# Fuzzy Predictive Model of Solar Panel for Decision Support System in the Management of Hybrid Grid

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**Abstract.** This paper describes the features of decision-making process about working modes of hybrid energy grid and indicates tasks, which has to solve the appropriate information system. In order to managing the hybrid electricity grid, it is necessary to have current data and forecast indicators of the functioning of its constituent elements. The fuzzy predictive model of power by solar panel is developed in this research. This model a certain way takes into account the uncertainty associated with both constructive, commutation influences and the impact of predicted insolation and temperature. In the developed model it is possible to use the results of direct measurements of insolation and temperature and the results of their operational forecasting.

**Keywords:** Fuzzy predictive model · Decision support system · Hybrid grid · Solar panel · Predictive model of insolation and temperature

## 1 Introduction

Modern world trends are associated with an increase in the cost of traditional fuel resources and are manifested in increasing the share of dispersed electricity production through renewable energy sources (RES). This leads to complicated planning and operational management of hybrid power system.

Insufficient level of research of RES operation issues, their influence on electric networks operation modes, the absence of typical decisions regarding the means of protection and automation of the electricity production process does not allow to make informed decisions during their operation. An important aspect in this direction is the complexity and methodological unity in decision-making regarding the improvement of operational characteristics of RES in their work in power grids.

In order to ensure decision-making in the decision support system when managing the hybrid electricity supply system, it is necessary to have current data and forecast indicators of the functioning of its constituent elements, namely, solar panels (SP), wind turbines, micro-hydro-electric power stations, diesel and gas generators, etc. [1, 2].


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The collection of current data is carried out using a variety of sensors. Forecast indicators can be obtained only on the basis of mathematical models [3].

In this research, attention is focused on the SP. Electrical parameters of the SP depend on external meteorological factors such as temperature and insolation, as well as on constructive factors such as the size, material and amount of photocells, the presence of concentrators and heat transfer, etc. All these parameters are characterized by some uncertainty. For example, the temperature and insolation depend on meteorological conditions that carry uncertainty. In addition, these parameters have some unevenness on the plane of the SP, which is difficult to measure, as well as a certain measurement error [4]. Constructive factors also depend on the quality of the technological process in their manufacture.

Usually, a local charge-level controller supports the maximum power selection from the SP, which is redistributed between the panel and the load, therefore, from the point of view of the decision-making system, the mathematical model of the SP should describe the dependence of the maximum power of the SP from external meteorological and constructive factors. Moreover, it is desirable that this model should take into account the uncertainty of the input information. The disclosure of this type of uncertainty is expedient to implement within the fuzzy approach.

## 2 Literature Review and Formulation of Problem

The mentioned problem was not investigated comprehensively, but solved only separate tasks.

Among recent developments in control techniques for advanced control strategies, fuzzy logic and multi agent systems have emerged due to its strong control action in an uncertain environment [5].

But traditionally, modeling of SP capacity is based on a deterministic approach. In most cases, the basis of constructing a mathematical model of the power of the SP is the model of the voltage-ampere characteristic of the individual photocell [6–8], obtained theoretically or based on the processing of experimental data. This is explained by the relative simplicity of the research of the characteristics of photocells. However, when calculating the characteristics of a large-scale SP, difficulties arise in the determination of various losses due to the non-identity of the photocells, switching, unevenness of temperature and insolation along the plane of the SP.

The introduction of the appropriate coefficients [9, 10] does not solve these problems, and attempts to improve the deterministic mathematical model of the SP leads to a significant complication [10].

Also, in a number of papers it is proposed to take into account the integrally defined losses due to experimental studies of non-photocells, and small SPs with the subsequent propagation of the result to the SP parameters of any plane [9]. However, this approach justifies itself within certain limits. In addition, errors are added due to the use of regression analysis for constructing a model of volt-ampere characteristics in conditions of small sampling of experimental data. In this case, it seems more expedient to apply a fuzzy regression analysis.

## 3 Definition of the Goal

The purpose of the article is to construct a fuzzy predictive model of solar cell power for a decision-making support system under the control of a hybrid electricity grid in conditions of uncertainty of external and constructive factors.

## 4 Basic Research Materials

The efficiency and cost-effectiveness of using renewable energy sources in a hybrid power grid depends on choosing the optimal mode of operation of the hybrid network and matching the capacities in it. The operation of such an electric grid is characterized by a rapid change in operating modes, depending on weather conditions and consumption.

Therefore, the set of tasks Z, which must execute a decision support system for the management of a hybrid power system, can be represented as follows.

$$Z = Z_{\mathrm{m}} \cup Z_{pg} \cup Z_{pu} \cup Z_{f}, \tag{1}$$

where $Z_m$ is the set of metrology data monitoring tasks, $Z_{pg}$ is the set of predictors for the electricity generation level, $Z_{pu}$ is the set of tasks for predicting electricity consumption, $Z_f$ is the set of tasks for the formation of solutions.

When creating predictive models of energy generation, it is necessary to take into account the uncertainty of the input data.

It is proposed to determine the maximum power of the SP in the form of a triangular fuzzy number, that is, a tuple

$$P = \langle P_{mod}, P_{min}, P_{max} \rangle, \tag{2}$$

where $P_{mod}$ is modal value, $P_{min}$, $P_{max}$ are left and right boundary interval of uncertainty.

In this case, the representation of fuzzy numbers with a triangular membership function is accepted in the form of:

$$\mu_P = \max\left[0, min\left(\frac{P - P_{min}}{P_{mod} - P_{min}}, \frac{P_{max} - P}{P_{max} - P_{mod}}\right)\right], \tag{3}$$

In the limit of uncertainty, all of the above parameters fall into an integral direction, which can not be directly determined and even those that are unknown.

To take into account the dependence of $P_{mod}$, $P_{min}$, $P_{max}$, $P_{opt}$, $m$, the experimental data presented in [11] were processed from external and constitutive factors, since these experiments were performed precisely in order to detect the influence of undetermined factors on the electrical characteristics of the SP. 16 groups of solar cells were investigated with a plane of 0.0403 m$^2$ in the range of temperature (12–70) °C and insolation (550–1260) W/m$^2$. As part of the group, photocells of various sizes are loaded to account for this kind of uncertainty. The unevenness of the temperature along the plane of the groups was established at ±1° C from the mean, and the insolation – within ±3%. Near the point of maximum power, several control points of the volt-ampere characteristics were recorded to account for the error of the controller, which regulates the maximum power selection from the SP.

For processing, a fuzzy regression analysis with two quality criteria was used: the degree of coincidence and the degree of uncertainty.

The procedure of fuzzy regression analysis, in contrast to the traditional one, generally uses two criteria: the degree of coincidence and the degree of uncertainty. Based on these two criteria, one criterion was formed by their superposition. The search for fuzzy regression coefficients is implemented as part of the nonlinear programming problem. The method of spatial grid with variable pitch was applied.

As a result of the processing of experimental data, the dependences included in the fuzzy model (1) (Fig. 1) are obtained in the form:

$$\begin{aligned} P_{mod} &= (0.0901E + 0.0873t - 0.00032Et)S, \\ P_{min} &= (0.0876E + 0.0499t - 0.00027Et)S, \\ P_{max} &= (0.0918E + 0.1055t - 0.00035Et)S. \end{aligned} \tag{4}$$

The average degree of coincidence (4) is 0.32, and the average degree of uncertainty does not exceed 0.11.

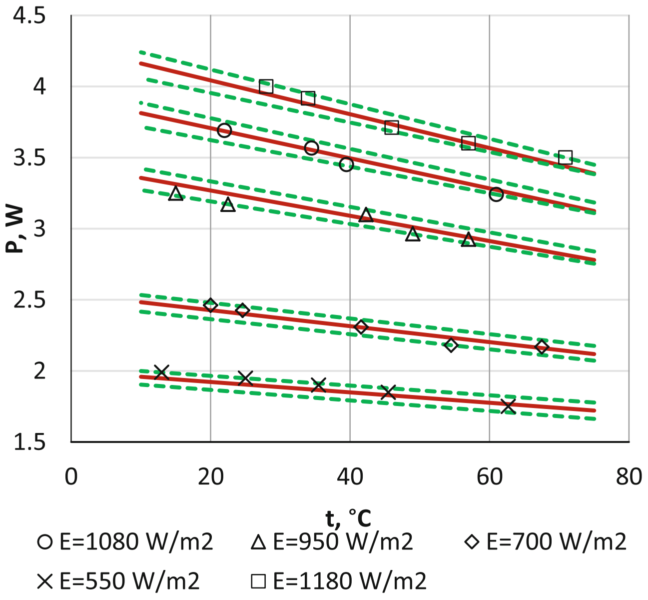


**Fig. 1.** Results of processing of experimental data by fuzzy regression analysis

It is difficult to establish definitely the correspondence of fuzzy estimates of the effectiveness of regression with traditional estimates. The closest such correspondence was to establish between the degree of coincidence and the mean absolute percentage error (MAPE). These parameters correspond to MAPE = 1.1% when all experimental data arrive at the limit of the interval of fuzziness.

In dependencies (4) S is the total area of solar panels included in the hybrid power supply system. If expressions (4) do not use the results of operational measurements of $E$ – insolation, t – temperature, and predictive data, then the dependencies (4) should be adjusted in accordance with the generalization of Zadeh, taking into account the forecast error.

We offer concrete data on insolation for the relevant period (day, month, season, year) to present in relative terms by dividing them by the magnitude of the corresponding maximum power. For periods of time during which insolation is observed, it is also envisaged the transition to relative values, which will ensure the correctness of the comparison of relative values of insolation for different months.

In order to determine the possible value of energy generated by the year, it is necessary to have statistics on insolation for the chosen location of the solar panels, namely data on the duration of the corresponding solar power during the calculation period.

For the development of a prediction model of insolation, the data are presented in the Tables 1 and 2. The results of the conversion carried out by dividing the hourly values of insolation for each month by the maximum value for 13:00 is given. Despite the fact that for February, April, June and July this maximum was observed at 14:00, in calculations conditionally selected 13:00 [12].

The values of insolation in these tables are averaged over the months of the year, and then they have a certain uncertainty, which can be disclosed with the help of a fuzzy regression apparatus [13].

It is proposed to construct a fuzzy predictive model that allows obtaining the value of insolation in the form of a fuzzy number with a triangular membership function, that is, in the form of a tuple (similar to dependencies (2))

$$E = \langle E_{mod}, E_{max}, E_{min} \rangle. \tag{5}$$

where $E_{mod}$ is modal value of a triangular number, $E_{max}$, $E_{min}$ are maximum and minimum values limiting the base set of fuzzy numbers.

Obviously, these parameters depend on Earth's motion in orbit around the Sun and from the rotation of the Earth around its own axis.

The construction of regression dependencies is divided into two stages.

The first stage is the construction of dependencies for maximal daily insolation during the year, which correlates with the motion of the Earth around the Sun in orbit. For this purpose from the Tables 1 and 2 selected maximal average insolation values. To obtain a model of regression dependence, a sinusoidal type function is chosen

$$E_i^{ma} = a_i + b_i \sin(d_i m - c_i), \tag{6}$$

**Table 1.** Average monthly insolation data for Ukraine

| Month | January | February | March | April | May | June |
|---|---|---|---|---|---|---|
| Time | 1 | 2 | 3 | 4 | 5 | 6 |
| 0.00 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0.04 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0.08 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0.13 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0.17 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0.21 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0.25 | 0 | 0 | 0.2 | 0.6 | 10 | 20.5 |
| 0.29 | 0 | 0 | 7.7 | 24.2 | 77.9 | 101.2 |
| 0.33 | 0.1 | 0.5 | 47.8 | 112.4 | 188.8 | 217.7 |
| 0.38 | 3.5 | 20.6 | 135.8 | 231.1 | 316.3 | 347.4 |
| 0.42 | 33.5 | 75.9 | 239 | 356.7 | 435.2 | 480.3 |
| 0.46 | 82.6 | 137.2 | 330.3 | 466.4 | 555.9 | 591.1 |
| 0.50 | 120.6 | 192.3 | 403.3 | 533.8 | 646.4 | 677.6 |
| 0.54 | 138.7 | 227.4 | 418.7 | 570.8 | 679.4 | 711.5 |
| 0.58 | 137.8 | 236.1 | 397.4 | 581.2 | 671.5 | 714.4 |
| 0.63 | 117.7 | 214.8 | 361.1 | 564.9 | 639.6 | 627.3 |
| 0.67 | 82.5 | 171.7 | 288.2 | 471.8 | 565.1 | 535.3 |
| 0.71 | 35.8 | 105.3 | 199.5 | 346.5 | 445.3 | 433.7 |
| 0.75 | 3.7 | 30.7 | 86.7 | 213.1 | 307.7 | 317.5 |
| 0.38 | 0 | 1.6 | 14.7 | 92.6 | 164.5 | 193.8 |
| 0.83 | 0 | 0 | 0.2 | 14.1 | 50.3 | 81.8 |
| 0.88 | 0 | 0 | 0 | 0 | 2.6 | 12.5 |
| 0.92 | 0 | 0 | 0 | 0 | 0 | 0.1 |
| 0.96 | 0 | 0 | 0 | 0 | 0 | 0 |

where $a_i$, $b_i$, $d_i$, $c_i$ are coefficients of regression, $m$ is month number, index $i$ takes values *mod*, *max*, *min*.

As a result of data processing, the regression coefficients are given, which are listed in Table 3.

The type of dependencies (6) is shown in Fig. 2.

At the second stage, dependencies were developed describing the change in insolation during the day. The basis for developing a kind of regression dependence is the Gauss curve chosen

$$E_i = E_i^{ma} \exp\left(-\frac{(h - n_i)^2}{2r_i^2}\right), \tag{7}$$

where $h$ – time during the day, in units of particles days, $n$, $r$ – coefficients of regression.

The results of processing are shown in Table 4 and on Fig. 3

**Table 2.** Average monthly insolation data for Ukraine (continuation of Table 1)

| Month | July | August | September | October | November | December |
|---|---|---|---|---|---|---|
| Time | 7 | 8 | 9 | 10 | 11 | 12 |
| 0.00 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0.04 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0.08 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0.13 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0.17 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0.21 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0.25 | 8.2 | 1 | 0.2 | 0 | 0 | 0 |
| 0.29 | 58.5 | 33.6 | 7.4 | 0.1 | 0 | 0 |
| 0.33 | 147.3 | 137.1 | 71.5 | 16.6 | 0.7 | 0 |
| 0.38 | 246.4 | 265.4 | 186.8 | 84 | 19.1 | 2.7 |
| 0.42 | 347.3 | 385.3 | 312.3 | 163.9 | 62.1 | 31 |
| 0.46 | 453 | 495.7 | 425 | 247.8 | 113.4 | 74 |
| 0.50 | 548.1 | 597 | 500.7 | 306 | 149.3 | 108.9 |
| 0.54 | 605.9 | 636.5 | 557.2 | 339.1 | 166.7 | 130.9 |
| 0.58 | 644.8 | 619.6 | 545.3 | 335.6 | 169.2 | 126.1 |
| 0.63 | 640.7 | 580.3 | 508.9 | 294.2 | 141.4 | 102 |
| 0.67 | 592.1 | 504.1 | 412.5 | 216.2 | 98.2 | 64.1 |
| 0.71 | 523.2 | 390.4 | 292.9 | 119.1 | 36.6 | 18.8 |
| 0.75 | 432.2 | 259.2 | 146 | 24.9 | 2.5 | 0.4 |
| 0.38 | 315.4 | 133.1 | 37.5 | 1.5 | 0 | 0 |
| 0.83 | 195.6 | 31 | 1.5 | 0 | 0 | 0 |
| 0.88 | 113.6 | 0.7 | 0 | 0 | 0 | 0 |
| 0.92 | 79.9 | 0 | 0 | 0 | 0 | 0 |
| 0.96 | 47.4 | 0 | 0 | 0 | 0 | 0 |

**Table 3.** Obtained regression coefficients for dependence (5)

| $a$ | $b$ | $c$ | $d$ | $i$ |
|---|---|---|---|---|
| 385.2 | 335.757 | 1.275 | 4.969 | *mod* |
| 384.2 | 355.724 | 1.151 | 4.687 | *max* |
| 349.8 | 333.199 | 1.206 | 4.885 | *min* |

Substituting (6) in (7), taking into account the data Tables 3 and 4 we obtain a fuzzy predictive model of insolation (Fig. 4). The estimation of the forecast error of the modal component of the fuzzy model on the MAPE indicator was 20.7%. The average degree of uncertainty was 4.15. Average degree of coincidence 0.48.

A similar approach is also applied to the construction of a fuzzy forecasting model of the daytime air temperature, which is included in the expression (4). The change in daytime temperatures during the year depends on Earth's orbiting around the Sun.

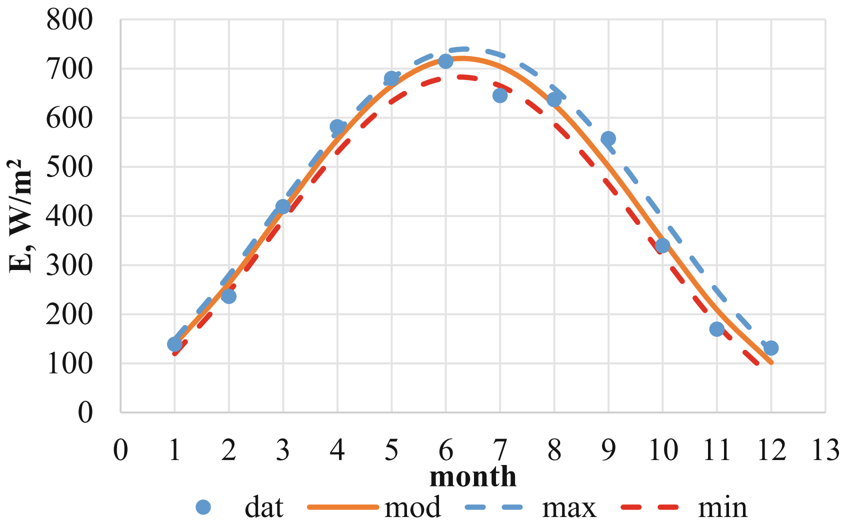


**Fig. 2.** Changing the maximum average insolation during the year

**Table 4.** Obtained regression coefficients for dependence (7)

| $n$ | $r$ | $i$ |
|---|---|---|
| 0.562014 | 0.11798 | *mod* |
| 0.562014 | 0.124167 | *max* |
| 0.562014 | 0.105833 | *min* |

Therefore, the sinusoidal function of the species is also chosen as the basis for developing a fuzzy forecast model

$$t_i = a_{ti} + b_{ti} \sin(d_{ti} m - c_{ti}), \tag{8}$$

where $a_{ti}$, $b_{ti}$, $d_{ti}$, $c_{ti}$ are coefficients of regression, $m$ is month number, index $i$ takes values *mod*, *max*, *min*.

As a result of data processing, regression coefficients are presented, which are given in Table 5.

The type of dependencies (8) is shown in Fig. 5.

For processing, data from researches on the temperature of air from the meteorological site GISMETEO.UA for 2016, 2017, 2018 years are used. The average degree of coincidence of dependencies (8) is 0.17, and the average degree of uncertainty does not exceed 0.8. These parameters correspond to MAPE = 21.1% when all experimental data arrive at the limit of the interval of fuzziness.

Since the variation in the power of a solar cell during a light depending on the temperature, lies within the uncertainty interval (Fig. 1), depending on the effect of the temperature on the power of the solar cell, there is sufficient dependence (8).

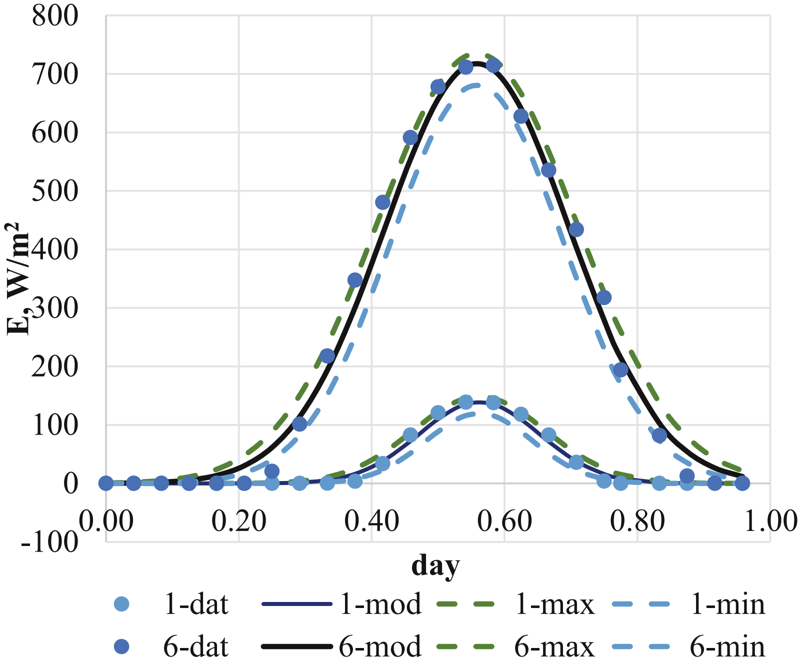


**Fig. 3.** Change of insolation during the middle of January (1) and June (6)

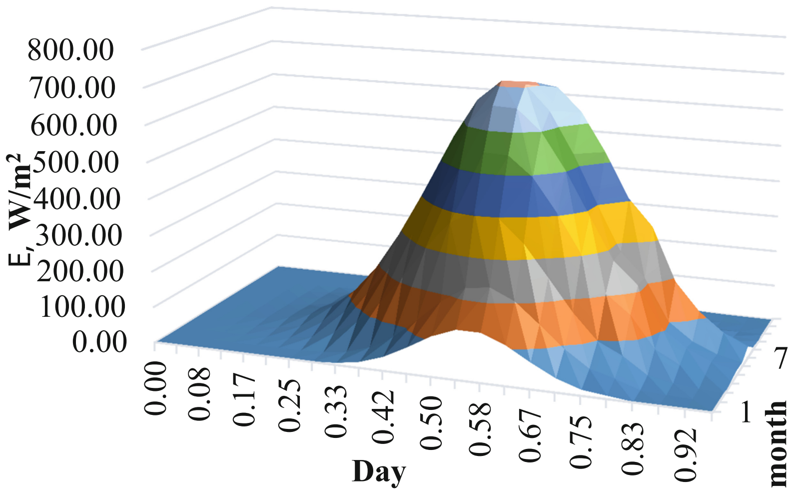


**Fig. 4.** Changing insolation during the year

Thus, according to the generalized operations Zadeh, the of dependence (3), which make up the forecast model (2), taking into account (7) and (8) will take the form:

**Table 5.** Obtained regression coefficients for dependence (8)

| $a_t$ | $b_t$ | $c_t$ | $d_t$ | $i$ |
|---|---|---|---|---|
| 11.85 | 16.16 | 1.942 | 5.554 | *mod* |
| 10.77 | 15.98 | 2.187 | 5.874 | *min* |
| 13.61 | 16.02 | 1.832 | 5.369 | *max* |

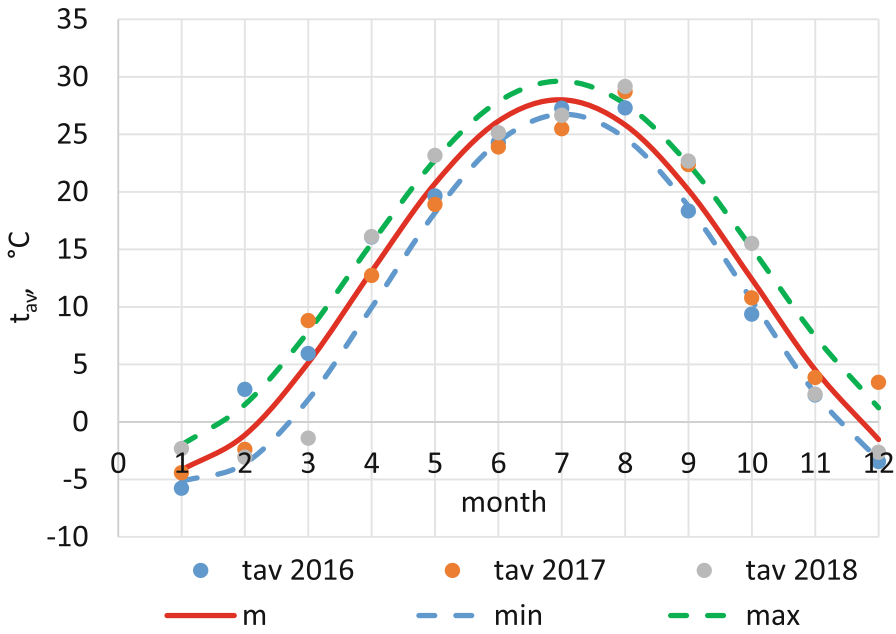


**Fig. 5.** Changing the average daily temperature during the year

$$
\begin{aligned}
P_{mod} &= (0.0901E_{mod} + 0.0873t_{mod} - 0.00032E_{mod}t_{mod})S,\\
P_{min} &= (0.0876E_{min} + 0.0499t_{min} - 0.00027E_{max}t_{max})S,\\
P_{max} &= (0.0918E_{max} + 0.1055t_{max} - 0.00035E_{min}t_{min})S.
\end{aligned}
\tag{9}
$$

The fuzzy predictive model (2), (9) can be used in the Mamdani fuzzy inference circuit. When forming the membership functions of fuzzy power levels of the SP, the rule of fuzzy conjunction should be used. For example, let us enter 3 power levels of the SP: low, medium, high ($P_l$, $P_m$, $P_h$) with the corresponding membership functions ($\mu_l$, $\mu_m$, $\mu_h$). Then, taking into account the fact that the predicted capacity of the SP is also a fuzzy number, the resulting level membership functions will be in the form:

$$\mu_{P_l} = \min(\mu_l, \mu_P); \mu_{P_m} = min(\mu_m, \mu_P);_{P_h} = min(\mu_h, \mu_P).$$

Using of predictive models in fuzzy logic inference schemes Mamdani expands the capabilities of the decision-making system.

## 5 Conclusions

The fuzzy predictive model of solar power panel is developed for the decision-support system in the control of a hybrid power system, which in a certain way takes into account the uncertainty associated with both constructive and commutation influences, and the effects of predicted insolation and temperature.

The accuracy of the forecast largely depends on the degree of uncertainty of the forecast insolation and air temperature. Therefore, in the developed model it is possible to use both the results of direct measurements of insolation and temperature, as well as the results of their operational forecasting.

Using of predictive models allows you to anticipate abnormal situations, and also to use management criteria that are not directly related to the operational parameters of the system, for example, the economic efficiency criterion.

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