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SIMULATION MODELING OF MULTI-PORT DC-DC CONVERTER IN MPPT SOLAR BATTERY CONTROLLERS UNDER NEURAL NETWORK CONTROL

В. Тігарєв, О. Лопаков, В. Космачевський, І. Прокопович, Є. Зудіхін. **Імітаційне моделювання багатопортового DC-DC перетворювача в MPPT-контролерах сонячних батарей під керуванням нейронної мережі.** Фотоелектрична система генерування – енергетична система, призначена для перетворення корисної сонячної енергії за допомогою фотоелектричних систем. Вона може складатися з декількох компонентів, включаючи масив сонячних батарей, DC/DC і DC/AC напівпровідникового перетворювача, акумуляторної батареї, фільтра або трансформатора, системи керування (CS). Залежно від сфери застосування фотоелектричні системи можуть експлуатуватися у складі автономної енергетичної установки, або працювати на мережу. Таким чином, можна виділити декілька основних конфігурацій фотоелектричних систем генерування. Автономна система генерування – найбільш поширена конфігурація фотоелектричних систем генерування, що містить акумуляторні батареї (AB). Ця система повністю незалежна від мереж централізованого електропостачання та підходить для комфортного енергозабезпечення споживачів. Використання AB дозволяє підвищити надійність фотоелектричної системи та розширити можливості застосування. Енергія від акумуляторів використовується під час недостатнього освітлення або коли навантаження перевищує генерацію сонячних батарей. Областю застосування таких конфігурацій є системи освітлення житлових та нежитлових об'єктів, енергозабезпечення будинків та будівель, системи безпеки та аварійне енергопостачання, енергопостачання віддалених житлових та нежитлових об'єктів, енергопостачання космічних апаратів тощо. Автономні системи генерування, як правило, містять два перетворювачі. DC/DC перетворювач виконує роль контролера заряду акумуляторних батарей. Система управління такого перетворювача може включати функцію відстеження точки максимальної потужності для максимального використання сонячної енергії. При цьому надлишки енергії запасатимуться в AB. За допомогою DC/AC перетворювача енергія постійного струму перетворюється на енергію змінного струму необхідної частоти та напруги. Перевагою такої системи є можливість використання сонячної енергії як вдень, так і в нічний час за рахунок енергії AB та можливість використання системи на віддалених об'єктах, де повністю відсутнє мережеве енергопостачання. Недоліком такої системи є втрати на подвійне перетворення сонячної енергії та висока вартість акумуляторних батарей. Штучна нейронна мережа (ANN) надає альтернативний спосіб вирішення складних завдань. Нейронна мережа при правильному виборі структури може обчислювати значення будь-якої безперервної функції з певною заданою точністю. Нейронна мережа не вимагає знання внутрішніх параметрів сонячного модуля, швидко навчається, має здатність до оптимізації та апроксимації. Отже, використання ШНС для відстеження точки максимальної потужності є актуальним завданням та має практичну та наукову значущість.
Ключові слова: багатопортовий DC-DC перетворювач, штучна нейронна мережа (ANN), акумуляторні батареї (AB), широтно-імпульсна модуляція (PWM), сонячні батареї (SP), силові ключі MOSFET

V. Tigarev, A. Lopakov, V. Kosmachevskiy, I. Prokopovych, Y. Zudikhin. **Simulation modeling of multiport DC-DC converter in MPPT solar battery controllers under neural network control.** Photovoltaic generation system - energy system, designed to convert useful solar energy through photovoltaic systems. It can consist of several components, including a solar array, DC/DC and DC/AC semiconductor converter, battery, filter or transformer, control system (CS). Depending on the application, photovoltaic systems can be operated as part of a self-contained power plant or operate on a network. Thus, it is possible to distinguish several basic configurations of photovoltaic generation systems. The standalone generation system is the most common configuration of photovoltaic generation systems, which contains rechargeable batteries (AB). This system is completely independent of the centralized power supply networks and is suitable for comfortable energy supply to consumers. The use of AB makes it possible to increase the reliability of the photovoltaic system and to extend the possibilities of using e.g. battery power is used during insufficient light or when the load exceeds the generation of solar cells. The scope of such configurations are lighting systems of residential and non-residential objects, power supply of houses and buildings, security systems and emergency power supply, power supply of remote residential and non-residential objects, Power

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supply to spacecraft, etc. Autonomous generation systems typically contain two transducers. The DC/DC converter acts as a battery charge controller. The control system for such a transducer may include the function of tracking the maximum power point for the maximum use of solar energy. The excess energy will be stored in AB. The DC/AC converter converts the DC current energy into the AC energy of the required frequency and voltage. The advantage of such a system is the possibility of using solar energy, both during the day and at night, due to the power of AB and the possibility of using the system at remote sites where there is no grid power supply. The disadvantage of such a system is the loss of double conversion of solar energy and the high cost of batteries. Artificial Neural Network (ANN) provides an alternative way to solve complex problems. A neural network, with the right structure, can compute the values of any continuous function with some predetermined accuracy. The neural network requires no knowledge of the internal parameters of the solar module, learns quickly, has the ability to optimize and approximate. Therefore, the use of INS to track the maximum power point is relevant and of practical and scientific importance.

Keywords: multi-port DC converter, artificial neural network (ANN), rechargeable batteries (AB), pulse width modulation (PWM), solar panels (SP), MOSFET power keys

1. Introduction

The role of solar energy in the future is determined by the potential for industrial use of solar cells and modules in uninterrupted power supply systems as well as secondary power supplies. The total amount of solar energy flowing to the Earth’s surface per week exceeds the energy of all the world’s reserves of oil, gas, coal and uranium [1, 2]. The largest theoretical potential, more than 2000 billion tons of conventional fuel, has solar energy. Ensuring energy security and ecologically balanced economic growth are currently priority areas for development, and the development of renewable energy could be one way to move in this direction. One of the main factors limiting their wide application is low efficiency. There are several main ways to improve solar energy efficiency:

1. One of the main ways to improve efficiency is the use of new technologies and materials (copper-indium-gallium selenide ($CuIn_xGa_{1-x}Se_2$) and cadmium telluride (CdTe), etc.). Researchers specializing in technology now have developed many options of hybrid solar cell manufacturing. [2, 3, 4].
2. Installation of solar panels at some distance from the ground and sun orientation. Large systems are equipped with automation, which changes the angle of tilt panels during the day;
3. Use of solar concentrators [5, 6];
4. High efficiency voltage converters;
5. Use of modern control systems for converters.

2. Analysis of literature data and problem statement

The transition to solar cell power point control is a modern trend in photovoltaic generation. Widely known MPPT authors such as Gielen F., Boshell D., Saygin M.D., Bazilian N., Wagner, Haas T., Krause R., Weber R., Demler M., Valenciaga F. and Puleston P.F. [5 – 8]. But classical, analog algorithms are not the best solution for the MPPT problem, despite their obvious advantages. These algorithms are quite slow to reach the maximum power point and are limited in operation accuracy [9]. To achieve higher accuracy, algorithms are subject to different modifications, but their dynamic characteristics are impaired. Consequently, the task of tracking the maximum power point is still relevant. A multiport DC-DC converter controlled by neural networks was not modeled in the works of the listed authors, so this study is of scientific interest. In this work, it is proposed to use a DC multiport converter as a converter. The three-port converter contains three ports. Two are designed to connect the solar battery and the battery, and the third is for load connection.

3. The purpose and objectives of the research

The aim of this study is to develop and simulate photovoltaic systems for generating electrical energy with increased efficiency due to intelligent control systems performed using artificial neural network. In order to achieve this objective, it is necessary to design and simulate a fast control system for DC and AC generating systems, The object of the study is simulation of multiport DC-based grid simulation The DC converter of the generation system is based on high-speed semiconductor MOSFET elements operating on DC and AC current.

4. Design and simulation of the multi-port DC-DC converter

The main results of scientific research are obtained by applying methods of mathematical modeling using analytical expressions. The development and research of a control system for semiconductor converters is solved with the application of the theory of automatic control. Studies of dynamic processes in photovoltaic generating systems on the basis of semiconductor converters are carried out with the help of analytical and graphical methods, and also by simulation in the application package Matlab Simulink. The practical significance of the work is that the proposed system of generating artificial neural networks makes it possible to quickly and dynamically reach the maximum power point of a solar array compared to other systems, working on one of the classic MPC tracking algorithms.

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The full DC/DC converter scheme is presented in Figure 1. The multi-port converter has a number of advantages over self-contained converters, for example, fewer components, some components of the scheme are common to all ports. As a result, the system has less weight and more compact assembly, resulting in a reduced cost of the converter. In addition, there is no need to coordinate transducers and transfer information between control systems. The advantages of such converters are confirmed by the authors [9, 10, 11]. The proposed system for converting electrical energy from solar batteries comprises a current control channel for the solar battery, a charge channel and a battery discharge channel. Thus, this circuit acts as a link between the solar battery and the battery, and also increases the output voltage for further conversion in the AC link.

4.1 DC-DC Converter

The inventive converter comprises a circuit for a voltage regulator which maintains a voltage on a bus at a fixed level. The control circuit is shown in Figure 1. The proposed power supply and energy conversion system comprises a current regulator for the solar battery and a charge-discharge regulator for the battery. Thus, this circuit acts as a link between the solar battery and the battery, and also increases the output voltage for further conversion in the AC link.

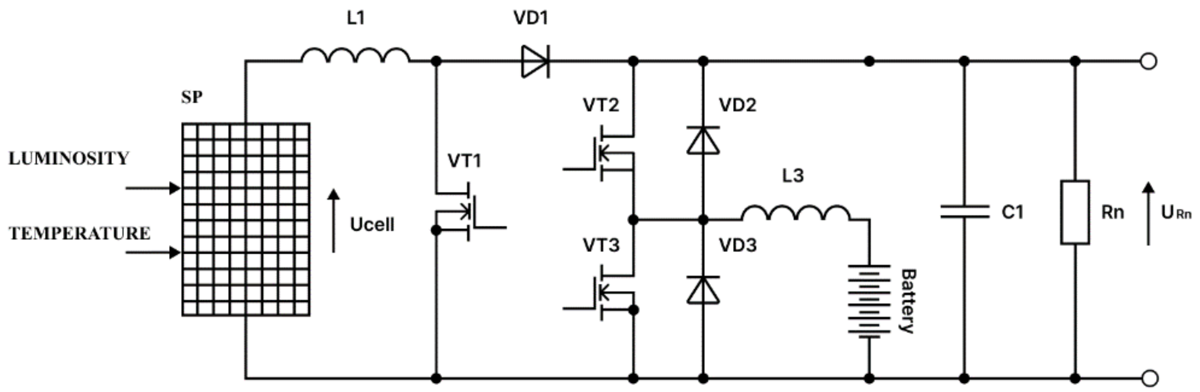

Fig. 1. Complete DC/DC converter circuit

The multiport converter contains three so-called ports. Two serve to connect the solar and battery, and the third to connect the load. Such a converter has a number of advantages over standard converters, such as a smaller number of components i.e. some components of the scheme are common to all ports, resulting in a system with a lower mass and a more compact package, which will provide lower converter cost. In addition, there is no need to harmonize the transducers and the transfer of information between the control systems i.e. often it is designed to be general. This transducer can work through three channels depending on which of the transistors the control pulses are received on.

Solar Current Channel

The substitution scheme is shown in Figure 2 as a step-up converter. Therefore, the voltage on the load should be more voltage on the solar battery. The stabilizer is controlled by pulse-width modulation. The control pulses are transmitted to the VT1 transistor.

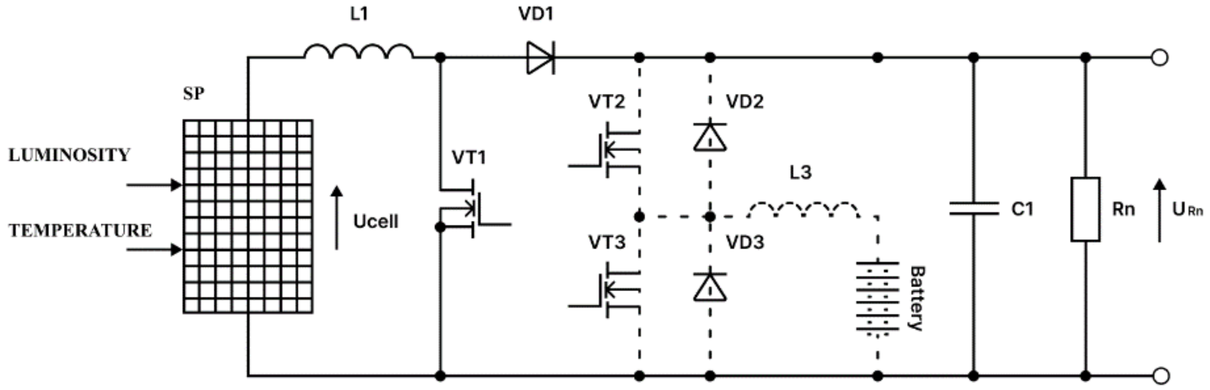

Fig. 2. Solar Battery Current Regulator

This circuit contains two switching elements (VT1, VD1) and two reactive elements (L1, C1). At the interval of energy accumulation in inductance, the transistor key is open, the voltage of the solar battery is applied to inductance. At the accumulation interval, a linear increase of inductance current from a zero level occurs. In this case, the diode is under reverse voltage and closed, and the container is slowly discharged on load. Energy storage and recovery intervals are described by the following equation systems:

$$\begin{cases} L\dfrac{di_L(t)}{dt} = U_C(t); \\ C\dfrac{dU_C(t)}{dt} = -\dfrac{U_C(t)}{R}, \end{cases} , \tag{1}$$

$$\begin{cases} L\dfrac{di_L(t)}{dt} - U_{in}(t) = -U_C(t); \\ i_L(t) - \dfrac{U_C(t)}{R} - C\dfrac{dU_C(t)}{dt} = 0. \end{cases} . \tag{2}$$

In formulas (1) and (2), enter L=$L$1, C=$C$1, U_{in}=U_{cell}, R=R_{n}.

Battery charge channel

The charge regulator shown in Figure 2 controls the battery charge in a variable current mode, depending on the luminosity level, while maintaining the voltage on the load. The VT2 transistor switch regulates the current flowing into the battery. The charging current decreases as the charge accumulates, thus avoiding the accumulation of gas in the accumulating elements, which in turn increases their lifetime. Thus, the operation of the charge regulator is similar to the operation of the stabilizer, and all the excess energy produced by the solar battery is stored in the battery, which leads to increased efficiency of the system as a whole. The transformation steps are described by the following equation systems:

$$\begin{cases} U_{in}(t) + L\dfrac{di_{L1}(t)}{dt} + L\dfrac{di_{L2}(t)}{dt} = U_{SP}(t) \end{cases} , \tag{3}$$

$$\begin{cases} L\dfrac{di_{L2}(t)}{dt} = -U_{SP}(t); \\ L\dfrac{di_{L1}(t)}{dt} + U_{in}(t) = -U_C(t); \\ i_L(t) - C\dfrac{dU_C(t)}{dt} - \dfrac{U_C(t)}{R} = 0. \end{cases} . \tag{4}$$

In formulas (3) and (4) we will also denote L=$L$2, C=$C$1, U_{in}=U_{cell}, R=R_{n}.

Battery discharge channel

The charge regulator in Figure 2 is a converter which increases the voltage obtained from the battery to the load voltage level by switching the VT3 key. The battery voltage, as with the solar battery current channel, is raised to the required level and stabilized on the load by storing energy in inductance and switching the power key. These processes are described by the following equation systems (5) and (6):

$$\begin{cases} L\dfrac{di_{L2}(t)}{dt} = U_C(t); \\ C\dfrac{dU_C(t)}{dt} = -\dfrac{U_C(t)}{R}, \end{cases} \tag{5}$$

$$\begin{cases} L\dfrac{di_{L2}(t)}{dt} - U_{SP}(t) = -U_C(t); \\ i_{L2}(t) - \dfrac{U_C(t)}{R} - C\dfrac{dU_C(t)}{dt} = 0. \end{cases} \tag{6}$$

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In formulas (5) and (6) we will denote: $L=L2$, $C=C1$, $U_{in}=U_{cell}$, $R=R_n$.

4.2 Configure the Neural Network for the Converter

Despite the advantages of the three-port converter, it is necessary to ensure timely switching between working channels. Therefore, the design of the control system becomes the most challenging task. The main component of such a control system will be the unit providing the converter operation at the maximum power point, that is, the control system must work with the maximum power point tracking algorithm. Because the characteristics of the solar panel are non-linear and the maximum power can be achieved only at one point. In order to extract maximum power from photovoltaic panels, regardless of weather and load conditions, it is necessary to work with maximum power to ensure maximum energy efficiency. Consequently, the control system that provides a maximum power point tracking function for all levels of solar radiation becomes the primary device for the successful operation of stand-alone systems. Since the characteristics of the solar battery are non-linear and maximum power can be achieved only at one point. To extract maximum power from photovoltaic panels regardless of weather conditions and load, it is necessary to operate at the maximum power point to ensure maximum energy efficiency. Consequently, the control system that provides a maximum power point tracking function for all levels of solar radiation becomes a key device for the successful operation of autonomous systems. The neural network comprises an input layer, two hidden layers and one output. The network input data are: the lighting, temperature, voltage and current of the solar module. The output neuron signal is equal to the voltage at which the maximum power of the solar module is achieved. Figure 3 shows the general ANN architecture that was used in the initial configuration of the control system to simplify the task of forming the control signal.

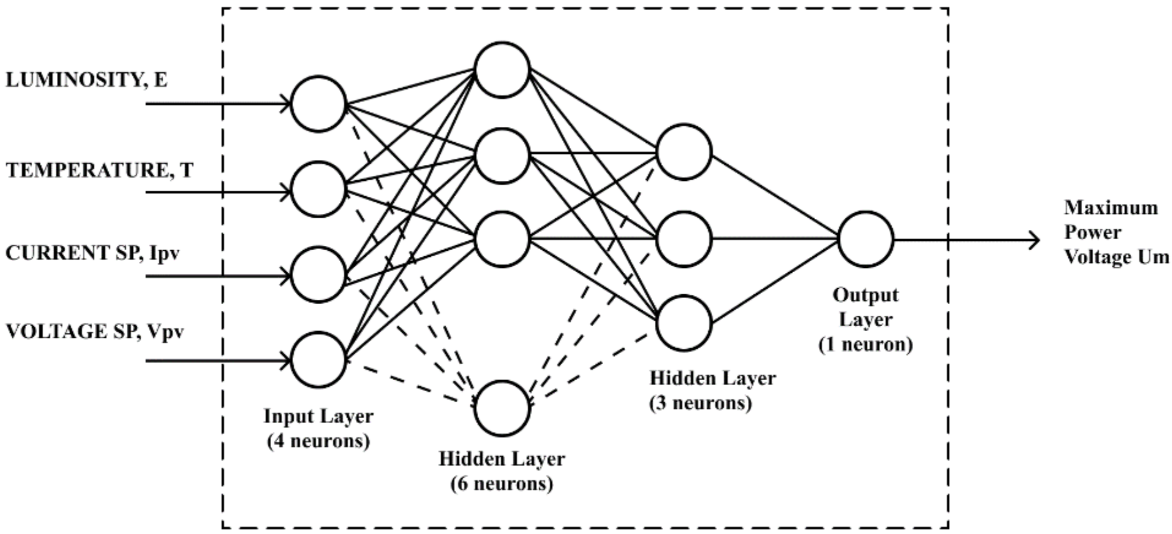

Fig. 3. Artificial neural network topology

The use of this neural network in the control system requires the use of additional sensors. This applies more to the use of light sensors. Since the luminosity of the system must be determined with sufficient accuracy for correct operation, there must be a sufficient number of sensors in the correct position. Faced with this problem, attempts were made to abandon the light sensor. The short-circuit current has a proportional dependence on illumination, it can be assumed that the solar panel's current data will be sufficient for ANN to operate correctly. Thus, according to the improved ANN methodology of creation and training, only the temperature, voltage and current values of the solar panel are received for the input of the neuronet.

4.3 Selection of input and output parameters for the artificial neural network

The structure of the system as a whole depends on which input data will be used in the artificial network. If a large amount of input data is used, then perhaps the number of INS neurons can be reduced to a minimum, but the number of sensors in the system increases, which imposes some difficulties in implementation. Thus, during the initial experiment, it was decided to use the instantaneous current and voltage values of the solar battery, lighting and temperature as input data for the artificial neural network. Output parameter-voltage at the maximum power point. Depending on how the control system is constructed (current or voltage), you can change the output parameter of the artificial neural network. The instantaneous current and voltage values of the solar battery must be fed into the grid inputs i.e. they are the basic parameters of the SP. There are also environmental values: light and temperature. Additional sensors will be needed to measure them and it is advisable to discard them altogether. We can only give up temperature if we know the temperature coefficient of the solar battery. But even if it is listed in the passport data, it does not guarantee that it is measured with high accuracy and will not change during the operation of the SP. Therefore, the temperature data will also be one of the required ANN input parameters. As for illumination, it is known that the current of the solar battery has a linear dependence on illumination and, therefore, the data on illumination will be «contained» in the current of the solar battery. Therefore, elimination of light and minimization of sensors is possible.

Data collection for learning

Each of the steps affects the structure and complexity of the neural network, but fundamental is the collection of data for learning and their preparation. One aspect of data production is adequacy. The number of training examples should be sufficient for training. The neural network requires that the number of training examples be several times greater than the number of weights, otherwise the network will not be able to generalize and will work well only on the data used to teach it. In addition, the sample size should be sufficient to form learning and test sets. The next aspect is diversity, i.e. it is necessary to provide a large number of different input-output combinations in instructional examples. Some problems can be encountered:

1. If the number of parameters is small, the same set of source data may be the same as the examples in different classes. Then it is impossible to train the neural network, and the system will not work correctly;
2. If the amount of data is large, processing and optimization can take quite a long time;
3. To get a lot of data you need to use specialized installations and it can take a long time. The last aspect is the uniformity of the class representation. Examples of different classes should be presented in a learning sample in approximately the same numbers. If one of the classes prevails, this may lead to «distortion» in the learning of the model, and this class will be determined by the model as the most likely for any new observations [12]. It is also worth noting that a large amount of training sample requires a large amount of memory for its storage, increases the time for ANN to inquire and collect information about the object. A learning sample with few data is not informative enough to characterize the behavior of an object with a decent quality. This will certainly result in the network being unable to predict the behavior of the object outside of the training sample.

4.4 Network topology selection

Which parameter will be the output of the artificial neural network, for different control systems, may differ. Control systems can be built on current and voltage at the maximum power point, as well as on the power itself, depending on the circuit used. In the case of an object such as a solar battery, the choice of the output parameter (current to MPP, voltage to MPP, power to MPP) will not give special consideration to the choice of topology of the artificial neural network for DC generation systems. As described earlier, neurons are combined into layers. The layer contains a collection of neurons with single input signals. The number of neurons in the layer can be any number and does not depend on the number of neurons in the other layers [13]. One of the problems when choosing a network topology is to choose the number of layers and neurons. An insufficient number of neurons in the hidden layer will not fully approximate the behavior of the object, and the prediction error will be large.

As a rule, the number of layers and neurons is chosen experientially and depends on:

1. Falsity of the task;
2. Number of data in the training sample produced;
3. “Noise pollution” of data;
4. Training sample dimensions;
5. Number of inputs and outputs;
6. The machine resources on which the network will be trained.

There is no strictly defined procedure for choosing artificial neural network architecture, but there are some simple rules [14, 15]:

1. If a function is defined on a finite set of points, a three-layer perceptron can approximate it.

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2. If the function is continuous and defined on a compact area, the three-layer perceptron is able to approximate it.

3. The rest of the functions that neural networks can learn can be approximated by a four-layer perceptron.

It follows that the maximum number of layers is four i.e. two hidden layers [15]. It is also important to note the specificity of the implementation of artificial neural networks. In a software implementation, it is recommended to stop at one hidden layer and increase the number of neurons to simplify subsequent calculations related to the implementation. For this maximum power point tracking task, it is recommended to use ANN with one hidden layer to minimize temperature related calculations as it changes rather rarely compared to changes in the current and voltage of the solar battery. As for the number of neurons in the hidden layer, they can be defined in several ways, for example empirically, i.e. by a way of selection, by determining the different number and evaluating how the network will change. There is also a more formalized method, this calculation according to formulas [16]. But this method is not true for all problems, and the most common method is to determine the number of neurons experientially, for example by using the method of half division. It can be concluded that determining the correct number of hidden layers and neurons is a very important task. If there are few neurons, the network will not be able to learn, and the network error will be very large. If there are too many neurons, then the learning time may be prolonged, and the network will retrain itself and will work with a big error on the examples not included in its learning sample. The main optimization criterion was accuracy. I.e. the number of neurons increased until the accuracy reached the optimal value. As far as retraining is concerned, the Matlab Neural Network Toolbox has a security feature that stops learning the neural network if it is retrained. The solution to the problem of retraining can be to increase the learning array. The next task when selecting a network architecture is to select the activation function. The neuron is fully described by its weights and activation function. After receiving a set of input data (an array of numbers), a neuron produces a certain number on the output. The activation function is of different types [17]. The most common activation features are:

1. Linear;
2. Non-linear with saturation (logistic or sigmoid);
3. Hyperbolic tangent.

Elliott's function was first introduced in 1993 by D.L. Elliott under the title "Best Activation Function for Artificial Neural Networks" [18]. The function is very close to the sigmoid and hyperbolic tangent of experimental modeling in Matlab software the function is computed more than 2 times faster than the exponential sigmoid function, which, for certain types of tasks, can lead to a significant increase in speed.

The next step is to choose the algorithm for the training. To train ANN, as a rule, the Levenberg-Marquardt algorithm is used. This algorithm is designed to optimize the parameters of nonlinear regression models. The standard error of the model on the learning sample is used as an optimization criterion. The Levenberg-Marquardt algorithm is based on a sequential approximation of the given initial parameter values to the desired local optimum. The Levenberg-Marquardt algorithm can be seen as a combination of the Gauss-Newton method and the gradient descent method. This algorithm has high convergence rate and computational robustness [19]. The learning process of an artificial neural network is the representation of an input learning sample of a certain volume. This is an iterative process, reducing the error function to an acceptable number of neurons. It is very difficult to know which algorithm will be the most accurate for this problem. This depends on many factors, including the complexity of the task, the amount of data in the learning set, the number of weights, etc. During the learning process, the network looks through the learning sample in a certain order. The viewing order can be sequential, random, etc. The neural network learning process involves adjusting the weight function and offset values to optimize network performance. Average quadratic error (MSE) is used as the network performance evaluation function. For a more accurate assessment of the reliability of the results of the network, you can use the comparison of reference values with the values obtained at the output of the network when a test array is submitted to the input. Ideally, the voltage obtained at the output of the neural network should be equal to the voltage at the maximum power point of the UMPP. In reality, there is some error in the ANN operation, and the points deviate from the ideal values. As noted earlier, only the solar panel voltage, the solar panel current and the temperature can be used as input to the neural network. In order to reduce the number of sensors, an experiment was carried out without regard to light. That is, only the temperature, voltage and current of the solar battery are reported as input to the neural network. The learning process was less successful than the neural network when the input light was present. Increasing the number of neurons in the hidden layer has resulted in the minimal average quadratic error MSE=0.00535. Table 1 presents the numerical results for the three levels of illumination, while Table 2 presents the results of the model without a light sensor.

Table 1

Results of the light sensor experiment

E, Watt/m^2	T,°C	I_{PV}, A	U_{PV}, V	Network response U_{max},V	Correct response U_{max}, V	Error, %
380	35.4	0.123	12.69	16.02	16.071	0.3
160	22.7	0.041	16.06	15.79	15.787	0.01
110	51	0.027	13.43	13.25	13.274	0.18

Table 2

Experimental results without a light sensor

T,°C	I_{PV},A	U_{PV},V	Network response U_{max},V	Correct response U_{max},V	Error, %
35.4	0.123	12.69	15.99	16.071	0.5
22.7	0.041	16.06	15.75	15.787	0.02
51	0.027	13.43	13.22	13.274	0.4

This neural network also contains one hidden layer, but the number of neurons needs to be increased to achieve the greatest precision. Since the most important task is to select the maximum power from the solar battery, it is possible to check how the generated PMPP power changes when the UMPP voltage fails. Having made the corresponding calculations, we find that the ΔP power error is 1.2%, which is significantly lower than the ΔU voltage error. For points where the voltage error does not exceed 1%, the relative power error was 0.6%. It can be concluded that the failure of the light sensor to reduce costs and operational problems due to various contaminants was the right solution. With proper configuration of the network topology, the accuracy of the work can be comparable.

4.5 Management system structure

In order for the transducer to function effectively, the maximum solar power must be selected for any of the channels. Depending on the channel of the converter, the operation of the control system was divided into modes depending on the operating conditions of the autonomous system as a whole. The operating conditions of the stand-alone system are: the daytime when the solar panel produces sufficient energy to power the load; evening or cloudy time when solar energy is not enough to load the required amount of energy; dark time when the solar battery is not producing energy. Based on these conditions, four modes of operation can be distinguished:

1. The first mode is to find the point of maximum solar battery power and stabilize the voltage on the load. Using an artificial neural network, it is estimated how much of the energy generated by the solar battery remains unclaimed and whether the battery can be connected.

2. If there is an excess of energy obtained from the solar battery, this system allows you to «transfer» part of the energy into the battery, connecting the charge channel Accumulator Battery. The control system, based on the data obtained from ANN, ensures a smooth transition from mode 1 to mode 2 so that when connecting the battery no stress failures on the load occur. The energy priority remains with the load, and the surplus energy from the solar battery is stored in the battery.

3. In the event that the illumination starts to decrease, the control system, receiving the task signal from the artificial neural network, gradually reduces the charging current of the battery to avoid overvoltage on the load. The maximum power is selected from the solar battery, and the power deficit is compensated by the battery.

4. Accumulator Battery provides a load stable voltage of the required level.

The simplified structure of the developed control system is shown in Figure 4.

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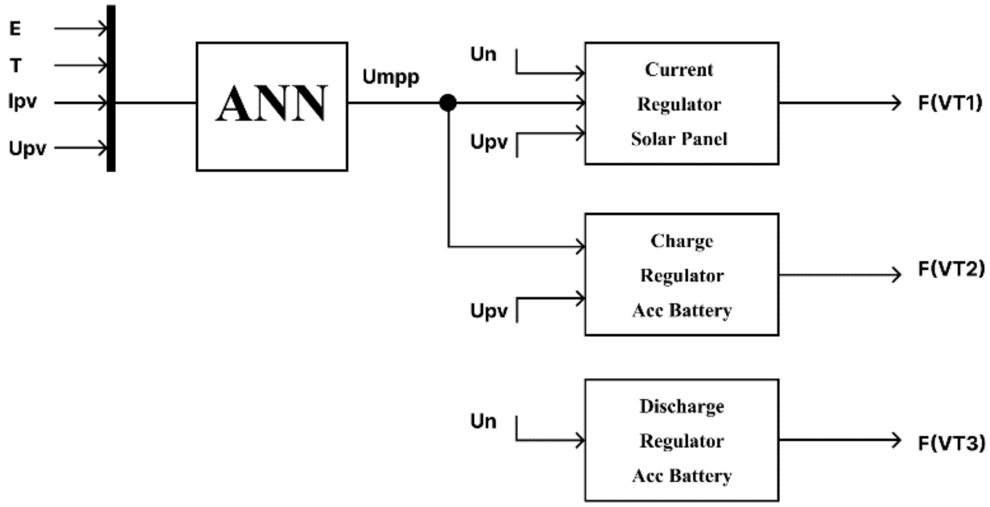

Fig. 4. Structure of the DC multi-port control system

The power circuit model and intelligent control system implemented on Matlab software elements are shown in Figures 5, 6. The control system has several main units:

1. The artificial neural network block. ANN provides the maximum power point tracking mode. The input to the network receives signals corresponding to the conditions in which the solar module is located: temperature, solar radiation, current and voltage on the output clamps of the solar module. The neural network generates two signals: a voltage signal corresponding to the maximum power voltage and a signal indicating the difference between the voltage at the maximum power point and the real voltage of the solar battery maximum power.

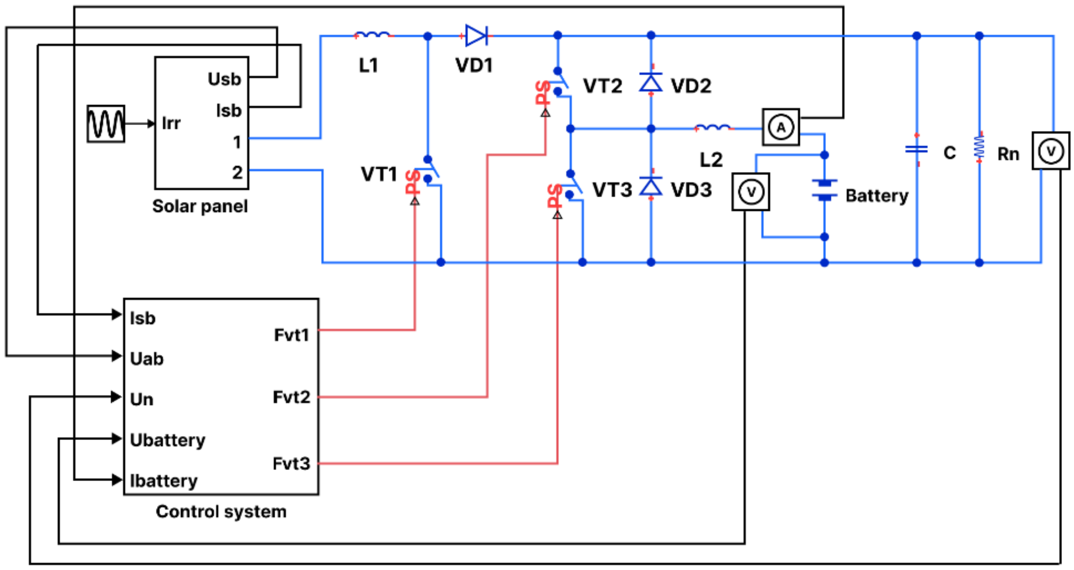

Fig. 5. Power circuit diagram of the transducer

2. Solar Panel current regulator. This unit compares the HIN signal with the solar battery voltage and determines the circuit operation mode. Next, the PWM block forms the control pulses coming to the VT1 transistor.

3. Accumulator Battery charge regulator. By comparing the solar battery voltage to the ANN maximum power voltage, the Latitudinal Pulse Modulation Controller (PWM) forms the pulses of control of the VT2 transistor, storing in the accumulator excess energy Solar Panel.

4. Accumulator Battery discharge regulator. Performs the function of voltage stabilization on load when powered by battery.

5. Also in the control system there are no charge and discharge blocks that provide protection against overcharging or full discharge of the battery, which greatly prolongs the life of Accumulator Battery.

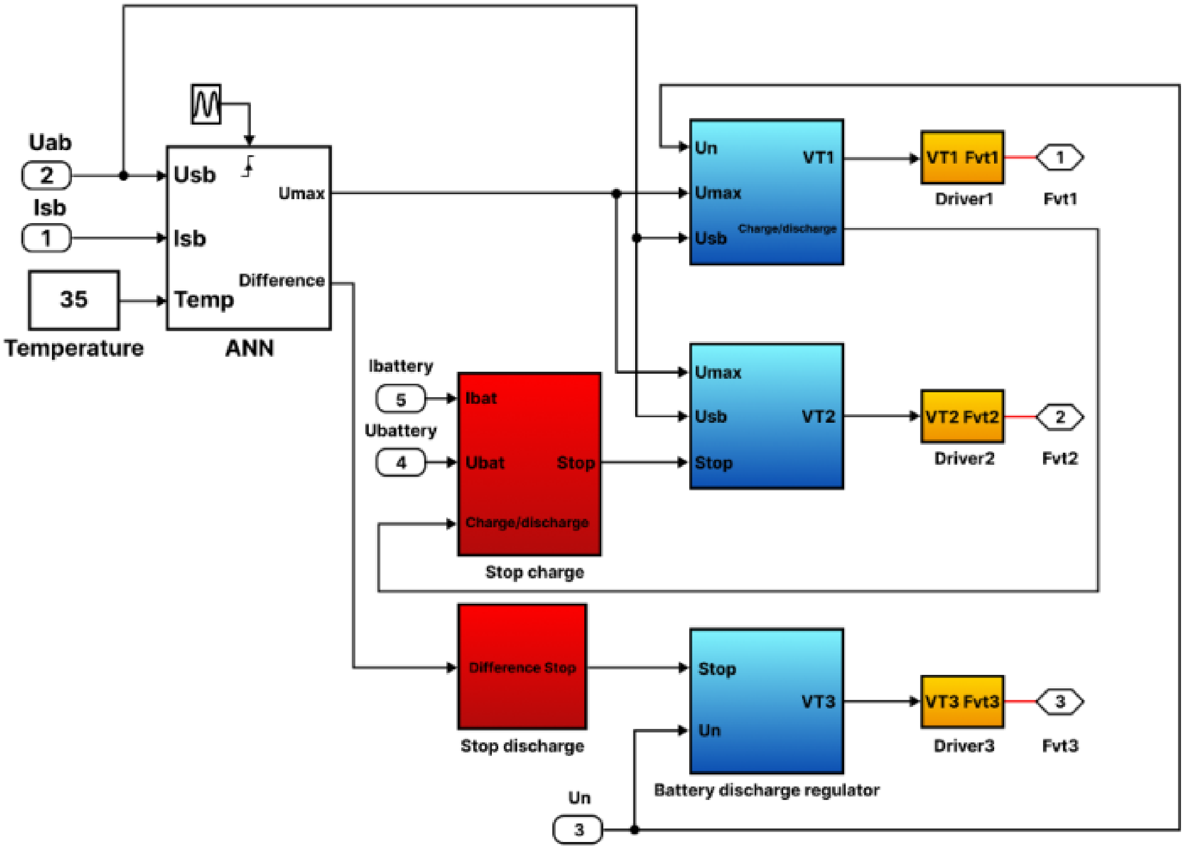

Fig. 6. Intelligent Control System

5. Simulation results

As the results of the numerical experiment are the current diagrams and voltage for the main modes of operation of the circuit. Figure 7 shows the time diagrams of the input and output voltage as well as the current of the battery. The luminosity level E=500 Watt/m^2, temperature T=35 °C. Analyzing the resulting graphs, it can be argued that this luminosity is sufficient to stabilize the voltage at 24 V. Excess energy is stored in the battery. The power supply from the neural net output is UMPPT=20.32 V. In this case the voltage on the solar panel in the settled mode is U_{SB}=20.49 V. Thus, the system takes maximum energy from the solar panel with an accuracy of 99.2%.

Further, the experiment was performed during the transition from low to high light. As can be seen in Figure 8 on the interval t1 at E=180 Watt/m^2, the voltage on the solar battery is not enough to power the load, hence the second channel is included in the work. I.e. the energy requirement of the system replenishes the battery connection. In this case, the maximum power from the solar battery is also selected, and the load is stabilized at 24 V. Simulating real conditions, the lighting is gradually increased to the level E=450 Watt/m^2 (interval t2). The output voltage is stabilized, the control system connects the battery charge channel, thereby storing excess energy.

Figure 9 illustrates the reduction in illumination to E=500 Watt/m^2. At the time of timet1, when the high light control system stores excess energy in the Accumulator Battery, increasing the charging current. Simulating real-world conditions, the illumination gradually decreased to the level of E = 360 Watt/m^2 (interval t2). You can see a short transition process of less than 0.01 seconds, but when the lighting is stabilized, the output voltage is set on the load, the control system connects the battery charging channel, thereby accumulating extra energy.

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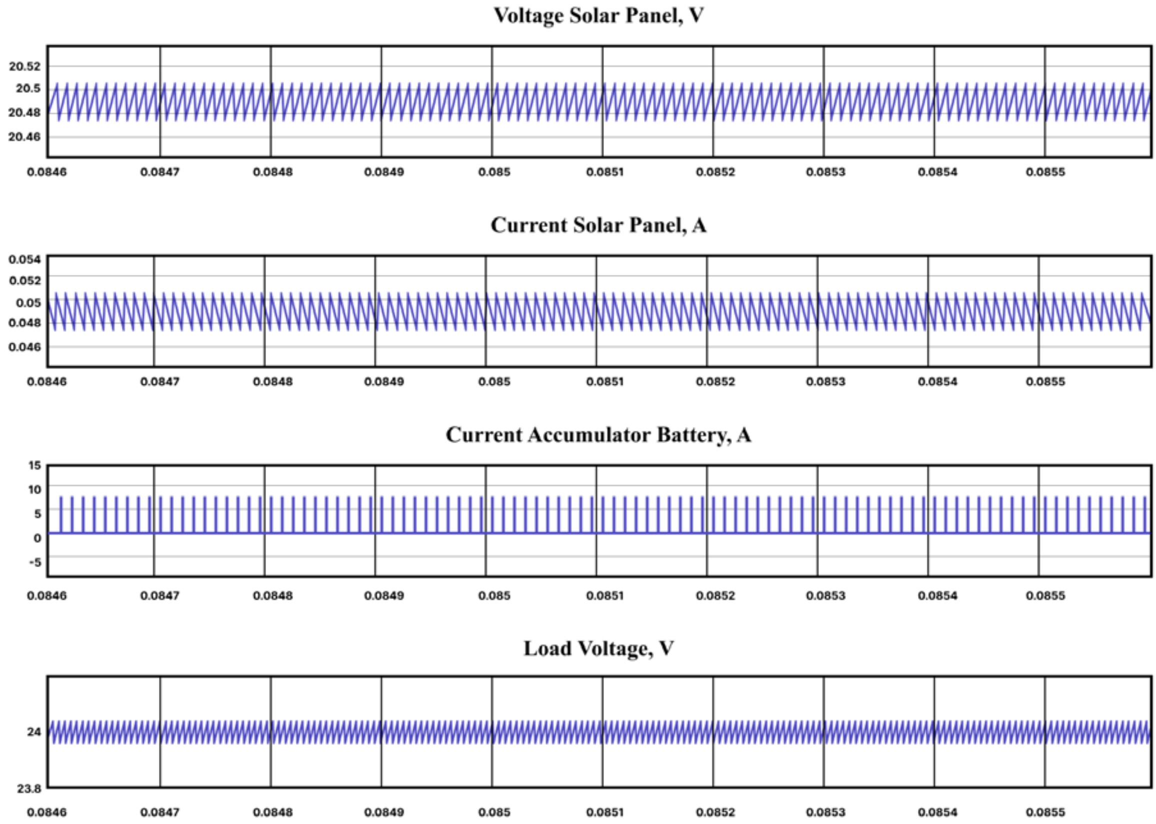

Fig. 7. Currents and stresses of the main elements of the scheme

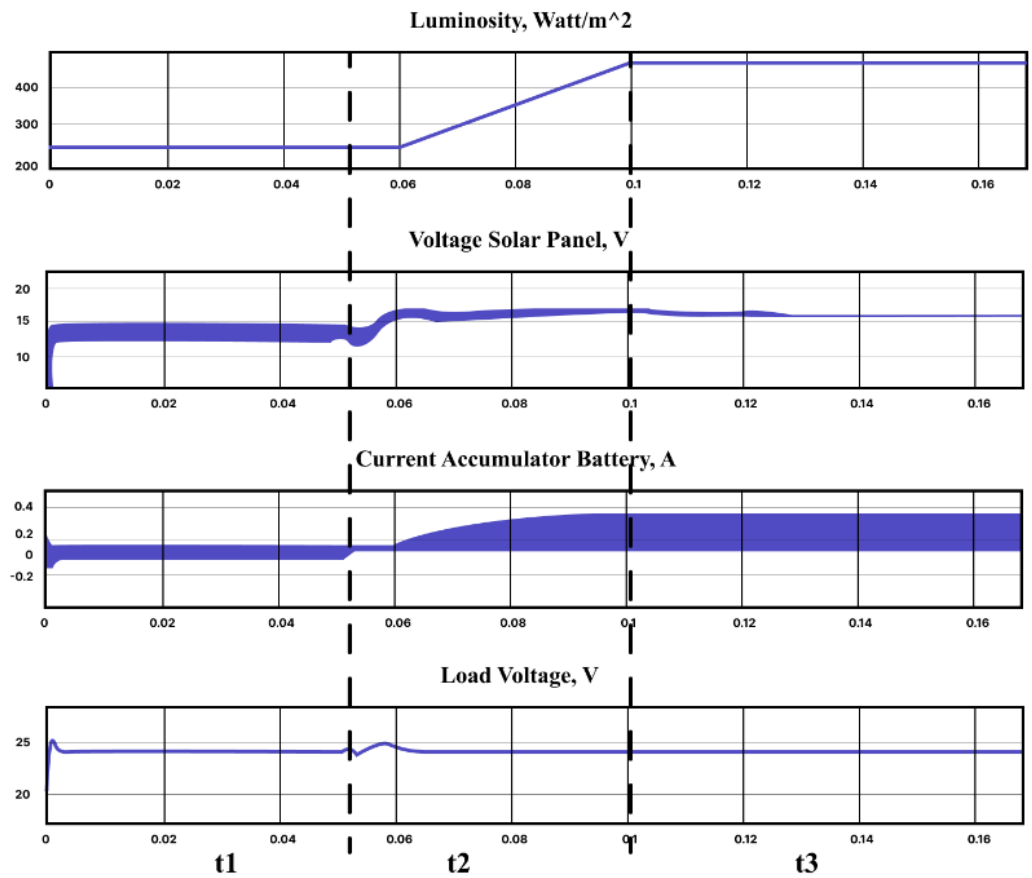

Fig. 8. Time diagrams of currents and voltages with increased illumination

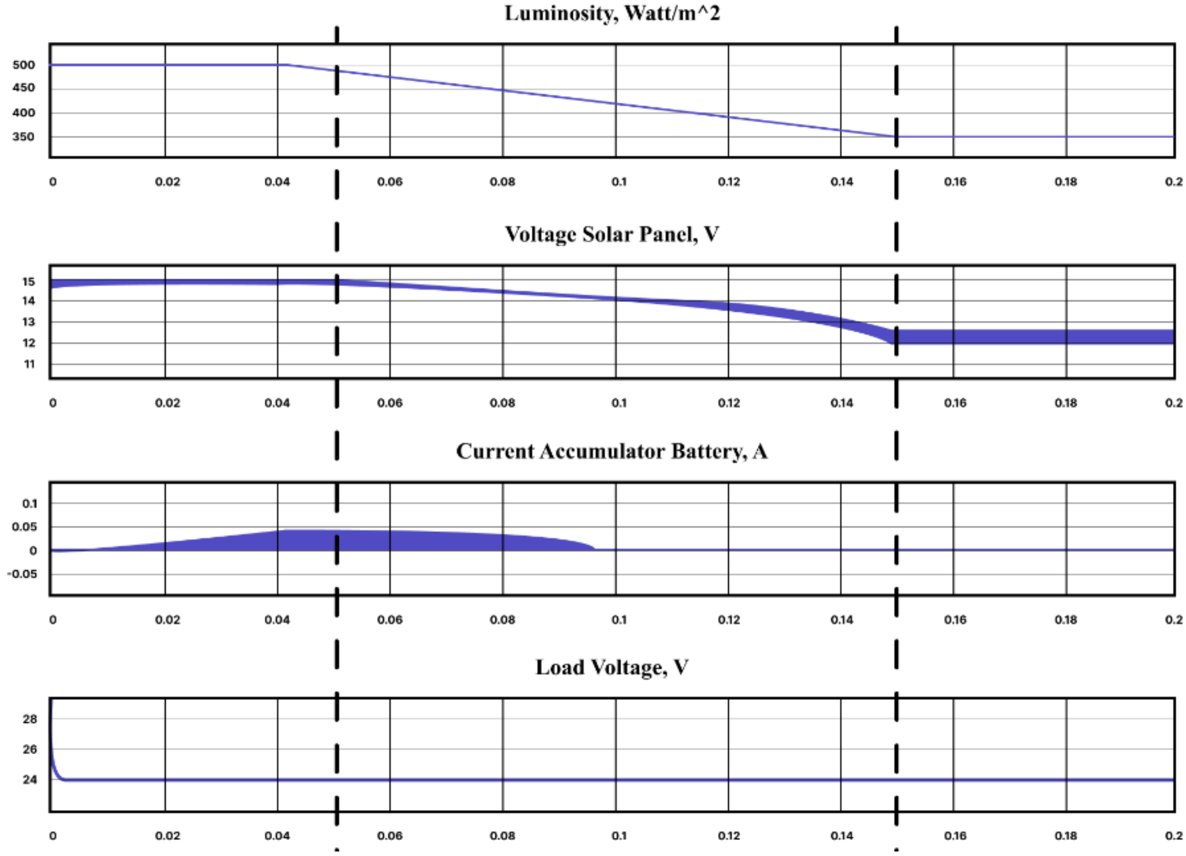

Fig. 9. Time charts with reduced illumination

Comparing this control system with the most common systems, also working on the basis of the algorithm of tracking the maximum power point (specified in the introduction), it is possible to say that this control system compared with the algorithm "Perturbation and observation" [20] most precisely defines the maximum power point, and compared to the algorithm "Increasing conductivity" [21] more quickly. When you change the installed power, the controls are configured differently. Systems based on "Perturbation and Observation" and "Increasing Conductivity" algorithms do not need to be reconfigured when changing power. The "Idle Voltage" algorithm, when replacing solar panels with a different type of battery, requires recalculation of the proportionality ratio between the idle voltage and the maximum power voltage. For the control system described in this article, if a single type of solar panel is used to increase the power of the stand-alone unit, then, depending on the connection, one of the ANN parameters should be reduced proportionally. If the connection is serial, then the voltage is reduced, and if the parallel – current. If you replace one type of solar cell with another, you need to retrain ANN by reassembling the teaching data. Once trained, this neural network can be used in various devices to calculate the maximum power point.

Conclusions

The simulation showed that the photovoltaic generation system based on the semiconductor three-port converter, the control system of which includes the artificial neural network, is a promising area of research and solves such problems as: reliability (in multi-port scheme the number of elements is reduced by the fact that some elements will work differently depending on mode); accuracy and speed (the neural network in the control system serves not only as a system for tracking the point of maximum power of the solar panel, but also quickly determines the mode of operation of the circuit). But when using a control system using neural networks, you should consider some features: if you increase the power of the stand-alone installation using the same type of solar panels, then depending on the connection, you need to proportionally change the ANN parameters. If one type of solar cell is being replaced by another, an artificial neural network with new input must be trained. After training, the neural network can be used in various devices to calculate the maximum power point. The rest of the off-line system can be easily calculated for any installed capacity. Failure of the light sensor does

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not impair the operation of the ANN as the number of neurons has increased. This solution does not significantly complicate the hardware implementation, but allows you to get rid of an external sensor, which can work incorrectly.

Simulation results show that the voltage at the maximum power point can be predicted by the neural network with an accuracy of 99.2%. The results thus show the effectiveness of this regulation. Artificial neural network-based maximum power point control systems are among the most efficient and promising ways to improve the energy efficiency of both off-grid and networked power plants. Advantages include rapid response to any changes in external conditions due to almost instantaneous generation of the signal coming from the neural network. The percentage of error between the maximum power voltage defined by the neural network, and the voltage of the solar panel at a certain point in time is 0.7%. In this case, the power error is about 4 times less, which is a good result, since getting maximum power is the main problem. As a rule, the solar cell's maximum power point is tracked in the DC link, and the voltage stabilization and conversion to AC voltage is done by an inverter. But this method, despite its advantages, is accompanied by losses due to multi-link transformation. As the experiment showed, the application of artificial neural networks in AC systems is a promising task. Even in a complex system, artificial neural networks perform well and allow maximum power point tracking with high accuracy and without lengthy transitions, which is a clear advantage. Experimental modeling showed good results. The only drawback of such a system is its complexity in software implementation, since not every microprocessor can handle such a task.

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