processor 3.40 GHz processor; 32.0 GB RAM; Samsung SSD 980 PRO 1000 GB SSD memory; NVIDIA GeForce RTX 3070 Ti video adapter (8 GB). The time taken for one epoch was 64 s.

Since short-term forecasting is the most important for the operational management of distributed energy systems, values were predicted in the period from 1 day to a week. This made it possible to achieve higher accuracy within the framework of the proposed hybrid approach (the use of neural networks and dynamic simulation models in the process of predicting the volume of solar energy generation).

In the case of long-term forecasting, there are a number of additional difficulties, for example, cyclical and seasonal variability and the need to use additional exogenous variables (for example, weather conditions, temperature, cloud indices in the vicinity of the studied object). However, the chosen LSTM-based structure can be expanded to these horizons by re-training using appropriately structured datasets and including additional characteristics.

Thus, the LSTM-based model can be effectively used to predict solar radiation under conditions of climate variability, providing accuracy comparable to modern methods in

this field. As a result, the obtained results can be used as input data for further loading into the input of the energy system simulation model. An example of historical and predicted values of solar insolation is shown in Table 4.

Table 4. Examples of historical data and predicted values.

№	Historical Data, W/m ²	Predicted Values, W/m ²
1	0.0	1.948
2	2.0	5.548
3	28.0	82.645
4	39.0	61.256
5	166.0	179.042
6	437.0	560.518
7	672.0	754.082
8	602.0	794.447
9	674.0	742.693
10	573.0	638.511
11	673.0	570.079
12	423.0	367.622
13	63.0	197.947
14	44.0	59.661
15	3.0	21.878
16	0.0	0.74

After the model is implemented, the predicted values are saved using Python 3.13.5 in the .csv format. This file is then converted to a file with the extension .dat that enters the input of the simulation model. As a result, two sets of data are formed, historical and predicted, shown in Figure 23.

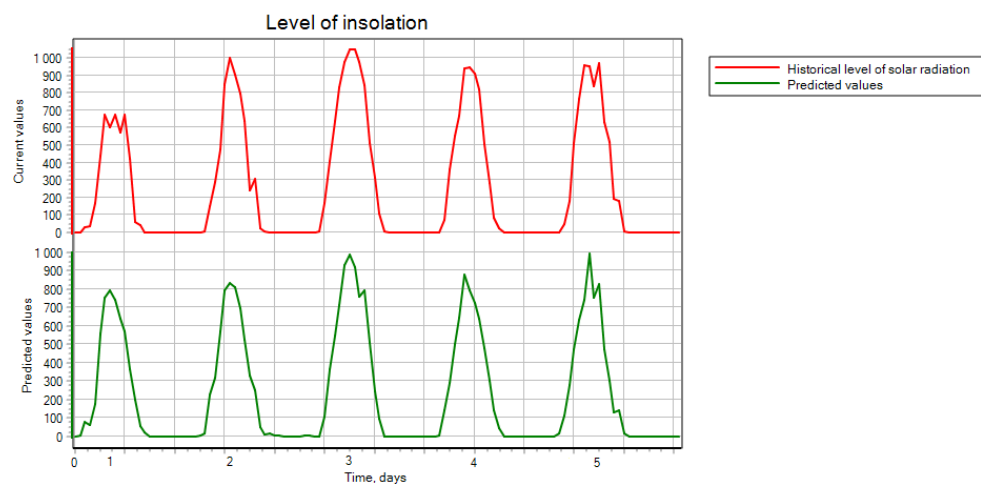


Figure 23. Visualization of input values.

By using data obtained during the construction of the forecasting model, it becomes possible to predict the generation volumes of power plants with a predetermined configuration, which is an integral element in organizing demand management policies in modern intelligent distributed energy systems based on renewable energy. The final result of the technical potential forecast obtained from the simulation model is shown in Figure 24.

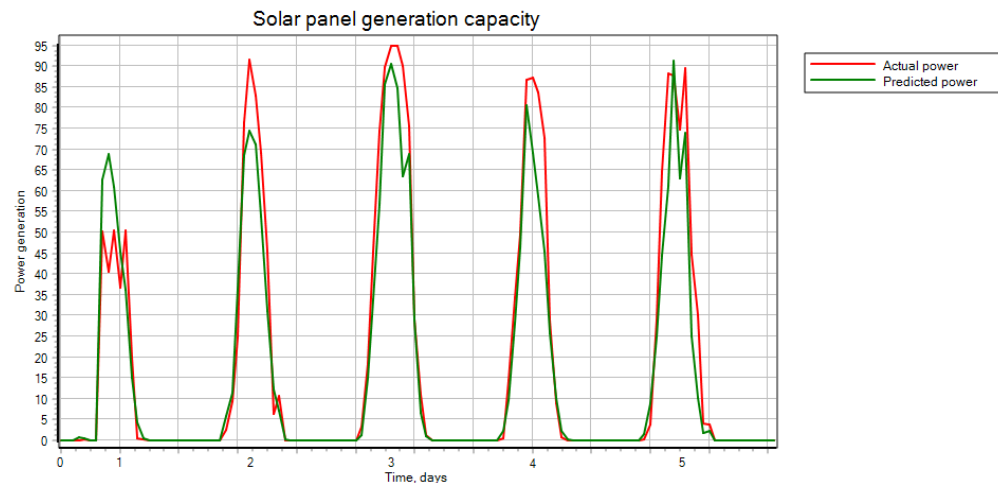


Figure 24. Comparison of power generation capacity of an energy plant based on actual and forecast data.

In the study, a single dataset (NSRDB) and a typical photovoltaic module configuration were deliberately chosen as a visual example to illustrate the functionality and integration of the proposed methodology. This approach allowed us to clearly present the workflow of combining intelligent forecasting with dynamic simulation modeling without introducing unnecessary complexity at the initial stage. It is important to emphasize that the methodology itself does not impose restrictions on the use of other datasets, geographic locations, or photovoltaic technologies. In practice, the structure is designed to be fully adaptable: when choosing a new region/research area, the LSTM model can be retrofitted/retrained on any available dataset corresponding to a different region, time horizon, or climatic conditions. If it is necessary to change the configuration of the energy system (for example, another photovoltaic module, changes in the load structure), the necessary adjustments can be made by updating the parameters of the corresponding blocks in the simulation model.

6. Conclusions

This paper presents a methodology for comprehensive assessment of solar energy technical potential based on the synergy of artificial intelligence and simulation-modeling technologies. As a result, the proposed approach allows for both actual and forecast values of solar radiation to be taken into account, making it particularly useful for analyzing energy scenarios in distributed energy systems with a high share of renewable energy sources. As part of the methodology, historical meteorological data on solar insolation is used to train a model based on LSTM, one of the most effective classes of recurrent neural networks adapted for processing time series, and the obtained forecast values of solar radiation, taking into account temporal and seasonal dynamics, serve as input data for the energy system simulation model implemented in the SimInTech environment, which allows modeling the behavior of the system under various climatic conditions and loads, as well as quantitatively assessing the technical potential of solar energy generation in specific territorial conditions.

The developed approach allows for more informed planning of solar power plant locations and assessment of their impact on the structure and reliability of the local power system. Thus, the developed methodology can serve as a basis for intelligent design of distributed energy systems that integrate renewable energy sources and digital demand management elements. Further development of the methodology may involve expanding the range of input factors (e.g., considering economic and infrastructure parameters) and

introducing adaptive algorithms for optimizing energy generation and storage based on forecast conditions.

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References

- Ozili, P.K.; Ozen, E. Global energy crisis: Impact on the global economy. In *The Impact of Climate Change and Sustainability Standards on the Insurance Market*; Wiley: Hoboken, NJ, USA, 2023; pp. 439–454.
- Gajdzik, B.; Wolniak, R.; Nagaj, R.; Žuromskaitė-Nagaj, B.; Grebski, W.W. The Influence of the Global Energy Crisis on Energy Efficiency: A Comprehensive Analysis. *Energies* **2024**, *17*, 947. [\[CrossRef\]](#)
- Bompard, E.; Ribeiro Serrenho, T.; Bertoldi, P. *Improving Energy Efficiency in Electricity Networks*; Publications Office of the European Union: Luxembourg, 2020; ISBN 978-92-76-22402-0.
- du Can, S.D.L.R.; Letschert, V.; Agarwal, S.; Park, W.Y.; Kaggwa, U. Energy efficiency improves energy access affordability. *Energy Sustain. Dev.* **2022**, *70*, 560–568. [\[CrossRef\]](#)
- Owusu, P.A.; Asumadu-Sarkodie, S. A review of renewable energy sources, sustainability issues and climate change mitigation. *Cogent Eng.* **2016**, *3*, 1167990. [\[CrossRef\]](#)
- IEA; IRENA; UNSD; World Bank; WHO. Tracking SDG 7: The Energy Progress Report. World Bank: Washington, DC, USA, 2023; Available online: <https://data.worldbank.org/indicator/EG.ELC.ACCS.ZS> (accessed on 29 September 2024).
- Skare, M.; Porada-Rochoń, M. Financial and economic development link in transitional economies: A spectral Granger causality analysis 1991–2017. *Oeconomia Copernic.* **2019**, *10*, 7–35. [\[CrossRef\]](#)
- Jankiewicz, M.; Pietrzak, M.B. Assessment of trends in the share of expenditure on services and food in the Visegrad Group member states. *Int. J. Bus. Soc.* **2020**, *21*, 977–996. [\[CrossRef\]](#)
- Piekut, M. Patterns of energy consumption in Polish one-person households. *Energies* **2020**, *13*, 5699. [\[CrossRef\]](#)
- Safa, H. The impact of energy on global economy. *Int. J. Energy Econ. Policy* **2017**, *7*, 287–295.
- Chen, G.Q.; Wu, X.D.; Guo, J.; Meng, J.; Li, C. Global overview for energy use of the world economy: Household-consumption-based accounting based on the world input-output database (WIOD). *Energy Econ.* **2019**, *81*, 835–847. [\[CrossRef\]](#)
- Islam, M.M.; Hasanuzzaman, M.; Pandey, A.K.; Rahim, N.A. Modern energy conversion technologies. In *Energy for Sustainable Development*; Academic Press: Cambridge, MA, USA, 2020; pp. 19–39.
- Buchatskiy, P.Y.; Teploukhov, S.V.; Onishchenko, S.V.; Lisov, D.N. Program Module for Locating Charging Stations for Electric Light Vehicles in a Settlement. In Proceedings of the 2024 International Conference on Information Processes and Systems Development and Quality Assurance (IPS), Saint Petersburg, Russia, 19 March 2024; IEEE: Piscataway, NJ, USA, 2024; pp. 12–16.
- Teploukhov, S.V.; Lisov, D.N.; Buchatskiy, P.Y.; Bychkov, T.Y.; Onishchenko, S.V. Development of the Module of Charging Stations Placement for Electric Transport Based on Genetic Algorithm. In Proceedings of the 2024 XXVII International Conference on Soft Computing and Measurements (SCM), Saint Petersburg, Russia, 22–24 May 2024; pp. 123–126. [\[CrossRef\]](#)
- Maka, A.O.; Alabid, J.M. Solar energy technology and its roles in sustainable development. *Clean Energy* **2022**, *6*, 476–483. [\[CrossRef\]](#)
- Roga, S.; Bardhan, S.; Kumar, Y.; Dubey, S.K. Recent technology and challenges of wind energy generation: A review. *Sustain. Energy Technol. Assess.* **2022**, *52*, 102239. [\[CrossRef\]](#)
- Shetty, C.; Priyam, A. A review on tidal energy technologies. *Mater. Today Proc.* **2022**, *56*, 2774–2779. [\[CrossRef\]](#)
- Singh, S.; Sarkar, P.; Dutta, K. Chapter 23—Bioenergy: An overview of bioenergy as a sustainable and renewable source of energy. In *Bioprospecting of Microbial Diversity*; Verma, P., Shah, M.P., Eds.; Elsevier: Amsterdam, The Netherlands, 2022; pp. 483–502.
- Liszka, D.; Krzemianowski, Z.; Węgiel, T.; Borkowski, D.; Polniak, A.; Wawrzykowski, K.; Cebula, A. Alternative Solutions for Small Hydropower Plants. *Energies* **2022**, *15*, 1275. [\[CrossRef\]](#)
- Alcayde, A.G.; Montoya, F.; Baños, R.; Perea-Moreno, A.-J.; Manzano-Agugliaro, F. Analysis of Research Topics and Scientific Collaborations in Renewable Energy Using Community Detection. *Sustainability* **2018**, *10*, 4510. [\[CrossRef\]](#)

21. Wang, Q.; Huang, R.; Li, R. Renewable energy and sustainable development goals: Insights from latent dirichlet allocation thematic and bibliometric analysis. *Sustain. Dev.* **2024**, *32*, 6339–6359. [\[CrossRef\]](#)
22. Seminario-Córdova, R.; Rojas-Ortega, R. Renewable Energy Sources and Energy Production: A Bibliometric Analysis of the Last Five Years. *Sustainability* **2023**, *15*, 10499. [\[CrossRef\]](#)
23. Busch, S.; Kasdorp, R.; Koolen, D.; Mercier, A.; Spooner, M. *The Development of Renewable Energy in the Electricity Market*; European Commission Discussion; European Commission: Brussels, Belgium, 2023; p. 187.
24. IEA. Tracking SDG7: The Energy Progress Report. 2024. Available online: <https://www.iea.org/reports/tracking-sdg7-the-energy-progress-report-2024> (accessed on 19 September 2024).
25. Verzijlbergh, R.A.; De Vries, L.J.; Dijkema, G.P.J.; Herder, P.M. Institutional challenges caused by the integration of renewable energy sources in the European electricity sector. *Renew. Sustain. Energy Rev.* **2017**, *75*, 660–667. [\[CrossRef\]](#)
26. Elistratov, V.V.; Denisov, R.S. Optimization of Hybrid Systems Operating Modes Based on Renewable Energy. In Proceedings of the 2019 16th Conference on Electrical Machines, Drives and Power Systems (ELMA), Varna, Bulgaria, 6–8 June 2019; pp. 1–4.
27. Ganesh, V.; Senthilmurugan, S.; Ananthanarayanan, R.; Srinivasan, S.S.; Lakshanasri, N.R.S. Integration Strategies of Renewable Energy Sources in a Conventional Community. In *Handbook of Smart Energy Systems*; Fathi, M., Zio, E., Pardalos, P.M., Eds.; Springer: Cham, Switzerland, 2023.
28. Buchatskaya, V.V.; Buchatskiy, P.Y.; Teploukhov, S.V.; Onishchenko, S.V. Multi-Criteria Assessment of Renewable Energy Sources Involvement in the Regional Energy System Based on the Hierarchy Analysis Method. In Proceedings of the 2025 XXVIII International Conference on Soft Computing and Measurements (SCM), Saint Petersburg, Russia, 28–30 May 2025; pp. 131–135. [\[CrossRef\]](#)
29. Nguyen, T.T.H.; Phan, G.Q.; Tran, T.K.; Bui, H.M. The role of renewable energy technologies in enhancing human development: Empirical evidence from selected countries. *Case Stud. Chem. Environ. Eng.* **2023**, *8*, 100496. [\[CrossRef\]](#)
30. Chauhan, A.; Saini, R.P. A review on Integrated Renewable Energy System based power generation for stand-alone applications: Configurations, storage options, sizing methodologies and control. *Renew. Sustain. Energy Rev.* **2014**, *38*, 99–120. [\[CrossRef\]](#)
31. Dorel, S.; Gmal Osman, M.; Strejoiu, C.-V.; Lazaroiu, G. Exploring Optimal Charging Strategies for Off-Grid Solar Photovoltaic Systems: A Comparative Study on Battery Storage Techniques. *Batteries* **2023**, *9*, 470. [\[CrossRef\]](#)
32. Roy, A.; Bandyopadhyay, S. *Wind Power Based Isolated Energy Systems*; Springer International Publishing: Cham, Switzerland, 2019.
33. Bagdadee, A.H.; Maitraya, A.M.; Islam, A.; Siddique, M.N.E.A. A review on hybrid energy generation: Cow dung biogas, solar thermal and kinetic energy integration for power production. *Energy Built Environ.* **2023**, *6*, 109–120. [\[CrossRef\]](#)
34. Ion, C.P.; Marinescu, C. Autonomous micro hydro power plant with induction generator. *Renew. Energy* **2011**, *36*, 2259–2267. [\[CrossRef\]](#)
35. Maheshwari, Z.; Ramakumar, R. Smart Integrated Renewable Energy Systems (SIRES) for rural communities. In Proceedings of the IEEE Power and Energy Society General Meeting (PESGM), Boston, MA, USA, 17–21 July 2016; pp. 1–5. [\[CrossRef\]](#)
36. Kanase-Patil, A.B.; Saini, R.P.; Sharma, M.P. Integrated renewable energy systems for off grid rural electrification of remote area. *Renew. Energy* **2010**, *35*, 1342–1349. [\[CrossRef\]](#)
37. Dincer, I.; Bicer, Y. (Eds.) Chapter 6—Integration of renewable energy systems for multigeneration. In *Integrated Energy Systems for Multigeneration*; Elsevier: Amsterdam, The Netherlands, 2020; pp. 287–402.
38. Simankov, V.S.; Buchatskiy, P.Y.; Teploukhov, S.V.; Cherkasov, A.N.; Onishchenko, S.V. Designing an Intelligent Information and Analytical System for Evaluating Solutions in Renewable Energy Based on Digital Twins. In Proceedings of the 2023 Seminar on Information Systems Theory and Practice (ISTP), Saint Petersburg, Russia, 30 November 2023; pp. 85–88. [\[CrossRef\]](#)
39. Joshi, U.; Shrestha, P.M.; Maharjan, S.; Bhattarai, A.; Bhattarai, N.; Chapagain, N.P.; Karki, I.B.; Poudyal, K.N. Estimation of Solar Insolation and Angstrom–Prescott Coefficients Using Sunshine Hours over Nepal. *Adv. Meteorol.* **2022**, 3593922, 1–15. [\[CrossRef\]](#)
40. Vaskov, A.G.; Narynbaev, A.F. Solar Radiation Estimation and Prediction Methods: A Review and Classification. *Vestnik MEI* **2020**, *4*, 49–61. (In Russian) [\[CrossRef\]](#)
41. Besharat, F.; Dehghan, A.A.; Faghih, A.R. Empirical models for estimating global solar radiation: A review and case study. *Renew. Sustain. Energy Rev.* **2013**, *21*, 798–821. [\[CrossRef\]](#)
42. Simankov, V.S.; Buchatskiy, P.Y.; Onishchenko, S.V.; Teploukhov, S.V. Review of Models for Estimating and Predicting the Amount of Energy Produced by Solar Energy Systems. *Russ. J. Earth Sci.* **2023**, *5*, 1–17. [\[CrossRef\]](#)
43. Panda, S.; Mohanty, S.; Rout, P.K.; Sahu, B.K.; Parida, S.M.; Kotb, H.; Flah, A.; Tostado-Véliz, M.; Abdul Samad, B.; Shouran, M. An Insight into the Integration of Distributed Energy Resources and Energy Storage Systems with Smart Distribution Networks Using Demand-Side Management. *Appl. Sci.* **2022**, *12*, 8914. [\[CrossRef\]](#)
44. Bedanokov, M.K.; Buchatskiy, P.Y.; Teploukhov, S.V.; Onishchenko, S.V. The Use of Climatic and Geospatial Data in Assessing the Potential of “Green Energy” and Designing Energy Systems with Renewable Energy Sources in the Republic of Adygea. *Russ. J. Earth Sci.* **2025**, *25*, 1–7. [\[CrossRef\]](#)
45. Izadyar, N.; Ong, H.C.; Chong, W.T.; Leong, K.Y. Resource assessment of the renewable energy potential for a remote area: A review. *Renew. Sustain. Energy Rev.* **2016**, *62*, 908–923. [\[CrossRef\]](#)

46. Painuly, J.P. Barriers to renewable energy penetration; a framework for analysis. *Renew. Energy* **2001**, *24*, 73–89. [\[CrossRef\]](#)
47. Tian, J.; Zhou, S.; Wang, Y. Assessing the technical and economic potential of wind and solar energy in China—A provincial-scale analysis. *Environ. Impact Assess. Rev.* **2023**, *102*, 107161. [\[CrossRef\]](#)
48. Chen, Y.; Xu, J.; Wang, J.; Lund, P.D.; Wang, D. Configuration optimization and selection of a photovoltaic-gas integrated energy system considering renewable energy penetration in power grid. *Energy Convers. Manag.* **2022**, *254*, 115260. [\[CrossRef\]](#)
49. Babatunde, O.M.; Munda, J.L.; Hamam, Y. Selection of a Hybrid Renewable Energy Systems for a Low-Income Household. *Sustainability* **2019**, *11*, 4282. [\[CrossRef\]](#)
50. Grigoras, G.; Scarlatache, F. An assessment of the renewable energy potential using a clustering based data mining method. Case study in Romania. *Energy* **2015**, *81*, 416–429. [\[CrossRef\]](#)
51. Purohit, I.; Purohit, P.; Shekhar, S. Evaluating the potential of concentrating solar power generation in Northwestern India. *Energy Policy* **2013**, *62*, 157–175. [\[CrossRef\]](#)
52. Angelis-Dimakis, A.; Biberacher, M.; Dominguez, J.; Fiorese, G.; Gadocha, S.; Gnansounou, E.; Guariso, G.; Kartalidis, A.; Panichelli, L.; Pinedo, I.; et al. Methods and tools to evaluate the availability of renewable energy sources. *Renew. Sustain. Energy Rev.* **2011**, *15*, 1182–1200. [\[CrossRef\]](#)
53. Voivontas, D.; Assimacopoulos, D.; Mourelatos, A.; Corominas, J. Evaluation of renewable energy potential using a GIS decision support system. *Renew. Energy* **1998**, *13*, 333–344. [\[CrossRef\]](#)
54. Acker, T.L.; Williams, S.K.; Duque, E.P.; Brummels, G.; Buechler, J. Wind resource assessment in the state of Arizona: Inventory, capacity factor, and cost. *Renew. Energy* **2007**, *32*, 1453–1466. [\[CrossRef\]](#)
55. De Vries, B.J.; Van Vuuren, D.P.; Hoogwijk, M.M. Renewable energy sources: Their global potential for the first-half of the 21st century at a global level: An integrated approach. *Energy Policy* **2007**, *35*, 2590–2610. [\[CrossRef\]](#)
56. Buchatskiy, P.Y.; Teploukhov, S.V.; Onishchenko, S.V.; Kuzmin, K.K.; Bychkov, T.Y. Software Tools for Evaluating Renewable Energy Sources. *Russ. J. Earth Sci.* **2023**, *5*, 1–8. [\[CrossRef\]](#)
57. REexplorer. Technical Potential Tool. Available online: <https://www.re-explorer.org/technical-potential-tool> (accessed on 9 October 2024).
58. Alquraish, M. Modeling and Simulation of Manufacturing Processes and Systems: Overview of Tools, Challenges, and Future Opportunities. *Eng. Technol. Appl. Sci. Res.* **2022**, *12*, 9779–9786. [\[CrossRef\]](#)
59. Lin, S.; Yao, W.; Xiong, Y.; Zhao, Y.; Shi, Z.; Ai, X.; Wen, J. MatPSST: A Matlab/Simulink-based power system simulation toolbox for research and education. *IET Gener. Transm. Distrib.* **2023**, *17*, 2272–2288. [\[CrossRef\]](#)
60. Behabtu, H.A.; Coosemans, T.; Berecibar, M.; Fante, K.A.; Kebede, A.A.; Mierlo, J.V.; Messagie, M. Performance Evaluation of Grid-Connected Wind Turbine Generators. *Energies* **2021**, *14*, 6807. [\[CrossRef\]](#)
61. Ahyaten, S.; Bahaoui, J. El Modeling of Wind Turbines Based on DFIG Generator. *Proceedings* **2020**, *63*, 16.
62. AlKassem, A.; Al Ahmadi, M.; Draou, A. Modeling and Simulation Analysis of a Hybrid PV-Wind Renewable Energy Sources for a Micro-Grid Application. In Proceedings of the 2021 9th International Conference on Smart Grid (icSmartGrid), Setubal, Portugal, 29 June–1 July 2021; pp. 103–106. [\[CrossRef\]](#)
63. Usman, A.A.; Abdulkadir, R.A. Modelling and simulation of micro hydro power plant using matlab simulink. *Int. J. Adv. Technol. Eng. Sci.* **2015**, *3*, 260–272.
64. Buchatskiy, P.Y.; Onishchenko, S.V.; Teploukhov, S.V.; Kuzmin, K.A. Modeling of Geothermal Heating System for an Individual Heating Station. In Proceedings of the 2023 7th International Conference on Information, Control, and Communication Technologies (ICCT), Astrakhan, Russia, 2–6 October 2023; pp. 1–5.
65. SimInTech. Available online: <https://simintech.ru/> (accessed on 20 August 2025).
66. PVGIS. Photovoltaic Geographical Information System. Ispra. 2024. Available online: https://re.jrc.ec.europa.eu/pvg_tools/en/#api_5.1 (accessed on 20 August 2025).
67. Buchatskiy, P.Y.; Teploukhov, S.V.; Onishchenko, S.V. Software and Hardware Complex for Evaluating the Potential of Wind and Solar Energy. In Proceedings of the 2020 International Conference on Industrial Engineering, Applications and Manufacturing (ICIEAM), Sochi, Russia, 18–22 May 2020; pp. 1–5. [\[CrossRef\]](#)
68. Golovko, S.V.; Zadorkin, D.A. Analysis of influence of climatic factors on selecting types of solar panels. *Bull. Astrakhan State Tech. Univ.* **2020**, *2*, 21–26. [\[CrossRef\]](#)
69. Jumayev, A. The analysis of influence of temperature on operating conditions photo-electric solar station. *Tech. Sci.-Theory Pract.* **2015**, *5*, 33–40.
70. Yashel Technologies. Model YASHEL, S-mini 100 Wt. Kazan. 2024. Available online: <https://yashel.tech/yashel-seriya-topsun-poli/> (accessed on 20 August 2025).
71. Shakirov, V.A.; Yakovkina, T.N.; Kurbatsky, V.G. Methodology of estimation of power generation by solar power plants using data of long-term observations of meteorological stations. *Bull. Irkutsk. State Tech. Univ.* **2020**, *24*, 858–875. [\[CrossRef\]](#)
72. Bennagi, A.; AlHousrya, O.; Cotfas, D.T.; Cotfas, P.A. Comprehensive study of the artificial intelligence applied in renewable energy. *Energy Strategy Rev.* **2024**, *54*, 101446. [\[CrossRef\]](#)

73. Simankov, V.; Buchatskiy, P.; Teploukhov, S.; Onishchenko, S.; Kazak, A.; Chetyrbok, P. Review of Estimating and Predicting Models of the Wind Energy Amount. *Energies* **2023**, *16*, 5926. [\[CrossRef\]](#)
74. Simankov, V.; Buchatskiy, P.; Kazak, A.; Teploukhov, S.; Onishchenko, S.; Kuzmin, K.; Chetyrbok, P. A Solar and Wind Energy Evaluation Methodology Using Artificial Intelligence Technologies. *Energies* **2024**, *17*, 416. [\[CrossRef\]](#)
75. Jailani, N.L.M.; Dhanasegaran, J.K.; Alkaws, G.; Alkahtani, A.A.; Phing, C.C.; Baashar, Y.; Capretz, L.F.; Al-Shetwi, A.Q.; Tiong, S.K. Investigating the Power of LSTM-Based Models in Solar Energy Forecasting. *Processes* **2023**, *11*, 1382. [\[CrossRef\]](#)
76. Suresh, V.; Janik, P.; Rezmer, J.; Leonowicz, Z. Forecasting Solar PV Output Using Convolutional Neural Networks with a Sliding Window Algorithm. *Energies* **2020**, *13*, 723. [\[CrossRef\]](#)
77. Fungtammasan, G.; Koprinska, I. Convolutional and LSTM Neural Networks for Solar Power Forecasting. In Proceedings of the 2023 International Joint Conference on Neural Networks (IJCNN), Gold Coast, Australia, 18–23 June 2023; pp. 1–7. [\[CrossRef\]](#)
78. Suanpang, P.; Jamjuntr, P. Machine Learning Models for Solar Power Generation Forecasting in Microgrid Application Implications for Smart Cities. *Sustainability* **2024**, *16*, 6087. [\[CrossRef\]](#)
79. Fentis, A.; Bahatti, L.; Mestari, M.; Chouri, B. Short-term solar power forecasting using Support Vector Regression and feed-forward NN. In Proceedings of the 2017 15th IEEE International New Circuits and Systems Conference (NEWCAS), Strasbourg, France, 25–28 June 2017; pp. 405–408. [\[CrossRef\]](#)
80. Al-Ali, E.M.; Hajji, Y.; Said, Y.; Hleili, M.; Alanzi, A.M.; Laatar, A.H.; Atri, M. Solar Energy Production Forecasting Based on a Hybrid CNN-LSTM-Transformer Model. *Mathematics* **2023**, *11*, 676. [\[CrossRef\]](#)
81. Lim, S.-C.; Huh, J.-H.; Hong, S.-H.; Park, C.-Y.; Kim, J.-C. Solar Power Forecasting Using CNN-LSTM Hybrid Model. *Energies* **2022**, *15*, 8233. [\[CrossRef\]](#)
82. Baelongandi, A.T.; Kambale, W.V.; Nzung, A.M.; Bampende, M.N.; Kadurha, D.K.; Kyamakya, K. Towards a Physics Informed Neural Network Approach for Modeling and Prediction of Renewable Energy Production: Use Case of Solar Cells. In Proceedings of the 2024 IEEE PES/IAS PowerAfrica, Johannesburg, South Africa, 7–11 October 2024; pp. 1–5. [\[CrossRef\]](#)
83. Wang, K.; Wang, L.; Meng, Q.; Yang, C.; Lin, Y.; Zhu, J.; Zhao, Z.; Zhou, C.; Zheng, C.; Gao, X. Accurate photovoltaic power prediction via temperature correction with physics-informed neural networks. *Energy* **2025**, *328*, 136546. [\[CrossRef\]](#)
84. Das, U.K.; Tey, K.S.; Seyedmahmoudian, M.; Mekhilef, S.; Idris, M.Y.I.; Van Deventer, W.; Horan, B.; Stojcevski, A. Forecasting of photovoltaic power generation and model optimization: A review. *Renew. Sustain. Energy Rev.* **2018**, *81*, 912–928. [\[CrossRef\]](#)
85. Konstantinou, M.; Peratikou, S.; Charalambides, A. Solar photovoltaic forecasting of power output using LSTM networks. *Atmosphere* **2021**, *12*, 124. [\[CrossRef\]](#)
86. Rajagukguk, R.A.; Ramadhan, R.A.; Lee, H.-J. A review on deep learning models for forecasting time series data of solar irradiance and photovoltaic power. *Energies* **2020**, *13*, 6623. [\[CrossRef\]](#)
87. NSRDB: National Solar Radiation Database. Available online: <https://nsrdb.nrel.gov/> (accessed on 20 August 2025).
88. Shejul, K.; Harikrishnan, R.; Gupta, H. The improved integrated Exponential Smoothing based CNN-LSTM algorithm to forecast the day ahead electricity price. *MethodsX* **2024**, *13*, 102923. [\[CrossRef\]](#) [\[PubMed\]](#)
89. Dudek, G.; Pełka, P.; Smył, S. A hybrid residual dilated LSTM and exponential smoothing model for midterm electric load forecasting. *IEEE Trans. Neural Netw. Learn. Syst.* **2021**, *33*, 2879–2891. [\[CrossRef\]](#) [\[PubMed\]](#)
90. Hayder, I.M.; Al-Amiedy, T.A.; Ghaban, W.; Saeed, F.; Nasser, M.; Al-Ali, G.A.; Younis, H.A. An Intelligent Early Flood Forecasting and Prediction Leveraging Machine and Deep Learning Algorithms with Advanced Alert System. *Processes* **2023**, *11*, 481. [\[CrossRef\]](#)
91. Liu, X.; Mou, X.; Zhang, Y.; Chen, H.; Wang, X.; Sun, X.; Wang, C.; Shong, R.; Li, Y. EDHD-FG-XGBoost: Entropy-driven high-dimensional feature gain XGBoost model for short-term wind power prediction and application. *AIP Adv.* **2025**, *15*, 065022. [\[CrossRef\]](#)
92. Jeong, S.H.; Lee, W.K.; Kil, H.; Jang, S.; Kim, J.H.; Kwak, Y.S. Deep learning-based regional ionospheric total electron content prediction—Long short-term memory (LSTM) and convolutional LSTM approach. *Space Weather.* **2024**, *22*, e2023SW003763. [\[CrossRef\]](#)
93. Bouktif, S.; Fiaz, A.; Ouni, A.; Serhani, M.A. Optimal Deep Learning LSTM Model for Electric Load Forecasting using Feature Selection and Genetic Algorithm: Comparison with Machine Learning Approaches. *Energies* **2018**, *11*, 1636. [\[CrossRef\]](#)
94. Elharrouss, O.; Mahmood, Y.; Bechqito, Y.; Serhani, M.A.; Badidi, E.; Riffi, J.; Tairi, H. Loss Functions in Deep Learning: A Comprehensive Review. *arXiv* **2025**, arXiv:2504.04242. [\[CrossRef\]](#)

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