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Review of Models for Estimating and Predicting the Amount of Energy Produced by Solar Energy Systems

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Abstract: Energy production based on renewable sources is a fundamental aspect of society's sustainable development. The involvement of renewable energy sources in the implementation of modern energy systems can significantly reduce the amount of harmful emissions into the atmosphere and provide greater flexibility of energy infrastructure. The first step in determining the feasibility of involving a particular energy source in the overall energy system of the region is a preliminary assessment of the energy potential to determine the possible percentage of substitution of traditional energy. To solve this problem, it is necessary to use the models of energy supply, which are currently presented in a wide variety. In this regard, this paper proposes to consider various models for estimating the solar energy potential, which can be divided into empirical models and models based on the application of modern intelligent data analysis technologies. Such models are based on many different climatic and geographical indicators, such as: longitude of sunshine, ambient temperature, serial number of the day of the current year, amount of precipitation, average and maximum values of wind speed and so on. The paper analyzed the existing models for estimating the amount of energy, which can be used in the system designed to determine the most optimal configuration of the energy system based on the use of various conversion technologies most relevant to the case under study, and also serve as the basis for creating digital twins designed to model and optimize the operation of the projected energy complex.

Keywords: potential assessment models, smart models, renewable energy, solar energy.

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1. Introduction

Currently, the energy sector has a great impact on the state economy, national security, which is critical for successful socio-economic development. The development of the energy complex plays a fundamental role in the world economic system and played a key role in the previous three technological revolutions. In accordance with the objectives of the policy of general decarbonization [*Iktisanov and Shkrudnev*, 2021], energy transformation is taking place, resulting in a significant increase in the share of clean energy capacity in the world, such as photovoltaic and wind energy [*IRENA, IEA and REN21*, 2018; *Liu et al.*, 2021].

Against the backdrop of the Covid-19 pandemic that has occurred, renewable energy worldwide has acquired record power generation capacity in 2020–2021 and is the only source with a net increase in total power generation capacity [*REN21*, 2020; *REN21*, 2021]. It is widely known that renewable energy sources have various advantages over carbon resources, such as: lower energy costs compared with traditional energy sources, no harmful emissions, contributing to the improvement of the overall world pollution and stimulating economic growth [*EPA*, 2018].

The situation is somewhat different in the Russian Federation. At present the percentage of energy production on the basis of alternative sources is about 0.69–0.75% [*Russia Renewable Energy Development Association (RREDA)*, 2022], which does not compare with European countries, where energy production on the basis of "green" energy reaches values of 25–30% (and up to 60% in some cases, for example, in Denmark) [*IEA*, 2023] of total energy production.

Despite such a small percentage of power generation on the basis of alternative sources, there is a constant growth of RES energy generation and commissioning of new power plants. Contributes to this overall concept of energy transformation and the adopted energy strategy for the period up to 2030 [*Energy strategy of the Russian Federation for the period until 2035*, 2020], which involves the process of optimizing the entire structure of the fuel and energy balance of the state, including by increasing the share of non-fuel energy to 13–14% of total energy production.

The implementation of such a strategy of energy transformation requires a comprehensive approach, consisting of many stages, the initial of which is the stage of assessing the involvement of a particular type of resource [*Simankov*, 2002] or a set of several resources to determine the economic efficiency of such an implementation [*Simankov and Buchatskiy*, 2021].

In this regard, the paper proposes an analysis of existing approaches to modeling and estimating the amount of solar energy, which is one of the most common renewable energy sources.

2. Materials and Methods

In general, models for estimating solar energy can be divided into the following groups [*Vaskov and Narynbaev*, 2020]:

1. mathematical models (linear and nonlinear empirical models);
2. models based on artificial intelligence methods and data mining.

Let us first consider the existing mathematical models for estimating and modeling the amount of solar energy inflow. These models are usually based on the following group of parameters [*Besharat et al.*, 2013]:

1. geographic, such as latitude and longitude, altitude above sea level, and albedo of the terrain;
2. geometric, taking into account the position of the converting elements in space;
3. physical parameters, allowing to take into account such factors as dusting and dispersion of air molecules;
4. meteorological parameters such as temperature, precipitation, humidity, cloudiness, etc.

2.1. Mathematical models to estimate the theoretical solar energy potential

According to the study [*Demain et al.*, 2013], all models can be divided into two groups:

1. isotropic models, which are rather simple models assuming uniform distribution of scattered radiation over the sky dome;
2. anisotropic models, which allow taking into account the scattering coefficients of solar radiation.

Thus, the incoming global solar radiation on the inclined surface, G_β, can be divided into three components:

1. the direct component of irradiation of the inclined surface – B_β;
2. scattered component – D_β;
3. the reflected component, which quantifies the radiation reflected from the ground to the inclined surface R_β:

$$G_\beta = B_\beta + D_\beta + R_\beta \tag{1}$$

Further studies showed that the diffuse component (scattered) consists of the following three components: $D_{\beta,\,\mathrm{iso}}$ – isotropic diffuse component; $D_{\beta,\,\mathrm{cs}}$ – circumsolar diffuse component; $D_{\beta,\,\mathrm{hb}}$ – horizon brightening component, so that the total solar radiation arriving at the surface is expressed as:

$$G_\beta = B_\beta + (D_{\beta,\,\mathrm{iso}} + D_{\beta,\,\mathrm{cs}} + D_{\beta,\,\mathrm{hb}}) + R_\beta \tag{2}$$

The calculation of the direct component B_β is purely geometric and is performed using certain expressions, so many models focus on the calculation of the diffuse component D_β, and in particular on the diffuse transfer coefficient R_d, which is the ratio of diffuse radiation on an inclined surface to radiation on a horizontal surface.

An isotropic model, called the Lew-Jordan model, was one of the first to be proposed [*Liu and Jordan*, 1962]:

$$R_d = \frac{1+\cos\beta}{2} \tag{3}$$

Later, various improvements to this model presented in [*Badescu*, 2002; *Hamilton and Jackson*, 1985; *Koronakis*, 1986] were considered, resulting in the following expression:

$$R_d = \frac{1}{4}(3+\cos(2\beta)\,) \tag{4}$$

There are a number of papers investigating and proposing anisotropic models to account for each component of diffuse radiation [*Bugler*, 1977; *Klucher*, 1979; *Ma and Iqbal*, 1983; *Muneer and Kambezidis*, 1997; *Perez et al.*, 1987; *Willmott*, 1982], but the authors of the study [*Demain et al.*, 2013] evaluated and examined these models, resulting in the selection of three most appropriate models.

The first of the selected models [*Bugler*, 1977] gives the best results for clear skies with the fewest clouds, according to which the diffuse transfer coefficient can be calculated as:

$$R_d = \frac{1}{2}(1+\cos\beta) + 0.05\frac{B_\beta}{D}\left(\cos\theta_i - \frac{1}{\cos\theta_z}\left(\frac{1+\cos\beta}{2}\right)\right) \tag{5}$$

Here we added the consideration of the angular height of the sun above the horizon, which increased the accuracy of the calculations. The author suggested using the anisotropic reduction factor, which made it possible to take into account the presence of partial shading.

The second of the models [*Willmott*, 1982] chosen by the authors shows the best results in partially shaded skies, with variable cloud cover (but not constant):

$$R_d = \frac{B_{Nb}}{S_o} + C_\beta\left(1 - \frac{B_N}{S_o}\right), \tag{6}$$

where $C_\beta = 1.011 - 0.20293\beta - 0.080823\beta^2$, β is expressed in radians. So is the solar constant (i.e., 1367 $\mathrm{Wm^{-2}}$).

The latter model [*Perez et al.*, 1987] is the most suitable for use in cloudy weather conditions. The author in his model proposed the input of specialized coefficients, which were obtained empirically:

$$R_d = F_1\frac{a}{b} + (1-F_1)\frac{1+\cos\beta}{2} + F_2\sin\beta, \tag{7}$$

where F_1 and F_2 are the sky brightness ratios for the near-solar region and the region above the horizon line, respectively.

There are a number of clear-sky models based on the atmospheric turbidity coefficient, which were discussed in [*Moldovan et al.*, 2020]. The use of such models makes it possible to estimate the amount of incoming solar radiation in the absence of cloudiness, but in the presence of some turbidity due to the presence of water vapor in the atmosphere or other aerosol compounds [*Rigollier et al.*, 2002].

To determine the amount of solar radiation arriving at the Earth's surface [*Bird and Hulstrom*, 1981], we can consider the model presented by the authors in [*Achituev and Enebish*, 2015]. The total solar radiation for the plane outside the Earth's atmosphere can be determined as follows:

$$H_0' = \left(\frac{t_s G_0}{\pi}\right)\left[\cos\varphi\cos\delta\sin\omega_s + \frac{2\pi\omega_s}{360}\sin\varphi\sin\delta\right], \tag{8}$$

where G_0 – solar constant, equal to $1340\,\mathrm{W/m^2}$, φ – geographical latitude of area, $\delta = \frac{23.45}{180}\pi\sin\left[\frac{284+n}{365}2\pi\right]$ – declination, n – number of day in year, $t_s = 480\arccos(-\tan\varphi\tan\delta$ – day duration, $\omega_s = \arccos(-\tan\varphi\tan\delta)$ – hour angle at sunset.

When taking into account the ellipticity of the orbit, the expression for calculating the real value of the extra-atmospheric daily solar radiation is converted into the following relation:

$$H_0\left[1 + ecos\left(\frac{360n}{365}\right)\right]H_0', \tag{9}$$

where $e = 0.333$ is the eccentricity of the orbit, n is the number of days in the year.

To determine the amount of radiation dissipated in the atmosphere, the clarity index K_T, equal to the ratio of the total daily radiation arriving at the Earth's surface to the total daily solar radiation arriving at the site outside the atmosphere, is used.

Using this index, the fraction of diffuse solar radiation can be calculated:

$$\frac{H_D}{H} = 1.39 - 4.03K_T + 5.53K_T^2 - 3.11K_T^3. \tag{10}$$

Thus, the total solar radiation arriving at the surface at angle β can be defined as:

$$H_\beta = H\left[\left(1 - \frac{H_D}{H}\right)R + \frac{H_D}{H}\frac{1-\cos\beta}{2} + \rho\frac{1-\cos\beta}{2}\right], \tag{11}$$

where ρ is the albedo of the terrain;

$$R = \frac{\cos(\varphi-\beta)\cos\delta sin\omega_s + \frac{\pi}{180}\omega_s\sin(\varphi-\beta)\sin\delta}{\cos\varphi\cos\delta\; sin\omega_s + \frac{\pi}{180}\omega_s\sin\varphi\;\sin\delta} \tag{12}$$

For this model, the necessary input data are the following parameters: geographic latitude of the area, data on total and reflected solar radiation, and the angle of inclination of the panel surface. The result is the value of solar radiation coming to the surface. This model has high accuracy (calculation error does not exceed 4%).

The authors in [*Simankov et al.*, 2000] considered different models to estimate the amount of solar insolation, allowing simulation in clear sky and cloudy conditions. In addition, two models for estimating cloud formation were considered:

- A model of the evolution of layered cloud cover;
- A statistical model of cloud cover.

In [*Simankov and Buchatskiy*, 2019], the authors presented a set of basic mathematical models for assessing renewable energy sources, among which there are models for estimating the energy potential of solar energy (a cloudless sky model and a cloudless sky model) and a model that allows forecasting the performance of a photovoltaic plant (Table 1).

The following study [*An et al.*, 2020] presents another model to estimate the total solar radiation arriving at the horizontal surface during the day. The proposed method is based on the use of a new algorithm for estimating illuminance with a 10-minute time step. The proposed algorithm used for illuminance estimation assumes that the solar radiation varies linearly over a 1-hour period, and the slope is estimated based on the values of

Table 1. Complex of mathematical models for RES evaluation.

Model name		Model type
Model of solar radiation input	model with a cloudless sky	$Q_{\text{day}}^{\text{possibility}} = \text{SA}\int_{t_{\text{sun}}^{\text{sunrise}}}^{t_{\text{sun}}^{\text{sunset}}}\left[\left(-B\cdot\omega - C\cdot r - D\frac{1}{\sin(\text{Al}(t))+}\right)\cdot\sin(\text{Al}(t))\right]dt$
	cloud cover model	$Q^{\text{day}} = Q_{\text{relative}}\cdot Q_{\text{possibility}}^{\text{day}},$ $f(Q_{\text{relative}}) = \frac{1}{B(a,b)}Q_{\text{relative}}^{(\text{a-1})}\cdot(1-Q_{\text{relative}})^{(b-1)},$ $B(a,b)=\int_0^1\left[Q_{\text{relative}}^{(}a-b)\cdot(1-Q_{\text{relative}})^{(b-1)}\right]d(Q_{\text{relative}})$
Wind flow energy inflow		$E=\frac{1}{2}q\bar{v}_w^3,$ $p(v_w)=\frac{k_1}{A_1}\left(\frac{v_\beta}{A_1}\right)^{k_1-1}\exp\left[-\left(\frac{v_w}{A_1}\right)^{k_1}\right]$
Model of a photovoltaic system		$I_H = I_\varnothing - I_0\left(\exp\frac{qU_H}{\text{AKT}-1}\right)$
Model wind turbine		$P_w=\frac{p_w^{\max}}{\varphi_{\text{nominal}}-\varphi_{\text{on}}}\left\{G_k(\varphi_{\text{nominal}})-G_k(\varphi_{\text{on}})-\exp\left(-\left(\frac{v_\beta}{A_1}\right)^{K_1}\right)\right\}$
Model energy storage (chemical current sources)		$U_{RB}=E(Q;I_{\text{EXT}})-1\cdot R_{\text{EXT}}(Q;I_{RB}),$ $E(Q;I_{RB})=E_0+\frac{\Psi_0}{Q_\Psi}(Q_\Psi-I_{RB}\cdot t)+\varphi_0\exp\left(-\frac{3I_{RB}\cdot t}{Q_\varphi}\right),$ $R_{\text{EXT}}(Q;I_{RB})=A_2\cdot\left(\frac{Q_\Psi-IAB\cdot t}{Q_\Psi}\right)^2+B_2\left(\frac{\alpha}{I_{RB}^\beta}-1\right)$

solar insolation during the last hour, the current hour, and the next hour. The approach proposed by the authors, consists of the following steps:

1. Calculation of the time of sunrise, solar noon and sunset;
2. Calculation of instantaneous solar irradiance in the middle of each hour using the following formula:

$$SG_{\text{mid},i} = \text{SI}_i/(t_{\text{end},i} - t_{\text{start},i}). \tag{13}$$

   where i is the current hour, t_{end} and t_{start} are the start and end times of each hour, G_{mid} is the instantaneous solar radiation at the midpoint in W/m^2, SI is the hourly solar insolation in Wh/m^2.
3. For normal hours between sunrise and sunset, the slope of the solar radiation arrival over a period of one hour is calculated based on the following expression:

$$\text{SLOPE}_i = \begin{cases} \min\left(\dfrac{SG_{\text{mid},i}-SG_{\text{mid},i-1}}{t_{\text{mid},i}-t_{\text{mid},i-1}}, \dfrac{SG_{\text{mid},i+1}-SG_{\text{mid},i}}{t_{\text{mid},i+1}-t_{\text{mid},i}}\right) SG_{\text{mid},i-1} \le SG_{\text{mid},i} \le SG_{\text{mid},i+1} \\ \max\left(\dfrac{SG_{\text{mid},i}-SG_{\text{mid},i-1}}{t_{\text{mid},i}-t_{\text{mid},i-1}}, \dfrac{SG_{\text{mid},i+1}-SG_{\text{mid},i}}{t_{\text{mid},i}+1-t_{\text{mid},i}}\right) SG_{\text{mid},i-1} > SG_{\text{mid},i} > SG_{\text{mid},i+1} \\ -1\times\min\left(\left|\dfrac{SG_{\text{mid},i}-SG_{\text{mid},i-1}}{t_{\text{mid},i}-t_{\text{mid},i-1}}\right|, \left|\dfrac{SG_{\text{mid},i+1}-SG_{\text{mid},i}}{t_{\text{mid},i+1}-t_{\text{mid},i}}\right|, \left|\dfrac{2SG_{\text{mid},i}}{t_{end,i}-t_{\text{start},i}}\right|\right) \text{else, when } t_{\text{mid},i} \le t_{\text{solarnoon}} \\ \min\left(\left|\dfrac{SG_{\text{mid},i}-SG_{\text{mid},i-1}}{t_{\text{mid},i}-t_{\text{mid},i-1}}\right|, \left|\dfrac{SG_{\text{mid},i+1}-SG_{\text{mid},i}}{t_{\text{mid},i+1}-t_{\text{mid},i}}\right|, \left|\dfrac{2SG_{\text{mid},i}}{t_{end,i}-t_{start,i}}\right|\right) \text{else, when } t_{\text{mid},i} > t_{\text{solarnoon}} \end{cases}$$

   where $i-1, i, i+1$ are the preceding current and next hours, respectively; $t_{\text{mid},i}$ is the middle of each hour; $t_{\text{solarnoon}}$ is the time of solar noon; SLOPE_i is the slope of incoming solar radiation during the hour.
4. In addition, we calculate the solar insolation for the first and last hours of radiation.

Thus, the method proposed by the authors allows us to obtain more accurate values of the incoming solar radiation, compared with the approaches described in [*Zhu et al.*, 2012], since greater accuracy is achieved by using different time intervals and values in the middle of the current hour.

There are a number of mathematical models such as the Justus method [*Justus et al.*, 1978], Leesen method [*Lysen*, 1982], maximum likelihood method [*Stevens and Smulders*, 1979], energy density method [*George*, 2014], Rayleigh distribution [*Tonsie Djiela et al.*, 2020], Mabchur empirical method [*Zohbi et al.*, 2014], energy pattern method [*Akdağ and Dinler*, 2009], energy distribution factor method [*Akdağ and Güler*, 2015] used to determine solar radiation potential based on the Weibull probability distribution, reviewed and analyzed in [*Koholé et al.*, 2023]. According to the conclusion of the authors, based on a statistical study of each of these methods, it was found that each of the considered approaches provides acceptable accuracy results for predicting the amount of solar radiation. The authors used the following approach, depicted in Figure 1, to test the adequacy of each of the models under study.

There are a number of models to estimate the solar radiation based on various astronomical parameters, which are considered below, before proceeding to consider these models [*Mghouchi et al.*, 2016]:

Distance to the Sun, which can vary since the orbit is elliptical:

$$C_t = 1 + 0.034\cos(j-2), \tag{14}$$

where j is the number of the day of the year.

Solar deviation [*Cooper*, 1969]:

$$\delta = 23.45\sin(0.986(j+284)). \tag{15}$$

Clock Angle:

$$\omega = 15(12 - T_{sv}), \tag{16}$$

where T_{sv} is the True Solar Time at a certain point, which can be calculated as:

$$T_{sv} = T_l - DT_l + (D_{\mathrm{hg}} + E/60)/60, \tag{17}$$

where T_l is local time, DT_l is the difference between local and standard time, D_{hg} is the time difference (4 minutes ahead by one degree), E is the time equation:

$$E = 450.8\sin(2\pi j/365 - 0.026903) + 595.4\sin(4\pi j/365 + 0.352835). \tag{18}$$

The height of the Sun:

$$h = \sin^{-1}(\sin(\varphi)\sin(\delta) + \cos(\varphi)\cos(\delta)\cos(\omega)), \tag{19}$$

where φ is the geographic latitude.

Azimuth of the Sun:

$$\psi = sin^{-1}(\cos(\delta)\sin(\omega)/\cos(h). \tag{20}$$

Duration of the day:

$$S_j = 24(1 - \cos^{-1}(\tan(\delta)\tan(\lambda))/\pi, \tag{21}$$

where λ is the geographical longitude.

Duration of the Sun's aurora:

$$S_e = \frac{2}{15}cos^{-1}\,(-\tan(\varphi)\tan(\delta)). \tag{22}$$

Using these characteristics, we can calculate the parameters forming the global solar radiation G, consisting of the direct I and diffuse D.

Thus, using Guard's model [*Saïghi*, 2002], we can calculate all these parameters:

$$I = I_0 C_t A_1\left(-\frac{A_2}{\sin(h)}\right)\sin(h). \tag{23}$$

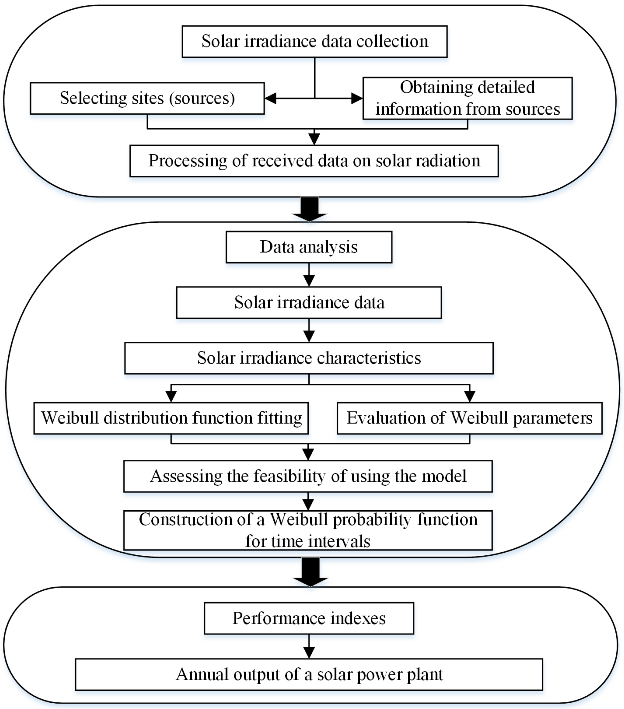

Figure 1. Research methodology for models to estimate solar irradiance based on the Weibull distribution [*Koholé et al.*, 2023].

$$D = I_0 C_t \left[0.271 - 0.2939 A_1 \exp\left(-\frac{A_2}{\sin(h)} \right) \right] \sin(h). \tag{24}$$

$$G = 0.271 I_0 C_t A_1 \sin(h) + 0.706 I_0 C_t A_1 \sin(h) \exp\left(-\frac{A_2}{\sin(h)} \right), \tag{25}$$

where I_0 is the solar constant equal to 1367 W/m^2, A_1 and A_2 are the atmospheric turbidity coefficients presented below (Table 2).

Table 2. Turbidity coefficients depending on climatic conditions.

Climatic conditions	Sky very clean	Normal conditions	Sky very polluted
A_1	0.87	0.88	0.91
A_2	0.17	0.26	0.43

Another model that is based on the same data is described in [*Perrin de Brichambaut*, 1975]:

$$D = 125C(\sin(h)\,)^{0.4}. \tag{26}$$

$$I = Rexp\left(\frac{-A}{B\sin(h+1)} \right) \tag{27}$$

$$G = I + D, \tag{28}$$

where R is off-ground radiation, A, B, and C are the dimensionless coefficients shown below (Table 3).

Using similar data, Capderou models [*Capderou*, 1985] and the Byrd and Halmstron model [*Bird and Hulstrom*, 1981] are also constructed.

Table 3. Values of R, A, B and C.

Atmospheric conditions	R	A	B	C
Clear skies	1210	1.67	3.9	0.67
Normal conditions	1230	1.61	3.1	0.47
Industrial zones	1260	2.23	4	0.45

Since each of the models must be tested for accuracy, there are different approaches to estimation [*Li et al.*, 2011; *Mghouchi et al.*, 2016]. Let us consider the approach presented in [*Li et al.*, 2011].

Model performance is evaluated using the following statistical error tests: mean absolute percentage error (MAPE), mean bias error (MBE), root mean square error (RMSE), correlation coefficient (r) and the Nash-Sutcliffe equation (NSE). These indices can be calculated as follows:

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{H_{\mathrm{dci}} - H_{\mathrm{dmi}}}{H_{\mathrm{dmi}}}\right| \times 100. \tag{29}$$

$$\mathrm{MBE} = \frac{1}{n}\sum_{i=1}^{n}(H_{\mathrm{dci}} - H_{\mathrm{dmi}}). \tag{30}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(H_{\mathrm{dci}} - H_{\mathrm{dmi}})^2}. \tag{31}$$

$$r = \frac{\sum_{i=1}^{n}(H_{\mathrm{dci}} - H_{\mathrm{dca}})(H_{\mathrm{dmi}} - H_{\mathrm{dma}})}{\sqrt{\left[\sum_{i=1}^{n}(H_{dci} - H_{dca})^2\right]\left[\sum_{i=1}^{n}(H_{\mathrm{dmi}} - H_{\mathrm{dma}})^2\right]}}. \tag{32}$$

$$\mathrm{NSE} = 1 - \frac{\sum_{i=1}^{n}(H_{\mathrm{dmi}} - H_{\mathrm{dci}})^2}{\sum_{i=1}^{n}(H_{\mathrm{dmi}} - H_{\mathrm{dma}})^2}. \tag{33}$$

where $H_{\mathrm{dci}}, H_{\mathrm{dmi}}$ are the i-th calculated and measured values respectively, $H_{\mathrm{dca}}, H_{\mathrm{dma}}$ are the mean values of the calculated and measured values respectively, n is the number of observations.

2.2. Models for estimating photovoltaic capacity

In addition to estimating solar power potential, there are a number of mathematical models. Designed to estimate the amount of energy produced by solar panels.

In [*Zhao et al.*, 2013], a model of photovoltaic power output is proposed. The output power of photovoltaic installations is mainly influenced by the intensity of solar illumination and the ambient temperature, which is reflected in the following expression:

$$P_{pv} = P_{\mathrm{STC}}\frac{G_c}{G_{\mathrm{STC}}}[1 + k(T_c - T_{\mathrm{STC}})] \tag{34}$$

where $P_pv$is the power output at the photocell surface temperature T_c and light intensity G_c , and k is the temperature power factor. G_{STC} is 1 kW/m^2 and T_{STC} is 25 °C. The P_{STC} is the nominal power output of the PV cells under standard test conditions, which can usually be specified by the manufacturer.

The surface temperature T_c of the PV cells is related to ambient temperature, light intensity, and wind speed and can be expressed as:

$$T_c = T_a + \alpha G_c. \tag{35}$$

Thus, the considered model allows us to determine the power output, taking into account not only meteorological factors, but also the inherent properties of the energy converter.

Another achievement of this work is the proposed optimization model, which includes the cost of battery life loss, operation and maintenance cost, fuel cost and environmental cost to obtain a set of optimal operating strategy parameters. By considering the lifetime characteristics of lead-acid batteries, a multi-objective optimization was achieved to minimize the power generation costs and maximize the lifetime of lead-acid batteries using the genetic algorithm of non-dominant sorting (NSGA-II).

The following work [*Achituev and Enebish*, 2015], proposes an approach to estimate solar radiation potential based on the following indices:

1. Environmental condition indices, which include ambient temperature, converter module temperature, average wind speed, humidity, and albedo;
2. Solar resource indices, which consist of indices such as: horizontal irradiance to the module surface, duration of sunshine, and refraction magnitude;
3. Performance indices of the photovoltaic module, which were derived from its characteristics:

$$Y_r = H_A/G_S \tag{36}$$

$$Y_A = E_{A,d}/P_{\max} \tag{37}$$

$$\mathrm{PR} = Y_A/Y_r \tag{38}$$

As a result of this integrated approach, it was possible to obtain accurate simulation results, which were verified using the experimental data obtained from the installations. This approach makes it possible to determine the most appropriate configuration of solar converter plants, based on the geographical features of the intended region of operation.

The study [*Guerra*, 2020] proposed a methodology for estimating the amount of energy produced by small photovoltaic plants based on the specific conditions of the proposed plant location region. Principal component analysis, correlation analysis and response surface method are used as basic methods, as a result of which it is possible to determine the most significant of climatic parameters in the region under study and build a characteristic equation using only them, thus reducing its complexity. The main disadvantage of such an approach is the complicated planning of the experiments and determination of the type of the supposed response surface, with complication of which the number of necessary points of experiments inevitably increases.

A number of works [*Narasimman et al.*, 2023; *Polasek and Čadík*, 2023; *Souhaila and Mohamed*, 2021] are devoted to modeling the operation of photovoltaic panels using modern intelligent technologies, due to which it is possible to build an accurate model for predicting the behavior of the energy system without using full-scale modeling and conducting a lot of physical experiments.

2.3. Models based on data mining techniques

There is a large number of very different models of solar radiation estimation based on machine learning using such approaches as: artificial neural network methods, fuzzy logic, radial basis functions, exponential smoothing, state space model, support vector method, Bayesian neural networks, recurrent neural networks [*Teke et al.*, 2015].

Let us consider some of the existing models presented in Table 4.

The block diagram of modeling methods based on data analysis is presented in Figure 2 [*Teke et al.*, 2015].

The use of the considered models is a necessary step in the implementation of the forecasting and planning system, because without organizing a preliminary calculation of the efficiency of the energy system functioning with the involvement of renewable energy sources it is impossible to start the process of implementation of the proposed system.

All considered models can be divided into the following categories [Tyunkov et al., 2019]:

- physical models based on data on weather conditions, solar radiation obtained by numerical weather prediction;
- statistical models based on the analysis of time series of different retrospective observations obtained during observations over a certain time interval;
- adaptive models based on artificial intelligence technologies to determine the existing relationship between meteorological characteristics and solar insolation
- hybrid models based on a combination of several types of models.

It is noted that hybrid models, which combine classical static and physical models when used together with intelligent forecasting models [Wu et al., 2014], have the highest accuracy, reaching small error values of the order of 5.21%.

Table 4. Linear and nonlinear methods used for modeling and forecasting solar radiation (time series analysis, artificial intelligence methods).

Proposed model	Used data	Estimated indicator	Reference
Seven different models based on the Angstrom-Prescott model	Monthly average daily extraterrestrial radiation, day length, relative humidity, maximum duration of sunshine, maximum air temperature, duration of sunshine, average daily sea level pressure, average daily vapor pressure	Mean monthly global horizontal radiation	[Robaa, 2009]
The Angstrom and Heliosat model	Database of global solar irradiance and duration of solar irradiance at ground level	Global solar radiation	[Rusen et al., 2013]
A model based on a trigonometric function that has only one independent parameter.	Number of day in the year	Daily global solar radiation	[Bulut and Büyükalaca, 2007]
Linear Regression Model	Data are presented as day-averaged maximum and minimum air temperatures and day-averaged solar radiation.	Solar radiation	[Ibrahim et al., 2012]
ANN and Regression Analysis	Average temperature, relative humidity	Global solar radiation on the horizontal surface	[Agbo et al., 2012]
ARIMA (autoregressive integrated moving average) and SARIMA time series prediction model	Data on solar radiation	Daily and monthly solar radiation	[Alsharif et al., 2019]
ARMA autoregressive moving average) and ARIMA autoregressive integrated moving average)	Solar radiation data	Daily global solar radiation	[Belmahdi et al., 2020]
AR (autoregressive moving average) and NAR (nonlinear autoregressive)	Solar radiation data	Daily global solar radiation	[Takilalte et al., 2019]

Continued on next page

Table 4. Linear and nonlinear methods used for modeling and forecasting solar radiation (time series analysis, artificial intelligence methods). (Continued)

Proposed model	Used data	Estimated indicator	Reference
Naive Bayes	Dew-point, temperature, sky coverage, and relative humidity	Global solar radiation for two days ahead	[*Kwon et al.*, 2019]
ANN and RNS	Wind speed, dew-point temperature, dry bulb temperature, relative humidity, and wind direction	Daily global solar radiation	[*Pang et al.*, 2020]
SVM and C-SVM	Minimum, maximum and average temperature	Daily global solar radiation	[*Guermoui et al.*, 2020]
CNN	Satellite images with data on temperature, humidity, wind speed, pressure, cloud vectors	Global solar radiation	[*Yuzer and Bozkurt*, 2023]
Combined empirical modeling and machine learning method for estimating daily global solar radiation	daily maximum dry bulb temperature daily minimum dry bulb temperature daily mean dry bulb temperature, daytime solar duration, daily mean wind speed, daily mean relative humidity and daily air pressure	Modeling estimates of solar radiation for a specific location where no solar radiation measurement equipment can be installed	[*Zang et al.*, 2022]
A model that combines two machine learning models (XGB and MARS) with a covariance matrix adaptation strategy evolution (CMAES) algorithm	wind speed maximum and minimum humidity,	Prediction of daily solar radiation	[*Goliatt and Yaseen*, 2023]
K-means clustering	maximum and minimum temperatures, vapor pressure deficit, and evaporation	Maximum solar irradiance on a sloping surface	[*Yin et al.*, 2023]
Artificial Neural Networks	hourly solar radiation data	Estimation of solar radiation on sloping surfaces	[*Cheng et al.*, 2019]

3. Results

In this work, we considered a number of existing models for estimating the solar radiation potential, necessary for constructing predictions of the theoretical values of the solar flux power arriving at the surface. Various types of models were identified, from the simplest ones, which allow calculating solar radiation under conditions of an absent region, to more complex ones, which allow taking into account such factors as atmospheric turbidity. The use of these models is a prerequisite for the implementation of a forecasting subsystem [*Simankov et al.*, 2021a, 2022] as part of a general information-analytical system for assessing renewable energy [*Simankov et al.*, 2021b] which allows assessing the efficiency of RES for a certain level of terrain scaling (local, regional). However, such a system should be based not only on classical models for assessing energy potential, but also on modern approaches based on methods of data mining and artificial intelligence, which results in

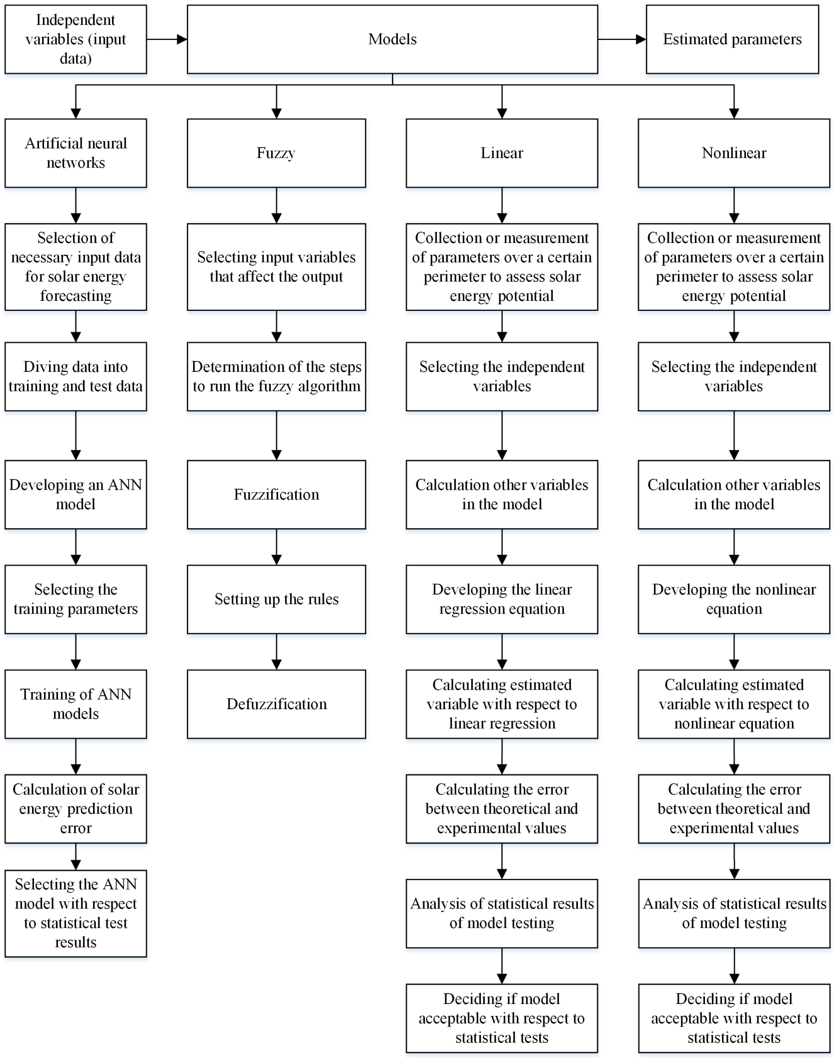

Figure 2. Block diagrams of models for estimating global solar radiation.

improved forecasting accuracy and the ability to determine the required level of scaling of this subsystem.

This subsystem is one of the key elements, because based on its results it is possible to start forming the structure of the energy system with the involvement of renewable energy sources.

At the same time, the considered models can be used not only as a tool for obtaining theoretical values of incoming energy, but also as a basis for implementing a subsystem based on digital twins [*Granacher et al.*, 2022; *Onishchenko et al.*, 2022], allowing the implementation of a virtual model of the projected energy system with RES to determine the most optimal structure of this system.

To obtain the highest accuracy of forecasting, it is necessary to implement the combined use of classical methods of modeling and modern methods based on artificial intelligence and data mining technologies. Such an approach will allow performing mutual verification of the models and specifying parameters to build the most optimal model based on neural networks, thereby reducing the overall error of calculations, for which existing intelligent models for assessing the energy potential of solar energy were considered.

The extensive range of models considered allows us to expand the range of input data required to implement the prediction, resulting in greater versatility due to the possibility of selecting those input parameters that are available to the potential user.

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