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DEVELOPMENT OF AN INTELLIGENT SYSTEM FOR THE PROGNOSTICATION OF ENERGY PRODUCED BY PHOTOVOLTAIC CELLS IN SMART GRID SYSTEMS

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Розроблено структуру процесу інтелектуального контролю та моніторингу системи типу MICRO NET. Запропоновано структуру експертної системи на основі використання адаптивного нейро-нечіткого логічного блоку формування висновку та керуючої інформації. Виконано вибір параметрів нейро-нечіткої мережі для складання добових та місячних прогнозів виробленої електроенергії на основі врахування показників спожитої та виробленої енергії. Проведено аналіз залежності точності прогнозу від вибору вхідних параметрів

Ключові слова: нейро-нечітка мережа, SMART GRID, MICRONET, фотоелектрична панель, прогнозування виробленої енергії

Разработана структура процесса интеллектуального контроля и мониторинга системы типа MICRO NET. Предложена структура экспертной системы на основе использования адаптивного нейро-нечеткого логического блока формирования заключения и управляющей информации. Выполнен выбор параметров нейро-нечеткой сети для составления суточных и месячных прогнозов произведенной электроэнергии на основе учета показателей потребленной и выработанной энергии. Проведен анализ зависимости точности прогноза от выбора входных параметров

Ключевые слова: нейро-нечеткая сеть, SMART GRID, MICRONET, фотоэлектрическая панель, прогнозирования произведенной энергии

1. Introduction

At present, modern power systems can accommodate generating power plants and consumers differing in their properties and capacities. In particular, more and more countries initiate introduction of renewable energy sources such as photovoltaic cell panels and wind-driven power-stations not only at the industrial level but also to encourage private households. It should be noted that the electrical supply networks previously consisted of just few varieties of power plants: thermal power plants, hydroelectric power planta and nuclear power plants which produced almost all energy [1].

In addition to introduction of renewable energy sources, new types of electric power consumers begun to appear who are capable not only to consume power, for example, to charge batteries but also generate power and return it back to the network. In particular, such type of consumers can include owners of modern electric mobiles and home appliances with integrated intelligent controllers implementing the Internet of Things concept [2].

It should be noted that both thermal power plants and photovoltaic panel stations with a capacity of tens of megawatts can operate currently in a common power net. Also, the use of different types of energy sources in one power net can result in power dispersal. This combination of different energy sources makes it possible to instantly respond to load changes at individual sites on the one hand and poses problems in its management on the other hand.

The Energorynok State Enterprise is responsible for support of the system ensuring functioning of the wholesale energy market in Ukraine [3, 4]. The task of this enterprise is to perform hourly and round-the-clock planning of the operating regime of the entire combined system on the basis of optimization of operating regimes of power plants. In order to prevent peak loads, hourly and round-the-clock electricity generation planning is carried out for optimal work of energy producers. And therefore, the more accurate the forecast, the less likely is occurrence of overloads and error conditions.

Intelligent power systems with an active-adaptive SMART GRID network are increasingly widely used in the European Union member-countries [5, 6]. One of the tasks of such systems is planning of load distribution throughout the country, in particular, based on an analysis of all energy producers, both industrial and private.

Consequently, to manage modern energy systems, it is necessary to create new and improve already existing information technologies which must execute in real time configuration and adjustment of individual nodes of the electric net at all levels including private households. In particular, to create such information systems and management technologies, it is necessary to have an exact forecast of the consumed and produced energy in order to be able to elaborate a load reallocation schedule.

An urgent task for the further development of information systems of a SMART GRID type, is to improve existing and develop new methods for monitoring parameters of energy resources for private households. This task can be solved by automatic prediction of energy generation by household renewable energy sources, for example, photovoltaic panels and wind generators.

2. Literature review and problem statement

It should be noted that the basis of the SMART GRID systems is continuous status monitoring of all power net participants through the use of smart energy meters. These devices make it possible to establish power consumption in more detail. Also, they have additional communication means for a rapid transfer of information to the main node of the SMART GRID system. Intelligent meters ensure measuring of current parameters of the electric power net which, for its part, makes it possible to diagnosticate power quality problems.

Techem Company is the undisputed leader in the production and service of smart energy meters. In particular, it has developed an intelligent system, Automative Smart Metering System Data, for monitoring consumption of water, heat, gas and electricity and transmit information to the main nodes via the radio channel [5].

Also, there are information systems that, in addition to transmitting data to the main center of the SMART GRID system, become a part of home nets such as Smart Home which further allows the household consumer to monitor the energy both consumed and given back. In particular, Advanced Metering Infrastructure (AMI) [6] is a commonly used system of this type. This system represents an integrated intelligent network of smart meters, communication elements and data management means ensuring monitoring of consumed and produced energy. Additionally, it is possible to control household appliances, for example, with the help of wireless sockets. It is worth to mention that these systems include specialized equipment and software.

In general, the SMART GRID control task can be formulated as follows [6–8]: it is necessary to find energy production by various power stations and power consumption by various categories of users connected to a common network in a specified period T (for example, day or month with hourly sampling) in which restrictions are met and management criteria are achieved. In particular, these management criteria can include the following:

$$\min\sum_i\sum_t q_i(t),\ \min\sum_i\sum_t I(c_j(t)>\varphi_{c_j(t)}), \tag{1}$$

$$\min\sum_i\sum_i\sum_t C(c_i(t),q_i(t)), \tag{2}$$

$$\sum_i q_i(t)=\sum_j c_j(t),\forall t\in[0..T], \tag{3}$$

$$L(c_j(t),q_i(t))<l_{ij},\ q_i(t)<Q_i-v_{qi}(t), \tag{4}$$

where q_i(t) is the amount of energy produced by the i-th station in the time interval $[t, t+1]$; $c_j(t)$ is the amount of energy consumed by the j-th consumer in the interval $[t, t+1]$; $C(c_i(t), q_i(t))$ are expenses for the transfer of energy from the i-th station to the j-th consumer; $L(c_i(t), q_i(t))$ is the direct transmission capacity of the i-th station to the j-th consumer; l_{ij} is the maximum direct throughput of transmission lines from the i-th station to the j-th consumer; $\phi_{cj(t)}$ is the amount of energy the overconsumption of which is taken into account as a peak amount and depends on the dynamics of consumption in a particular segment; $I(c_j(t)>\phi_{cj(t)})$ is an indicator function; Qi is the maximum possible produced volume of the i-th station; $v_{cj(t)}$ is the reserve of the i-th station, which cannot be used at present $[t, t+1]$.

When the specified criteria are fulfilled, the net is considered to be working in a normal mode, that is, frequency and voltage in the net of the entire SMART GRID system are within the permissible limits. Consequently, in accordance with the main tasks of this study, it is necessary to find the value of $q_i(t)$ which satisfies the specified constraints at the set throughputs. And, in general, the values of the $c_i(t)$ and $q_i(t)$ parameters for the required period are not known, but only the history of consumed and produced energy is known.

It is necessary to point out that the traditional tasks of prognostication of the amount of consumed and produced energy are solved based on the use of regression models. Since these series of consumption and generation of electricity are not stationary, regression models can give a serious error [2, 9, 10]. Therefore, when solving problem of this type, a rather promising method for solving prediction problems is the use of a structure of artificial neural networks, in particular adaptive neural-fuzzy structures.

Besides, based on the analyzed literature [3–6], it can be concluded that virtually all existing solutions for integration of private households into the common SMART GRID system use their own specialized devices, in particular smart energy meters. The essential disadvantage of these devices is inability to perform local forecasts of the produced and consumed energy.

The drawback of the existing studies [3] for predicting energy production is impossibility of making forecasts for longer periods of time, for example, a week or a month. One more significant drawback is inability of adjusting the input parameters by the user in order to improve quality of the forecast. The main problem of integration of private households [4, 11] into the SMART GRID system is the lack of universal approaches to merging existing MICROGRID systems into a single system with a single control element. Moreover, it becomes rather difficult to the owner of the generating station to monitor and obtain a prognosis of the generated energy for a certain period of time [12] due to the lack of appropriate software. This is especially important if the household uses the “Green Tariff” for commercial purposes.

Also, there are methods for predicting the energy produced by photovoltaic panels based on the analysis of solar activity, in particular, Total Sky Imagery and Model Output Statistics methods [13]. The main disadvantage of these methods is a rather short prediction period, in the range of 3 to 6 hours.

In studies [14] related to the development of an information system for energy management of home appliances in such systems as Smart Home, significant disadvantages include non-consideration of available autonomous renewable energy sources (RES). In particular, if a household is to be an autonomous MICROGRID 'island' [12] without the use of the Green Tariff, there may be a situation of improper redistribution of energy. That is, by turning off unnecessary devices in order to save energy, you can conversely increase energy consumption due to the work of RES. This is due to the peculiarities of operation of conventional energy meters.

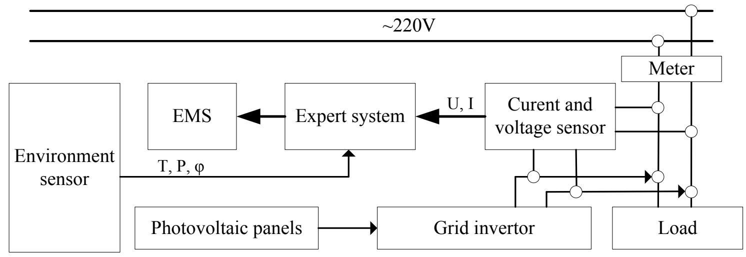

Fig. 1. Structure of the process of intellectual control and monitoring of a system of MICROGRID type

3. The aim and objectives of the study

This study objective was to develop a method for prognostication of the power produced by household photovoltaic stations for an intelligent power system with an active-adaptive network of the SMART GRID type. This will enable to reduce energy consumption by private households, increase efficiency of functioning of power networks and reduce negative impact of energy systems on the environment.

To achieve this goal, the following tasks were set:

– design an expert system structure as a part of the Smart Home system with available external interfaces prior to integration into the common SMART GRID system;

– select information input signs and an optimal structure of the neural-fuzzy network, in particular the number of input terms and the number of internal layers and neurons;

– solve the problem of training the neural-fuzzy network to the optimal level according to the specified criterion.

4. Materials and methods for studying the intellectual control and monitoring of the energy produced by household photovoltaic cells

To date, a private household possessing energy generation and storage systems can be attributed to the MICROGRID system as a part of the common SMART GRID system [5, 6]. When designing information systems to control and monitor operation of MICROGRID system it is important to keep in mind that they can work offline, so management should be done remotely via the common Energy Management System (EMS). This system must receive all information about the current state of the power generating units. Also, the system is a part of the common SMART GRID system.

The structure of the intellectual control and monitoring process of the MICROGRID type system (Fig. 1) for private households is proposed which allows the user to realize monitoring of the current state of the private household power system, namely, monitoring and prognostication of consumption and generation of electricity. In particular, for organization of remote control and monitoring by all MICROGRID systems, the global satellite navigation system GPS with the help of which synchronizing of measurements is made and a GSM module to transmit corresponding values to the main node of the common SMART GRID system are available. Also, the proposed system uses devices to measure values of current and voltage obtained directly from the common electrical supply network and generated by the network inverter. As environment measuring means, a temperature (T) sensor, a pressure (P) sensor and a relative humidity (φ) sensor which are also used for weather prognostication were taken.

An expert system is a control unit that "learns" throughout entire operation life. That is, it replenishes or corrects its knowledge base depending on the changes in the internal or external factors of the premises, accounting for the week days or the year's seasons in which it operates. Voltage and current values are taken as input parameters.

Logical-functional scheme of the expert system is presented in Fig. 2.

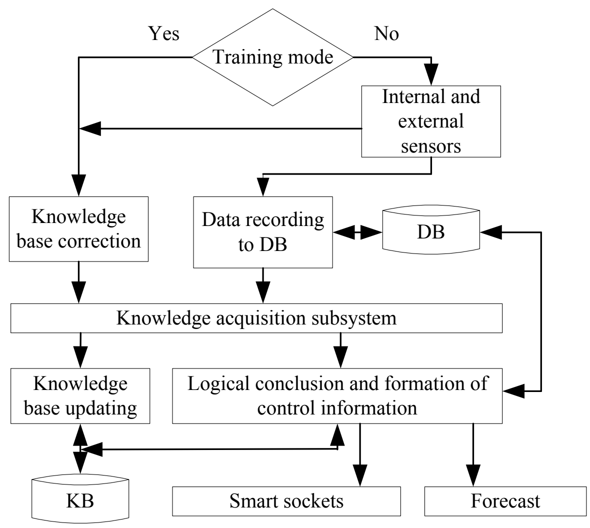

Fig. 2. Logic-functional scheme of the expert system operation

To implement the Logical Conclusion and Formation of Control Information unit, it is proposed to use an adaptive system of neural-fuzzy output. This system enables automated generation of a forecast for consumed and produced energy and additionally forms control information to regulate and balance consumer's load depending on the values of the energy produced by photovoltaic cells. Modeling of the control processes is performed in the MatLab environment with the Fuzzy Logic Toolbox package [6].

The Logical Conclusion and Formation of Control Information unit can form controlling influence on household electrical appliances, for example, by using smart sockets, in order to balance consumption of power at the moments of maximum power generation by photovoltaic cells. Also, the main functions of this unit include formation of forecasts of consumed and produced energy for a certain period, in particular, for a day, a week or a month.

The Logical Conclusion and Formation of Control Information unit contains a system of fuzzy output. This system is presented as a neural-fuzzy five-layer network of direct error propagation. The network implements a system of fuzzy output of zero order of Sugeno type and has the following input variables: IVG (the season); IT (local time); ICO (local weather forecast); ICP (ambient temperature); IEI (amount of energy consumed in percentage terms); IEO (amount of energy produced in percentage terms). The network output includes two linguistic variables OU and OP which, depending on the values of the input variables, form control information for the actuating device, that is, switching on/off home appliances and the forecast of the amount of energy generated for the EMS system.

Four terms are used for linguistic estimation of IVG input variable, six terms for IT variable, five terms for ICO variable, five terms for ICP variable, ten terms for IEI variable and ten terms for IEO variable. Set TIVG={"winter", "spring", "summer", "autumn"} is used as a term-set of the first linguistic variable IVG which is written in symbolic form as TIVG={IVGZ1, IVGL2, IVGL3, IVGL4}. Set TIT={"early morning", "morning", "noon", "evening", "late evening", "night"} is used as a term-set of the second linguistic variable IT which is written in a symbolic form as TIT= ={ITR, ITU, ITP, ITV, ITPV, ITN}. As a term-set of the third linguistic variable ICO, the set TICO={"rain", "overcast", "cloudy", "clear", "sun"} is used which is written in a symbolic form as TICO={ICOH, ICOP, ICOK, ICOJ, ICON}. As a term-set of the fourth linguistic variable ICR, the set TICR={"cold", "cool", "comfortable", "hot", "very hot"} is used which is written in a symbolic form as TICZ={ICZH, ICZP, ICZK , ICZJ, ICZN}. As a term-set of the fifth linguistic variable IEI, the set TIEI={«10%», «20%», «30%», «40%», «50%», «60%», «70%», "80%", "90%", "100%"} is used which is written in a symbolic form as TIEI={IEI1, IEI2, IEI3, IEI4, IEI5, IEI6, IEI7, IEI8, IEI9, IEI10}. As the term-set of the sixth linguistic variable IEO, the set TIEO={«10%», «20%», «30%», «40%», «50%», «60%», «70%», « 80% 90 "," 100% "} is used which is written in a symbolic form as TIEO={IEO1, IEO2, IEO3, IEO4, IEO5, IEO6, IEO7, IEO8, IEO9, IEO10}. The term-set of the output linguistic variable OU is the set of values for smart sockets of household devices TOU={*Uj*}, *j*=1,...3. Depending on the obtained values, you can select the following modes of smart sockets: *U*1: turn off the socket; *U*2: turn on the socket; *U*3: do nothing. The term-set of the output linguistic variable OP is a set of values for determining the relative amount of generated energy which depends on the generating power of the photoelectric power station and is an individual value for each MICRO GRID: TOR={*Uj*}, *j*=1,...11. Depending on the values obtained, you can allocate the following amounts of the generated power: *U*1: 0 %, *U*2: 10 %, *U*3: 20 %, *U*4: 30 %, *U*5: 40 %, *U*6: 50 %, *U*7: 60 %, *U*8: 70 %, *U*9: 80 %, *U*10: 90 %, *U*11:100 %.

The neural-fuzzy network consists of 5 layers that have the following purpose:

Layer 1. Defines the fuzzy terms of the input parameters. The outputs of this layer represent values of the membership function at concrete values. Each node of the layer is adaptive with the $\mu Ai(\chi)$ membership function where χ is the value of the *i*-th node, *i*=1,..., n; *Ai* is a linguistic fuzzy variable associated with this node. For the terms of input variables, trapezoidal membership functions were chosen.

Layer 2. Defines parcels of fuzzy rules. This layer is non-adaptive. Each node is connected to those nodes of the first layer which form preconditions of the corresponding rule. It performs fuzzy logical operation AND by the parameters of the rule parcels. The outputs of the neurons of this layer are the measure of truth of the parcels of each *j*-th rule of the system knowledge base calculated by the formula:

$$w_j = \min|\mu_{IVGj}(IVG), \mu_{ITj}(IT),$$

$$\mu_{ICOj}(ICO), \mu_{ICZj}(ICZ)|, \tag{5}$$

where *j*=1,..,200 defining the total number of rules of the fuzzy output system.

Layer 3. It normalizes the degrees of rule execution. Non-adaptive nodes of this layer calculate the relative degree (weight) of the fuzzy rule execution by the formula:

$$\overline{W_j} = w_j / \sum_{j=1}^{200} w_j. \tag{6}$$

Layer 4. A non-fuzzy number *Uj* which specifies the result of each *j*-th rule is considered as a fuzzy set with a Singleton membership function. Adaptive nodes of the fourth layer calculate contribution of each fuzzy rule in the output of the network by the formula:

$$y_j = \overline{W_j} U_j, \quad i = 1,..,200. \tag{7}$$

Layer 5. The non-adaptive node of this layer summarizes contributions of all rules:

$$y = \sum_{j=1}^{200} y_j. \tag{8}$$

The software implementation of the neural-fuzzy network was obtained in the Matlab Fuzzy Logic mathematical package using the program ANFIS m-function, using IVG, IT, ICO, ICP, IEI, IEO as output variables, and OU and OP as outputs. The fuzzy output system has been configured automatically. During training, the network node parameters are configured as to minimize standard error (RMSE) based on the following dependences:

$$\min_w \sum_i (y(W, x_i) - w(i))^2, \tag{9}$$

where *W* is the parameters for network instruction, $y(w, x_i)$ is the predicted value of the generated energy at time *i* for a given vector of input factors x_i, *w(i)* is the active value of the energy produced at time *i*.

The method of reverse error propagation based on the gradient method of the fastest descent was chosen as a training algorithm for ANFIS net to determine parameters of the membership function.

The process of filling the database (DB) of the expert system is fulfilled in a few steps. The first step is record of the values of consumed and produced power, temperature, the year's season and time to the database for some time *T*. Time *T* is chosen according to EMS requirements and can range from a day to a month.

An example of the values of the expert system database is presented in Table 1 and, accordingly, the table structure corresponds to the first normal form.

The task of the knowledge acquisition subsystem consists in updating the knowledge base on the basis of the data received from sensors. It should be noted that the expert system may be in the state of training and in the normal state. The purpose of the training mode is creation of control information for executive devices and a forecast for the EMS system in the unit of logical output.

Table 1

An example of an expert system database

Record number	Weather forecast	Season	Day	Time	Value of the produced power, W	Value of the consumed power, W
1	Sunny	Summer	21	11.00	180	1000
2	Cloudy	Summer	22	12.00	121	2000
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Interaction of the DB with the KB can be demonstrated in this way. Let {d/D} be the set of values of produced energy (β) written in terms of domains *D*. Then {τ/*T*} is the set of current values with the help of which forecast of generated energy (β) is defined and which are recorded in terms of domains *T*. {/*T*} is the results of the current data on the generated power. In determining the forecast, the results of the current data are entered to the DB are received and a list of results is obtained at the output:

$$\forall\beta\{\bar{\tau}/T\}\rightarrow KB\rightarrow\{d/D\}. \qquad (10)$$

In the case of the inverse problem: forecast of the generated energy is obtained at the input and the set of new records of the database is obtained at the output. Then we get the following dependence:

$$\{d/D\}\rightarrow KB\rightarrow\{\tau/T\}_1,\ldots,\{\tau/T\}_n. \qquad (11)$$

It should be noted that various factors {μ} may occur in the process of determining the forecast of the generated energy when filling the DB.

Factors should be understood as, for example, repair of photovoltaic cells, lack of electricity, etc. Therefore, in the general case, dependence (5) will take the following form:

$$\forall\beta\exists\{\mu\}\subseteq KB:\forall\mu\cdot\{\bar{\tau}/T\}\xrightarrow[\mu]{}\{d/D\}. \qquad (12)$$

It should be noted that formation of the final forecast for EMS does not take into account physical and chemical properties of photovoltaic cell panels which can introduce some error in the calculations.

5. The results obtained in simulation of operation of the proposed intellectual system for predicting the energy produced by photovoltaic panels

As a result of the studies, simulation of system operation was carried out on the basis of the proposed approach. In particular, a situation was simulated for one 300 W photovoltaic panel and a load within 3 kW was chosen. It should be noted that the power values are obtained with the use of current sensors and the weather forecast is obtained on the basis of the use of current values of temperature and pressure.

The training sample was obtained based on the Monte Carlo method. The structure of the training sample corresponds to the structure of the expert system database and is shown in the Table 1. The amount of the training sample was 17,280 records proceeding from the fact that the 12-day system operation was simulated at a sampling interval of 1 min.

The information intelligent system for prognostication of the amount of generated power uses a unit of neural-fuzzy output to provide the EMS system with rapid and more accurate (error within 5 %) information. The initial value of the training step in the direction of the anti-gradient of criterion *E* at changing parameters of the membership function was set equal to $\alpha=10^{-4}$. The permissible change of the step per one iteration was 15 %. To train the network, the value of the training criterion was on average *E*=2,068 and it was *E*=0.147 after 500 iterations.

The main feature of the proposed structure of the expert system as a component of the SMART GRID system is automatic generation of a forecast of the generated energy with ability to perform control of household appliances. As a result, in the period when there is increase or decrease in energy production, the ES is able to reduce the cost of the energy resource used by managing the work of domestic appliances. The results of the ES simulation are shown in Fig. 3.

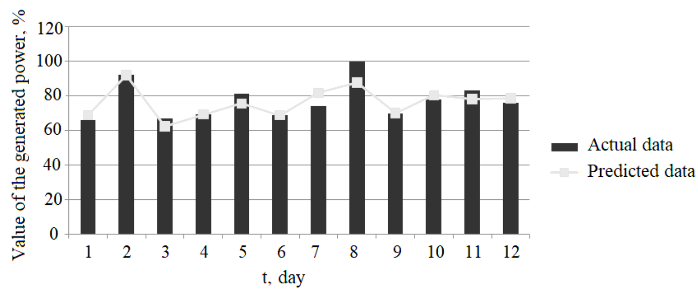

Fig. 3. Results of simulation of the expert system operation

It should be noted that the rather large discrepancies between actual and predicted data on the generated power are due to inaccuracy of local weather forecasts. In particular, clear weather was forecast for some day but in fact it was cloudy with clarifications which has resulted in the forecast inaccuracy.

6. Discussion of the results obtained in the study of the proposed structure of the intellectual system for prognostication of the produced energy

Solution of the problem of prognostication and monitoring of produced energy was proposed on the basis of the mathematical apparatus of neural-fuzzy networks. It should be noted that the problem of monitoring and analysis of current data received from objects can be attributed to the classification problems. To solve problems of this class, many methods are used. In particular, classification by means of decision trees, Bayesian classification, classification by the method of reference vectors and artificial neural networks [10, 14]. On the basis of the considered methods, it was found out that the use of neural-fuzzy systems is optimal since development of intelligent systems on their basis helps solve problems of image recognition, prognostication and classification. Also, the main advantage of using ANFIS is a smaller amount of the training sample compared to other methods and faster convergence than in conventional neural networks.

In absence of integration with the common SMART GRID system, the proposed structure of the intelligent energy prognostication system may be a part of the household MICROGRID system or a part of the Smart Home system and operate autonomously.

The advantage of the proposed system is flexibility in its adjustment since it uses a fuzzy output system as a unit of logical conclusion. The structure of the fuzzy system makes it possible to easily edit parameters of term-sets which in turn can improve quality of the forecast in accordance with the features of operation.

Disadvantages of this intelligent system include impossibility of working with wind power generators. This is due to the fact that the process of energy generation by photovoltaic panels is stationary within its confidence interval in contrast to the wind power generators. Eventually this feature affects the forecast quality.

The prospect of development of this direction consists in a solution of the problem of imbalance of the energy produced and sent to the net, for example, through creation of an intelligent power router. The purpose of this device is to avoid the situation of generation of energy and sending it to the network in the households which do not have a Green Tariff system. However, in solving problems of this kind, there is a probability of arising difficulties with the quality of the net, in particular, voltage fluctuations, presence of higher harmonics, etc.

One more promising line of further activity is to improve the method of prognostication of the produced energy by taking into account physical and chemical properties of photovoltaic cell panels.

7. Conclusions

1. The structure of the process of intellectual control and monitoring of systems of MICROGRID type as a part of the common SMART GRID system based on the use of an expert system with an adaptive neural-fuzzy logic unit was proposed. It enables automatic prognostication of consumed and produced energy for certain periods of time (user-selected, e. g., day or month). Additionally, it is possible to carry out load balancing based on the estimation of forecast indicators. This possibility is achieved by using additional means for household appliances, such as smart sockets controlled on the bases of the received value of control action (OU output).

2. According to the structure of the expert system's unit of logical conclusion, the year season, time, weather, the amount of energy produced and the amount of energy consumed were chosen as informative features. The structure of a neural-fuzzy network consisting of 5 layers was developed. This system features ability to change the number of terms of incoming variables in order to improve quality of the forecast. In particular, in systems with small generating capacities, in order to take into account the smallest values, it is expedient to increase (e. g. 2-fold) the set of values of the TOP variable.

3. It was found in training a neural-fuzzy network, that to achieve a lower value of the mean-square error of training and improve forecast quality, it is necessary to use a training sample with a high value of input data or a larger value of the number of training periods. But with the increase in the number of training periods, the overall time of training a neural-fuzzy network increases which in turn affects the overall reaction of the system. It was empirically determined that the optimal number of neurons in the inner layer (N) is 250. In this case, the root mean square error lies within the value of E=10^{-3} which results in the best prognostication with a deviation of 5 %.

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