Machinery & Energetics
Vol. 15, No. 4. 2024

Journal homepage:
https://technicalscience.com.ua/en

UDC 621.316.1:519.8
Doi: 10.31548/machinery/4.2024.118

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Mathematical modelling of solar power converters

Abstract. The study was conducted to develop a mathematical model of photovoltaic systems using artificial neural networks. A mathematical model of the photovoltaic system was established, a simulation process was implemented considering key parameters, and a maximum power point tracking method was applied to improve the efficiency of the system. In this research, a mathematical model of photovoltaic system based on artificial neural networks was developed and tested to improve the efficiency of solar panels. The model showed high accuracy in predicting the maximum power point under varying environmental conditions such as illumination and temperature. Analysis of the data demonstrated that the use of neural networks for maximum power point tracking significantly reduces energy losses compared to traditional tracking methods. Experimental results confirmed that the proposed approach provides more stable and accurate detection of the maximum power point in real time. The findings showed that the implementation of such a system could significantly improve the overall performance of PV plants, especially under erratic solar conditions, making it promising for applications in different climatic zones. In addition, the model was shown to be robust to changes in input data parameters, making

Article's History: Received: 26.07.2024; Revised: 01.11.2024; Accepted: 27.11.2024.

Suggested Citation:
Sadykov, M., Temirbaeva, N., Narymbetov, M., Shabikova, G., & Turduev, I. (2024). Mathematical modelling of solar power converters. *Machinery & Energetics,* 15(4), 118-135. doi: 10.31548/machinery/4.2024.118

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it adaptive to different types of solar panels and operating conditions. It was also found that the neural network-based system reduces PV plant operation and maintenance costs by minimizing the need for manual calibration and monitoring. The resulting model will improve the accuracy and efficiency of maximum power tracking of solar panels under varying environmental conditions

Keywords: maximum power; illumination; temperature; prediction; neural networks

INTRODUCTION

Mathematical modelling of solar converters occupies an important place in improving their efficiency and reliability. With the increasing interest in renewable energy sources such as solar panels, more and more attention is being paid to the development of methods for optimizing their performance. Current approaches based on artificial neural networks allow for improved prediction and control, minimizing energy losses under changing environmental conditions. The development of mathematical models capable of accurately tracking the maximum power point (MPP) in real time is an important step towards increasing the performance of solar converters and their adaptability to different climatic conditions. These models help to ensure more efficient utilization of solar energy, which in turn helps to improve the resilience of the systems and makes them more attractive for deployment in different regions. Given current energy trends and challenges, integrating such models into the operation of solar plants can significantly reduce maintenance costs and improve overall performance, making research in this area particularly relevant.

The problem of improving the efficiency of solar power converters remains relevant in light of global climate change and the need for sustainable energy sources. C.G. Villegas-Mier *et al.* (2021) investigated the use of artificial neural networks to improve the efficiency of solar panels. In their work, the authors demonstrated that such networks significantly improve MPP prediction accuracy, which in turn can lead to more efficient utilization of solar energy under different conditions. A.M. Soomar *et al.* (2022) investigated methods for optimizing the performance of photovoltaic systems under varying solar activity. From their study, it was evident that adaptive models outperform conventional approaches by providing higher efficiency under variable environmental factors. K. Fatima *et al.* (2022) emphasized the integration of intelligent systems into MPP tracking. This solution helps to reduce energy losses and improve the overall performance of solar installations, which is important for reliability. C.D. Hewitt *et al.* (2021) proposed the development of adaptive models that take into account the climatic characteristics of different regions. They point out that this approach is important to improve the efficiency of solar systems, ensuring that they perform optimally in different climatic conditions. A. Elnozahy *et al.* (2021) discussed improving the stability of solar systems based on neural networks. The results of their study show that process automation can achieve more reliable operation of solar installations and minimize the risks of failures.

A. Mellit & S. Kalogirou (2021) analysed the impact of intelligent solutions on reducing operating costs. The paper demonstrated that minimizing manual calibration greatly simplifies the maintenance of solar plants and reduces their operating costs. K.B.M. Kiran *et al.* (2021) examined the robustness of models to changes in input parameters. In the study, the authors concluded that such models are more effective under a variety of operating conditions, making them promising for future use. M.A. Mari *et al.* (2021) emphasized the long-term reliability of the proposed solutions. Their research opened new perspectives for future research in the renewable energy field, allowing the improvement of solar energy technologies. P. Sharma *et al*. (2021) considered the possibility of integrating the new models into global energy networks. The authors highlighted that such integration could significantly expand the application horizons of solar technologies and increase their international availability. Nevertheless, there remain gaps in research on the impact of long-term operation on the stability of the models, as well as the need to better analyse the interaction of new technologies with existing energy systems. In addition, research does not fully cover the integration of renewable energy into existing energy infrastructure, which requires further attention. The aim of the study was to develop a mathematical model using neural networks to optimize the performance of solar panels under changing conditions.

The objectives of the study were:

1. Analysing the role of mathematical modelling in optimizing the performance of solar converters.

2. Reviewing various approaches to the use of artificial neural networks in the context of predicting the maximum power output of solar panels.

3. Evaluating the results of implementing these models in real-life operating conditions and their impact on the overall performance of the systems.

MATERIALS AND METHODS

In this study, the equivalent external characteristics' method was used to mathematically model the operation of a photovoltaic system. The main objective of this approach was to create a mathematical model of a high-power photovoltaic system that takes into account the key parameters of a real power source such as short circuit current, no-load voltage, maximum current, operating point voltage, temperature and illumination intensity, and physical properties of the solar cells. The modelling was carried out in MATLAB/SIMULINK environment, where the model parameters were carefully calculated to describe the operation of the photovoltaic power source. An important step in the process was the simplification of the complex mathematical equations detailing the operation of the photovoltaic cells, allowing the formulas to be optimized to accurately calculate current and voltage in response to light and temperature conditions.

One of the key steps was the use of a mathematical model including an equivalent circuit of the photovoltaic system based on an equivalent circuit consisting of a current source, diodes, and resistors connected in series and parallel. This model was used to calculate the dependence of the system current and power on temperature and illumination level, which is important for evaluating its performance (Fig. 1).

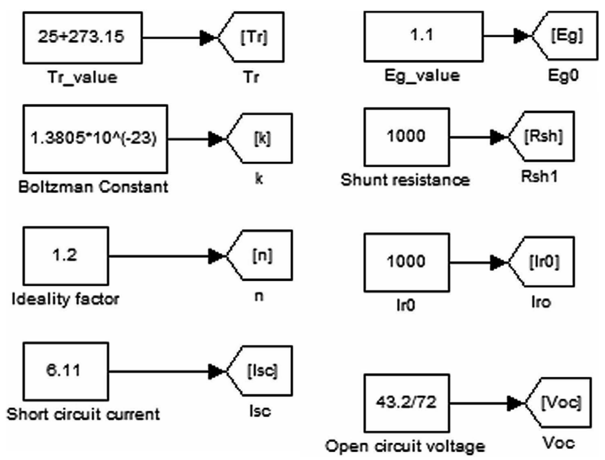

Figure 1. Parameters set before running the model

Note: Tr – reference temperature (298.15 K), n – diode ideological factor (1.2), k – Boltzmann constant, q – elementary charge, Isc – short circuit current under standard test conditions (STC), Eg0 – silicon forbidden bandwidth, Rs – series resistance, Rsh – shunt resistance

Source: created by the authors

As part of the study, a simplified version of the equations describing the operation of the photovoltaic system was created, making it easier to account for the effects of temperature and changes in solar radiation intensity on its operation. The main focus was on the equations for calculating the short-circuit current, no-load voltage, and maximum current and voltage at the operating point of the system. In order to obtain accurate results, a simulation modelling process of the solar module was developed based on the above equations. The process was carried out in a step-by-step manner where each circuit component including the photocurrent source, and the reverse saturation current of the module was modelled separately. Separate circuits were also created to simulate each equation at each stage of the calculation, which provided higher simulation accuracy and facilitated further analysis of the performance of the photovoltaic system.

In the investigated photovoltaic system, six modules were used, each module comprising six solar cells connected in series. This configuration was chosen to achieve the required power level. To improve the overall efficiency of the system, maximum power point tracking was implemented, which significantly improved its performance under varying light and temperature conditions. The use of modern technology in the simulation process will ensure high reliability and accuracy of the results, which will optimize the performance of photovoltaic systems and improve their efficiency in real-world conditions.

In this study, neural networks were used to optimize the mathematical modelling of photovoltaic systems. Specifically, artificial neural networks were applied and trained on historical data to predict power output as a function of temperature and lighting intensity. This approach allowed the identification of non-linear dependencies that are difficult to describe using traditional methods. Neural networks were also used to identify deviations in system performance, which increased the accuracy of the modelling and enabled effective monitoring and control of the photovoltaic plants, improving their overall performance.

RESULTS

Mathematical model of photovoltaic systems

Photovoltaic cells are the heart of solar cells. Their operation is based on the principle of converting light energy into electrical energy by means of a PN junction. The equivalent circuit of a photovoltaic cell includes photocurrent, which depends on the light intensity, and diode current, which is determined by the voltage on the cell. The external characteristic of a photocell describes the voltage dependence of the output current and allows calculating its parameters (1):

$$I = I_{ph} - I_{sat}\left(\exp\left(\frac{q(U+IR_S)}{Ak\theta}\right) - 1\right) - \frac{U+IR_S}{R_{sh}}. \qquad (1)$$

The parameters A, k, q, R_s and R_{sh} are included in the equation describing the solar cell voltampere characteristic. The ideality factor A characterizes the quality of the p-n junction, while the resistances Rs and Rsh account for ohmic losses in the base and emitter layers, respectively. To develop a mathematical model of a high-power photovoltaic system, the method of equivalence of external characteristics is applied. This method is based on the comparison of real solar cell characteristics, such as short-circuit current, no-load voltage and maximum power, with the parameters of a simplified electrical circuit (Katche *et al.*, 2023). The aim of the method is to create a universal model that allows simulating the behaviour of a photovoltaic system, regardless of the number and type of elements used. The mathematical model is created based on (Fig. 2).

Model description:

i. the term $(U+IR_s)/R_{sh}$ in equation (1) is much smaller than the photogenerated current and is ignored;

ii. under normal conditions, the resistance R_s is less than the forward conduction resistance of the diode, which allows us to ignore the coefficient $IR_s/Ak\theta$. In this case, I_{ph} can be equated to I_{sc}, which leads to a simplification of equation (1) to the following form (2):

$$I = I_{ph} - I_{sat}\left(\exp\left(\frac{IR_S}{Ak\theta}\right) - 1\right). \quad (2)$$

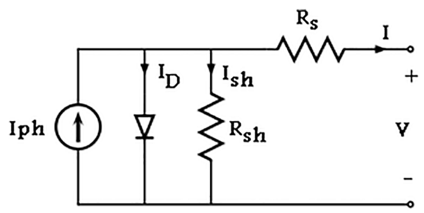

Figure 2. Schematic diagram showing the process of converting light energy into electrical energy in a solar cell

Note: I_{ph} – photocurrent current; I_d – diode current; I_{sh} – bypass current; R_{sh} – shunt resistor; R_s – series resistor; I – current, v – voltage

Source: created by the authors

If $C_1 = I_{sat}/I_{sc}$ and $C_2 = AR\theta/q$, then the above formula is expressed as (3):

$$I = I_{sc}(1 - C_1\left(\exp\left(\frac{U}{C_2 U_{oc}}\right) - 1\right)), \quad (3)$$

where U is the voltage at the terminals of the solar cell; U_{oc} is the open circuit voltage.

To find C_1 and C_2, the following two conditions are used:

i. in the open circuit state $I = 1$, $U = U_{oc}$;

ii. at the point of maximum power $U = U_m$, $I = I_m$.

When substituted into equation (ii), the authors obtain (4, 5):

$$C_1 = \left(1 - \frac{I_m}{I_{sc}}\right)\exp\left(-\frac{U_m}{C_2 U_{oc}}\right), \quad (4)$$

where U_m is the maximum voltage.

$$C_2 = \left(\frac{U_m}{U_{oc} - 1}\right)(1n\left(1 - \frac{I_m}{I_{sc}}\right))^{-1}. \quad (5)$$

Based on this, taking into account the change in temperature $\Delta\theta = \theta - \theta_{ref}$ and the change in light intensity $\Delta S = S/S_{ref} - 1$, it turns out (6-9):

$$I'_{sc} = I_{sc}(1 + \Delta S)(1 + a \times \Delta\theta), \quad (6)$$

$$U'oc = Uoc(1 - c \times \Delta\theta \ln(e + b \times \Delta S), \quad (7)$$

$$I'm = Im(1 + \Delta S)(1 + a \times \Delta\theta), \quad (8)$$

$$U'm = Um(1 - c \times \Delta\theta)\ln(e + b \times \Delta S), \quad (9)$$

where $\theta_{ref} = 25°C$ and $S_{ref} = 1$ kW/m^2 – ambient temperature and luminous intensity under standard conditions, respectively; $a = 0.0025°C^{-1}$ – current temperature coefficient under standard conditions; $b = 0.5$ – constant; $c = 0.00288°C^{-1}$ – temperature coefficient of voltage under standard conditions; e – base of natural logarithm.

As input data for the model, the main technical characteristics of the solar panel are used. Based on mathematical equations (3-8), a simulation model is created in MATLAB/SIMULINK environment, where current and power are output quantities depending on temperature and illumination level. The model is an electrical circuit including diodes, current source and resistors and allows simulating the operation of the solar module under different conditions (Fig. 3).

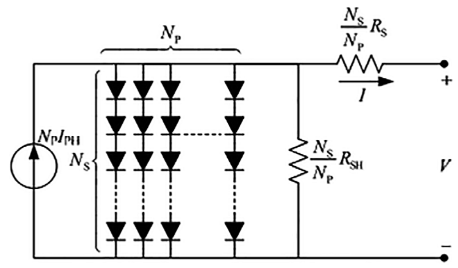

Figure 3. Electrical diagram corresponding to the actual behavior of a photovoltaic cell

Source: created by the authors

The mathematical model describing the dependence of current on voltage in a solar cell is as follows. The photocurrent of the module, i.e., the current generated by light, is (10):

$$I_{ph} = [I_{sc} + K_i(T - 298)] \times Ir/1000. \quad (10)$$

The dependence of the current on the voltage in a solar cell is described by the following equation. The current created by light is (11):

$$I_{rs} = I_{sc}/[\exp(qV_{OC}/N_S knT) - 1]. \quad (11)$$

Maximum module current (12):

$$I_0 = I_{rs}\left[\frac{T}{T_r}\right]^2 exp\left[\frac{q \times E_{go}}{nk}\left(\frac{1}{T} - \frac{1}{T_r}\right)\right]. \quad (12)$$

Current generated by solar panel (13-15):

$$I = N_p \times I_{ph} - N_p \times I_0 \times \left[\exp\left(\frac{\frac{V}{N_s} + I \times \frac{R_S}{N_P}}{n \times V_t}\right) - 1\right] - I_{sh}, \quad (13)$$

$$V_t = \frac{k \times T}{q}, \quad (14)$$

$$I_{sh} = \frac{V \times \frac{N_P}{N_S} + I \times R_s}{R_{sh}}, \quad (15)$$

where N_p is the number of panels connected in parallel; R_s is the resistance in the circuit; R_{sh} is the additional resistance; V_t is the temperature-dependent voltage.

The photocurrent given by equation (10) was numerically simulated and presented graphically in Figure 4 (at standard illumination intensity).

The dependence of the reverse current on various parameters is described by equation (11). The results of the numerical solution of this equation are presented in Figure 5.

The saturation current of the module is presented in equation (12) and modelled in Figure 6.

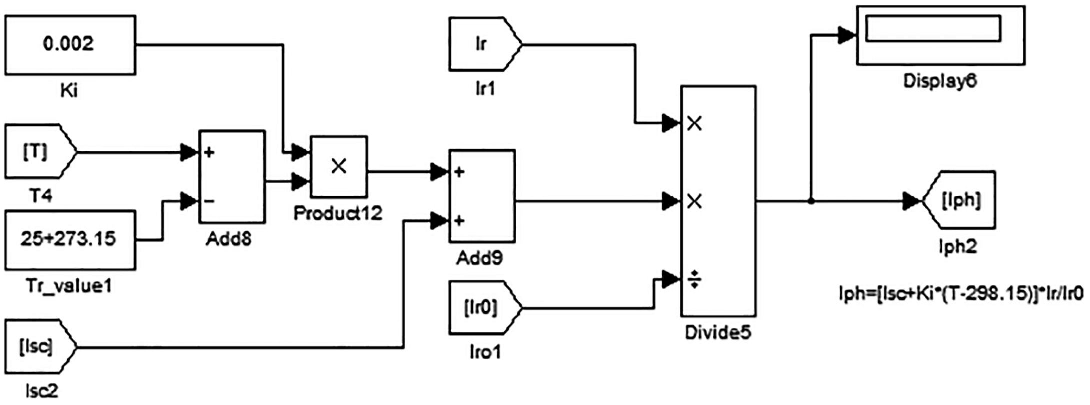

Figure 4. Simulated circuit for equation (10)

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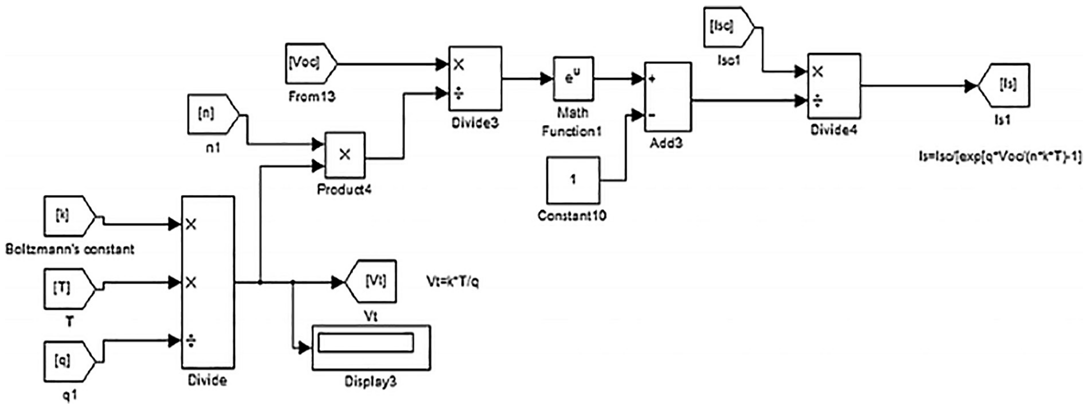

Figure 5. Simulated circuit for equations (11-14)

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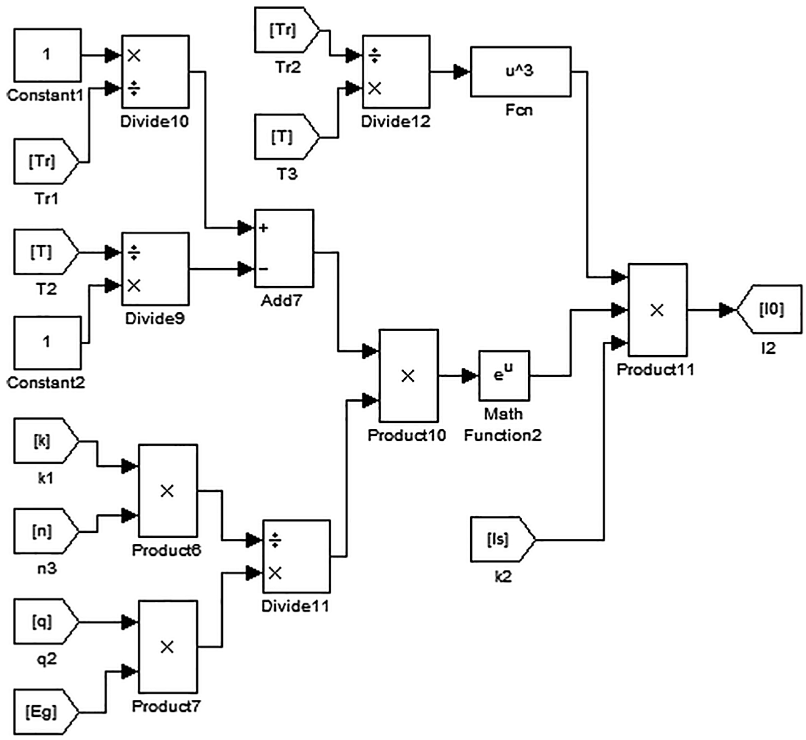

Figure 6. Simulated circuit for equation (12)

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It was simulated circuits for equation (15) (Fig. 7) and equation (13) (Fig. 8).

The simulation process of the solar module is shown in Figures 3-8. The photovoltaic system consisting of 6 modules with 6 elements connected in series was simulated and shown in Figure 9. Simulation can be used to evaluate the performance of photovoltaic modules and arrays under various operating conditions. Changes in solar radiation, temperature, and partial shading have a significant impact on the system output.

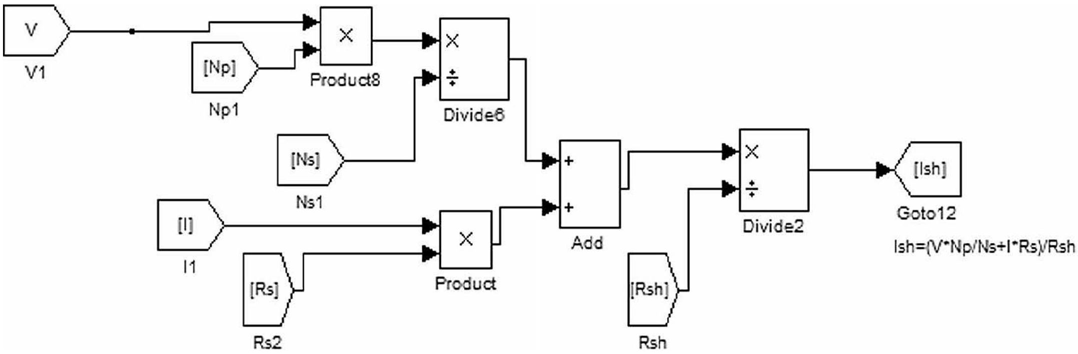

Figure 7. Simulated circuit for equation (15)

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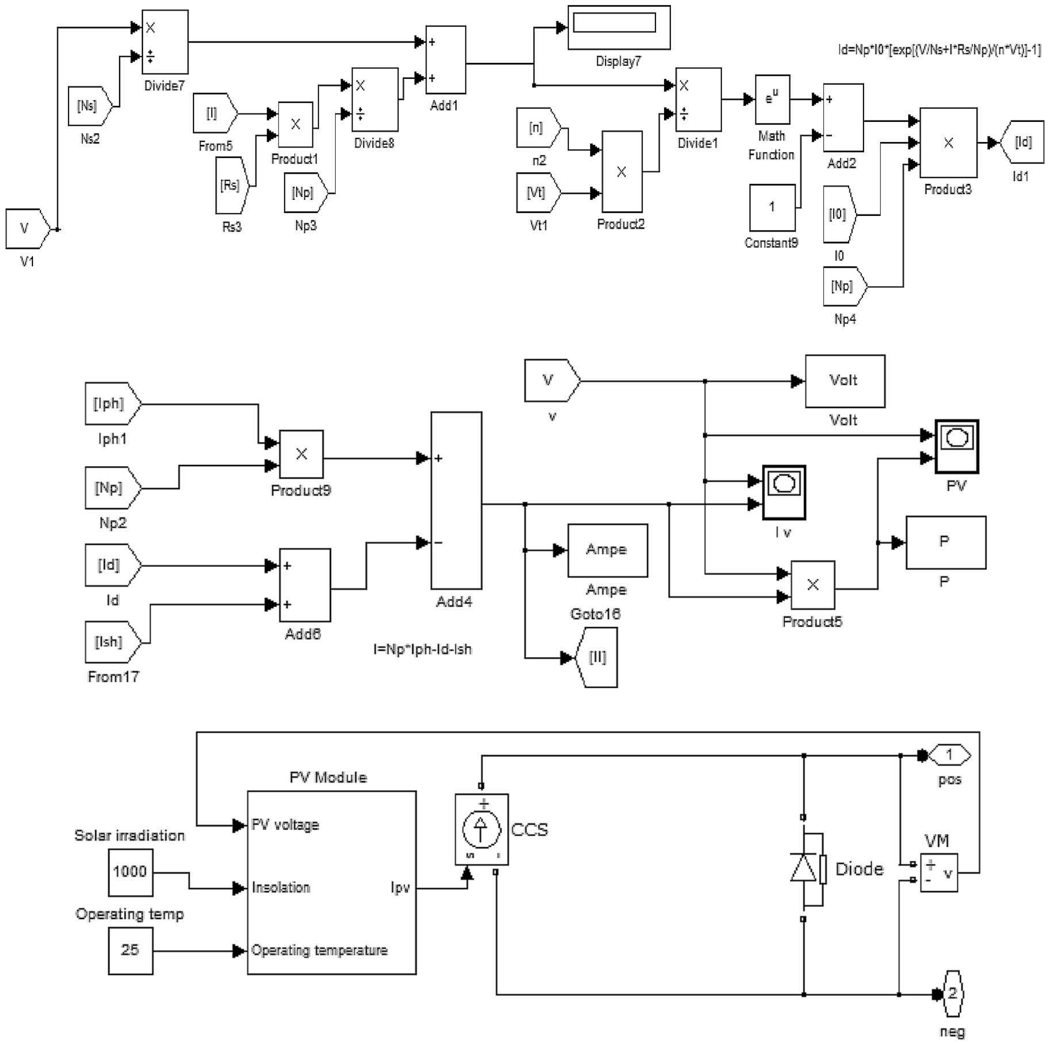

a

b

Figure 8. Modelling of a photovoltaic system

Note: a) block diagram corresponding to equation (13); b) simulation model of solar power plant

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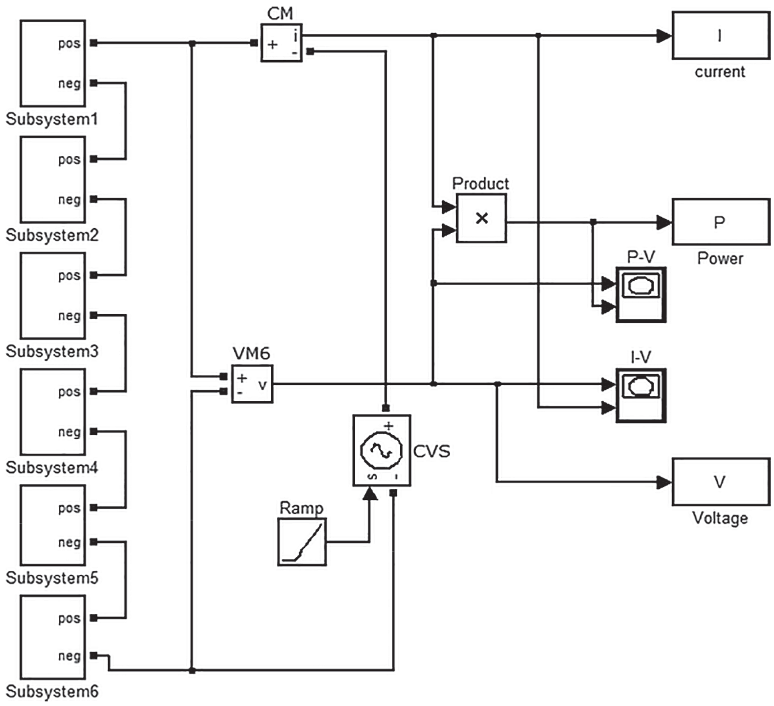

Figure 9. Model simulating the operation of a solar battery
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Optimization algorithms: MPPT in solar panels

Maximum power point tracking (MPPT) algorithms are used to improve the efficiency of solar energy conversion. Figure 10 shows a block diagram of a solar generator including a DC-DC converter with an MPPT algorithm.

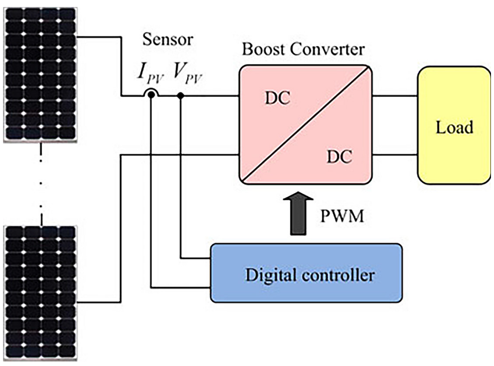

Figure 10. Structural diagram of the photovoltaic installation
Note: I_{pv} – current generated by solar panels (A); V_{pv} – voltage generated by solar panels (V); PWM – pulse width modulation – a method of power control in electronic devices by changing the width of DC pulses
Source: created by the authors

Boost converter, controlled by the MPPT algorithm, ensures maximum efficiency of the solar photovoltaic system. MPPT, in turn, uses data on solar radiation, temperature and other parameters to optimize the output power. Artificial intelligence allows increasing the speed and accuracy of the MPPT algorithm (Sarang *et al.*, 2024). The structural diagram of the system is shown in Figure 11.

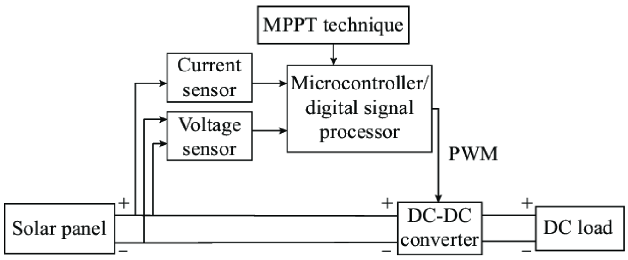

Figure 11. Scheme of the solar energy optimization algorithm
Note: PWM – pulse width modulation – a method of controlling power in electronic devices by changing the width of DC pulses
Source: created by the authors

Designing a traditional control system requires mathematical modeling, since the developer needs to create a mathematical model of the control object before monitoring it. Numerous artificial intelligence algorithms demonstrate satisfactory results, among which the algorithms of artificial neural networks (ANN, Artificial Neural Networks (ANN). In general, an ANN is a computational model that imitates a biological neural network (Pulvermüller *et al.*, 2021). In such a model, a neuron is a processor that first linearly weights the input data, then calculates the sum using a nonlinear function called the activation function (activation function, AF), and finally sends the results to the next neurons. The model of a regular neuron (Figure 12) is given by the relation:

$$z = \sum_{m=1}^{M} W_m x_m + \alpha, \tag{16}$$

where z is the final variable, which is the sum of the products, M is the total number of elements in the sum, W_m is the weighting coefficient for the mmm -th element, x_m is the value of the mmm-th element, which affects the final value, α is a constant or free term added to the sum.

Figure 12 shows a three-layer neural network, where the input layer receives a vector of features characterizing the solar battery (IPV and VPV), the hidden layer performs a nonlinear transformation of the input data, and the output layer generates a vector of output values.

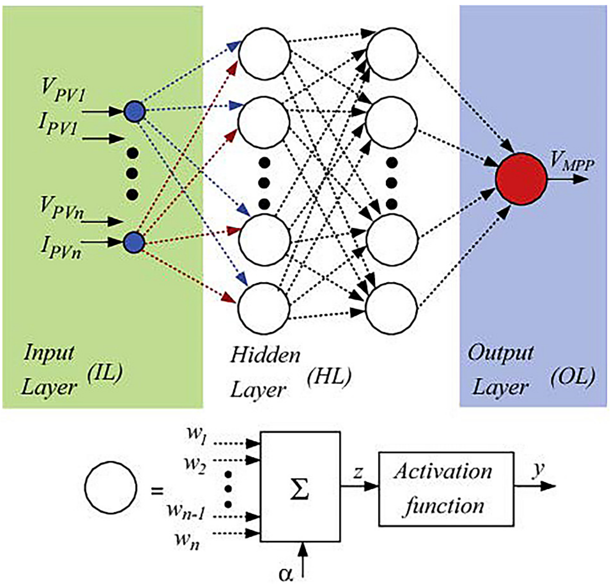

Figure 12. Neural network for solar panels

Note: V_{pv1}, V_{pvn} – input variables. V are the voltages measured on the photovoltaic panels (PV). Index "n" indicates the number of such panels or voltage sources used as input to the neural network, I_{pv1}, I_{pvn} – the corresponding currents for the same photovoltaic panels. These pairs of data (voltage and current) represent the state of each panel, Input Layer (IL) is the input layer of the neural network, Hidden Layer (HL) is the hidden layer of the neural network, Output Layer (OL) is the output layer consisting of one neuron that produces the predicted value – the voltage at the maximum power point, VMPP is the target variable denoting the voltage of maximum power point (Maximum Power Point), at which the photovoltaic system generates maximum electrical power

Source: created by the authors

ANN is used to train and test the nonlinear relationship between IV and PV characteristics. Using input data such as current, voltage, solar radiation, temperature and metrology data, ANN extracts these parameters and continuously learns to optimize the operation of the solar energy system to achieve maximum power. To implement the maximum power point tracking (MPPT) algorithm based on artificial neural network, a supervised learning method is used (Fig. 13). Solar radiation and temperature data are used as training data (Abouzeid *et al.*, 2024). A trained neural network controls a DC/DC converter to obtain maximum power from a photovoltaic array.

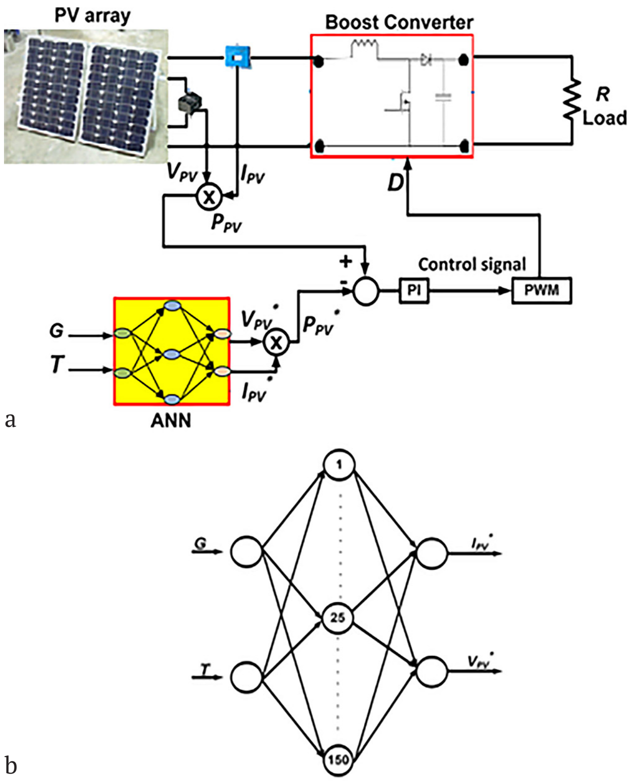

Figure 13. Modelling the operation of a photovoltaic system using a neural network

Note: a) system diagram; b) neural network structure

Source: created by the authors

Photovoltaic inverters are classified into two types (Salem *et al.*, 2024): stand-alone inverters for isolated systems (SAPV) and grid-connected inverters for systems connected to the general power grid (GCPV) (Fig. 14).

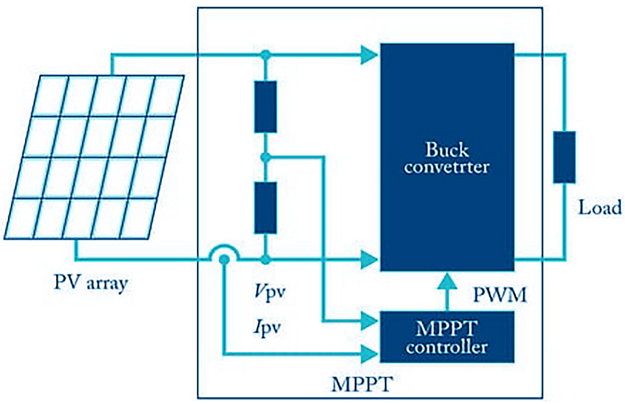

Figure 14. Autonomous SAPV system with MPPT inverter

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The volt-ampere characteristic (IV curve) is the most important parameter of a photovoltaic module, determining its electrical properties (Fig. 15). The maximum power point (MPP) on this curve corresponds to the optimal operating conditions of the module.

MPPT control using artificial neural networks (ANN) is being actively researched in photovoltaic systems (Roy *et al.*, 2021). The neural network demonstrates the ability to adaptively track the maximum power point in a wide range of meteorological parameters. The system operation diagram is shown in Figure 16.

Fuzzy logic (FL) provides an effective tool for designing controllers in systems with high uncertainty. A hybrid technique combining FL with artificial neural networks, better known as Adaptive Neuro-Fuzzy Inference System (ANFIS) (Figure 17), serves as a tool for dealing with nonlinear systems (Nabavi-Pelesaraei *et al.*, 2021).

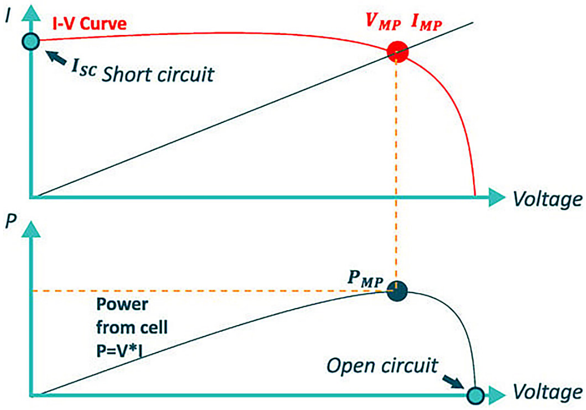

Figure 15. Volt-ampere characteristic of a photovoltaic module
Source: created by the authors

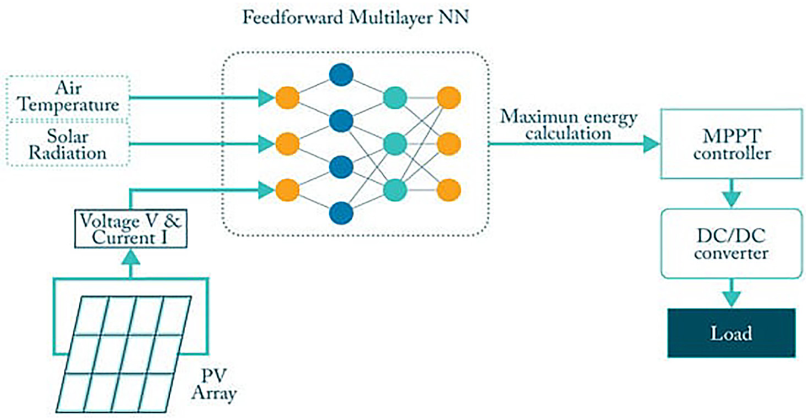

Figure 16. Neural network diagram for MPPT control
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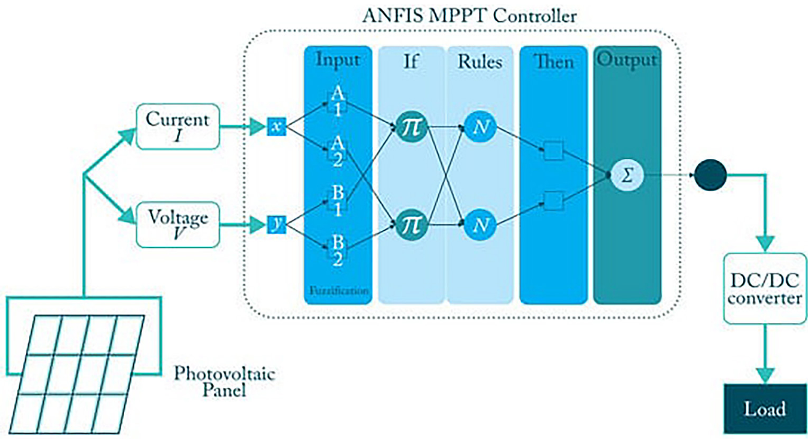

Figure 17. Block diagram of the ANFIS controller with 2 inputs
Source: created by the authors

Using a hybrid approach combining artificial neural networks and genetic algorithms in combination with the traditional P&O method allows optimizing the input data and increasing the efficiency of the MPPT algorithm. The scheme of such a solution is shown in Figure 18.

To improve the efficiency of solar energy conversion, it is proposed to use the MPPT algorithm based on artificial neural networks (Fig. 19). The model is trained on data obtained under various operating conditions, which allows it to adapt to dynamic changes in the external environment and ensure optimal operation of the system in a wide range of conditions (González-Castaño *et al.*, 2021). Figure 20 shows the DC/DC converter.

This figure illustrates the operating principle of a direct current to direct current (DC-DC) converter, where the listed elements play a key role in regulating electrical energy. The step-up converter, which operates on the principle of discontinuous conduction mode, consists of passive elements (choke, diode, capacitor) and an active element (switch). The P&O algorithm implemented in the converter control system ensures tracking of the maximum power point of the photovoltaic module by periodically changing the pulse width of the control signal (Osmani *et al.*, 2021). The disadvantage of the algorithm is the presence of output power fluctuations in the steady state, which can negatively affect the operation of subsequent elements of the system. Figure 21 illustrates the P&O algorithm.

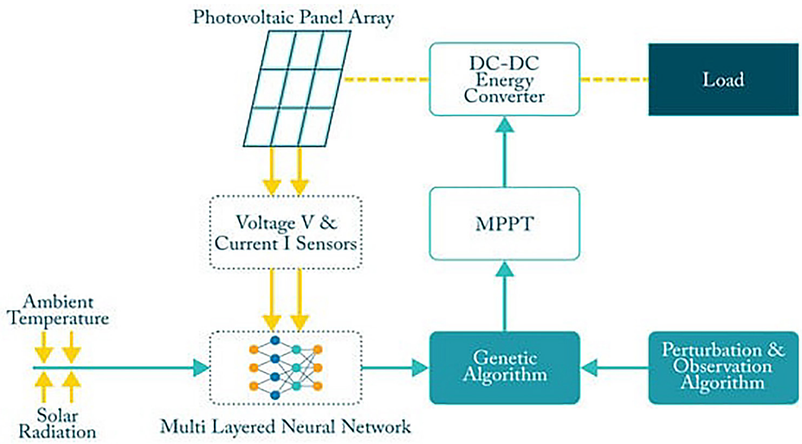

Figure 18. Structural diagram of a hybrid controller that optimizes solar battery energy production
Source: created by the authors

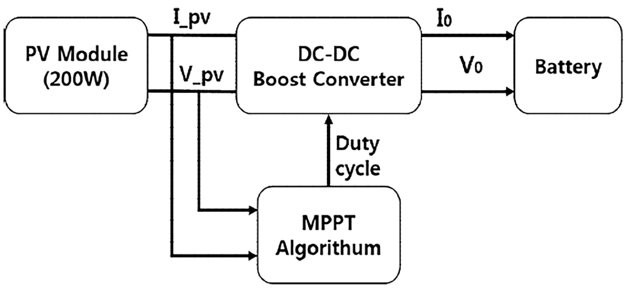

Figure 19. Solar energy production system
Source: created by the authors

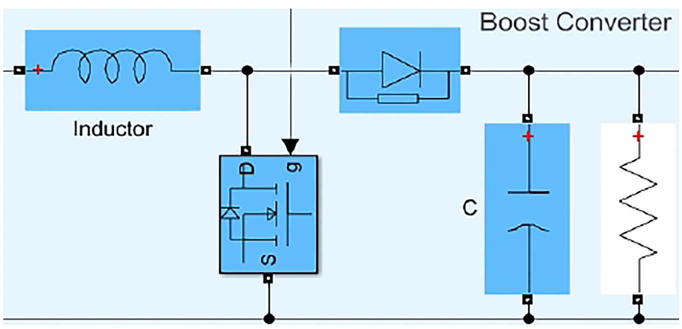

Figure 20. DC-DC converter
Note: D is a diode that ensures one-way flow of current in a DC-DC converter, s is a switch that controls the on/off of the circuit to regulate voltage and current, g is a control element for the key transistor used to change the state of the key, C is a capacitor that accumulates and smoothes the voltage, ensuring stable output voltage
Source: created by the authors

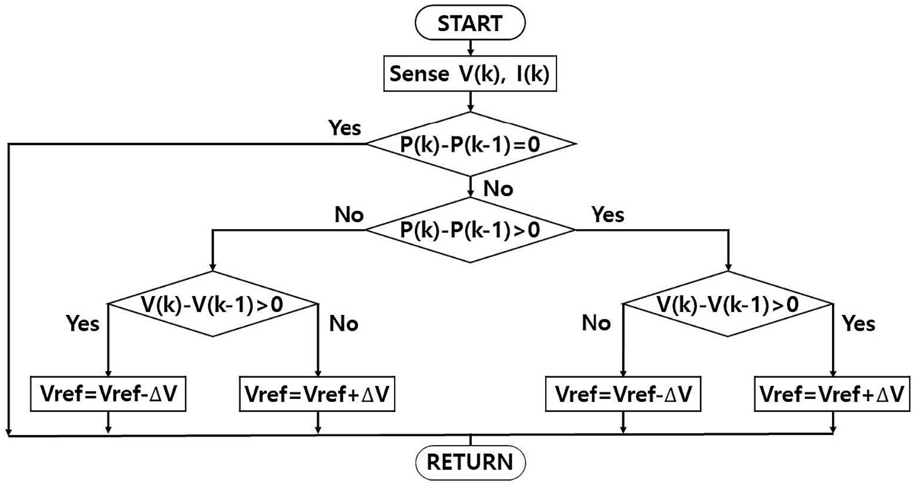

Figure 21. P&O Algorithm

Source: created by the authors

InC algorithm, based on the slope analysis of the voltage-power characteristic of a photovoltaic module, is one of the most common methods for tracking the maximum power point (Restrepo *et al.*, 2021). The method is characterized by high stability and ease of implementation and is widely used in combination with the P&O algorithm. Figure 22 illustrates the control principle of InC.

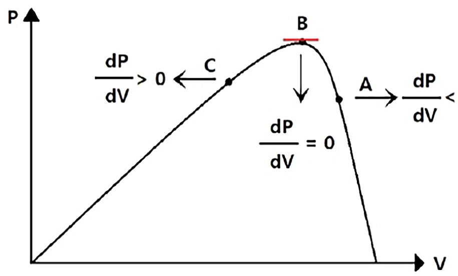

Figure 22. InC management theory

Source: created by the authors

Equation (17) has a positive slope of the VP characteristic curve, indicating the left MPP point, equation (18) has a negative slope, indicating the right MPP point, and equation (19) has a slope of 0, indicating the MPP point.

$$\frac{dp}{dV} = \frac{d(V \times I)}{dV} = I + V\frac{dI}{dV} > 0 \text{ (point C)}, \tag{17}$$

$$\frac{dp}{dV} = \frac{d(V \times I)}{dV} = I + V\frac{dI}{dV} < 0 \text{ (point C)}, \tag{18}$$

$$\frac{dp}{dV} = \frac{d(V \times I)}{dV} = I + V\frac{dI}{dV} = 0 \text{ (point C)}. \tag{19}$$

InC is an algorithm that overcomes the shortcomings of P&O and has the advantage that the solar panel output voltage always corresponds to the maximum power point voltage and does not deviate from the MPP tracking control. However, it requires significant computation and there is a high probability that the MPPT will not work due to sudden changes in solar radiation. Figure 23 illustrates the InC algorithm.

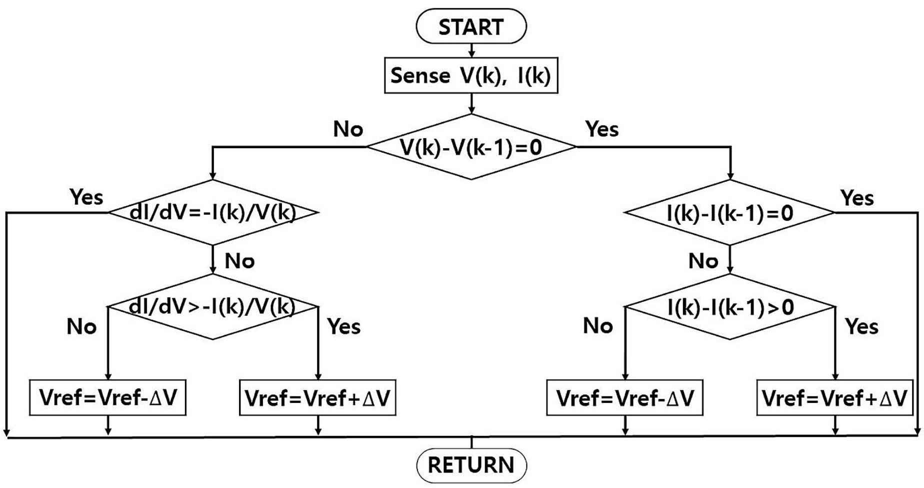

Figure 23. InC Algorithm

Source: created by the authors

Where V(k) and I(k) represent the current values of voltage and current, respectively, while V(k-1) and I(k-1) reflect their values at the previous step. dV and dI characterize the changes in photocurrent and photovoltage, and ΔV is the difference between the current and previous voltage values.

Neural networks in solar system management

The model combines the traditional MPPT algorithm with an artificial neural network to more accurately and quickly determine the maximum power point. The neural network, trained on current and voltage data under different lighting and temperature conditions, allows the MPPT algorithm to adapt to dynamic changes in the external environment (Fig. 24).

The model based on the neural network trained using the fuzzy logic controller enables the implementation of adaptive control of the DC-DC converter to track the maximum power point of the photovoltaic module. Taking into account the influence of temperature and solar radiation on the module parameters, the model provides higher efficiency compared to traditional MPPT algorithms. Figure 25 shows the photovoltaic modules and the neural network modules. Temperature and solar radiation are fed through IL Ctrl, which controls the photocurrent. The series resistance Rs and parallel resistance take into account the voltage drops and leakage current in the modules, and the output values are Ipv and Vpv. Figure 26 shows module schemes in fuzzy management.

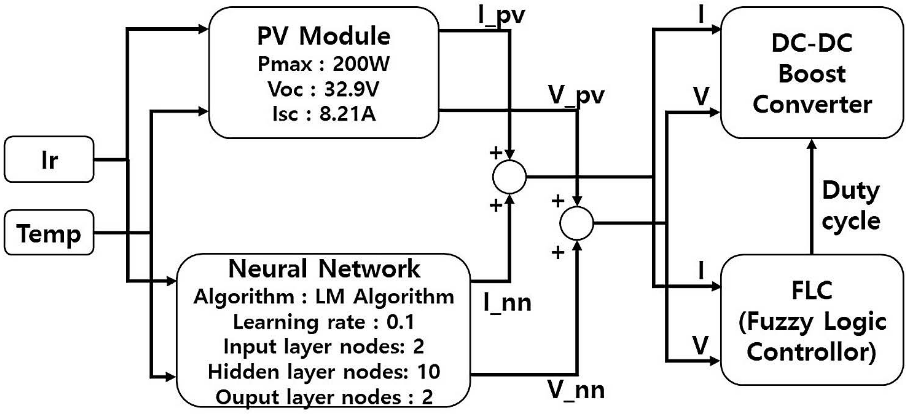

Figure 24. MPPT model

Source: created by the authors

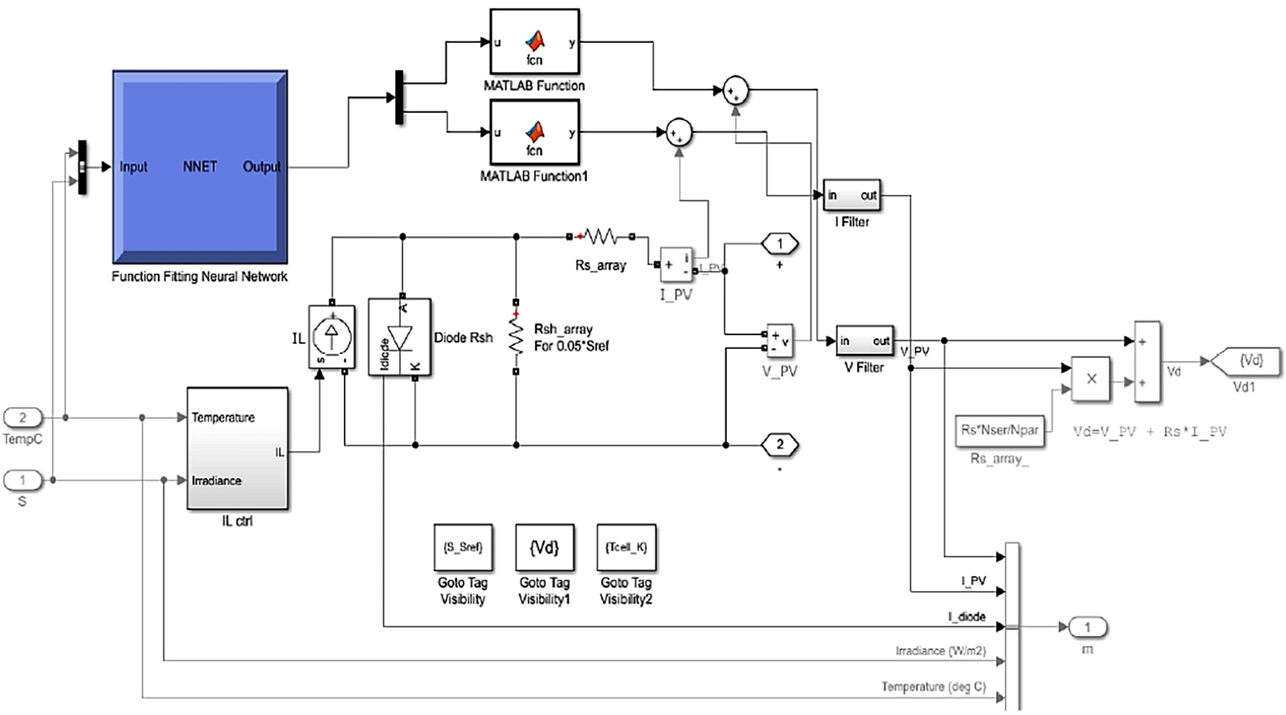

Figure 25. Photovoltaic and neural networks module

Source: created by the authors

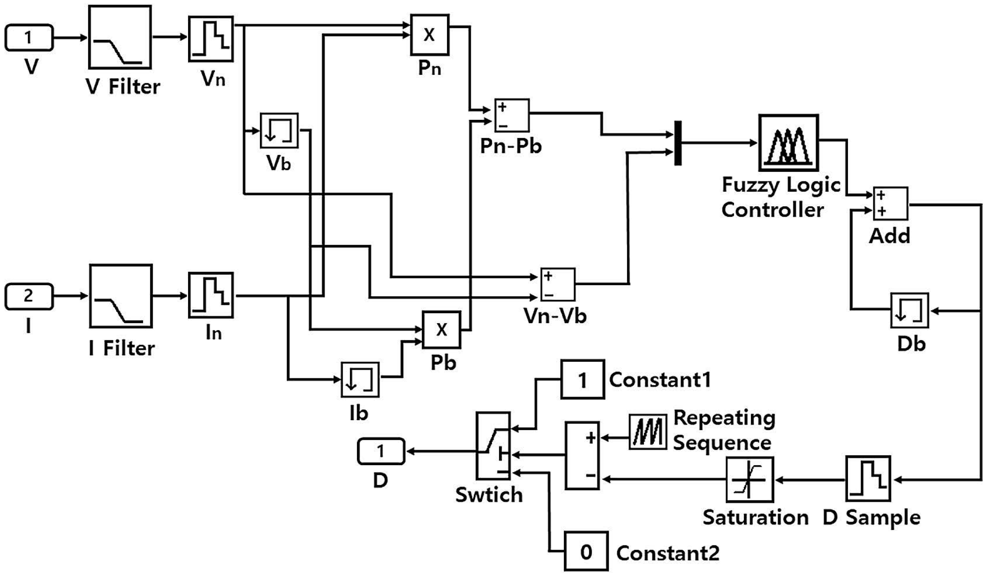

Figure 26. Fuzzy control circuit module

Source: created by the authors

Fuzzy Logic Controller (FLC) analyses how the solar panel power changes and sends a command to the converter to change the output voltage to achieve the best result. The input nodes of the artificial neural network are temperature and solar radiation, and the output nodes are the volt-ampere current MPP. The temperature range for the photovoltaic cells was from 0°C to 50°C in 5°C increments, and the solar radiation range varied from 200 to 1200 W/m^2 in 200 W/m^2 increments.

Since the temperature and solar radiation ranges to be used as input data are different, the data ranges must be the same or the distribution must be the same. In addition, since small input and output data are required for efficient AI training, the independent variables, temperature and solar radiation data, were normalized using min-max normalization, as shown in the equation (20):

$$\widetilde{d_i} = \frac{d_i - \min\,(1{:}d)}{\max(1{:}d) - \min\,(1{:}d)}, \tag{20}$$

where d_i – temperature and solar radiation data, min (1:*d*) represents the smallest value among each element, and max (1:*d*) represents the largest value among each element.

Nftool is a neural network tuning tool that performs training, validation, and testing by specifying the number of input units, output units, and mid-level nodes of an artificial neural network and choosing algorithms such as Levenberg Marquardt (LM), Bayesian regularization, and scaled confluent gradient. In this model, Nftool was used to build an artificial neural network with 2 input nodes, 10 mid-level nodes, 1 middle-level, and 2 output nodes. Figure 27 shows the structure of the artificial neural network.

Thus, the analysis of the theory and practice of modelling solar energy systems with ANN networks demonstrates the potential advantages of ANN in modelling these devices, such as high accuracy, generalization ability and short computation time compared to other theoretical and experimental modelling methods. Despite the simplifications applied in modelling based on ANN, their use eliminates the need to solve complex mathematical models.

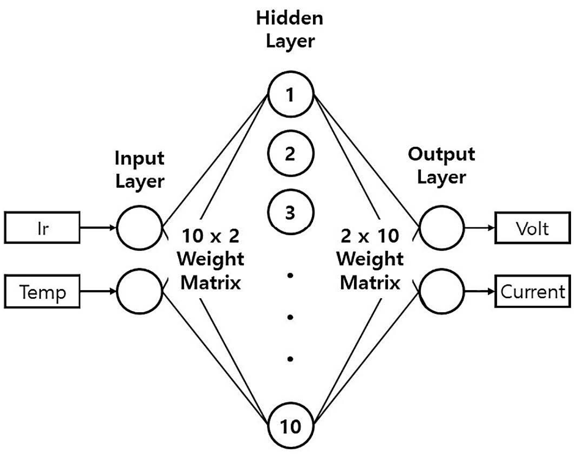

Figure 27. ANN structure

Source: created by the authors

DISCUSSION

In this study, a mathematical model of PV system based on artificial neural networks was developed and tested. The main result showed that the proposed model significantly improves the prediction accuracy of the maximum power point under varying environmental conditions such as illumination and temperature. The model also showed high real-time stability, which is important for improving the efficiency of solar power converters. This was also investigated by M. Talaat *et al.* (2022) where the results confirmed that predicting the maximum power point (MPP) of solar panels depends on the accuracy of tracking algorithms. These algorithms must take into account changing weather conditions to work correctly. The stability of the predictions is critical for optimizing power generation and reducing losses.

Studies by N. Ghadami *et al.* (2021) also showed that neural networks can learn efficiently from solar data and operating conditions. They are able to adapt to changing external factors, providing accurate control of the panels. This helps to improve system efficiency and reduce energy losses. It is worth noting that the use of neural networks in solar panel control not only improves their performance, but also minimizes the impact of human error. Automated systems with learning algorithms can respond faster to changes in operating conditions than traditional methods (Kudabayev *et al.*, 2022). This is especially important in a variable climate, where the accuracy of prediction directly affects the performance of the entire system. The results confirmed that neural networks are more efficient than traditional maximum power tracking methods such as perturbation and observation and incremental conductance algorithms. Neural networks are better at adapting to changing conditions, which significantly reduces power loss under erratic solar activity (Stoliarov, 2024). This is especially important for systems operating in regions with variable climatic conditions, where traditional methods are less efficient. A. Zafar *et al.* (2022) concluded that traditional solar panel control methods are often based on fixed maximum power point tracking algorithms. Neural networks, in contrast, have the ability to learn and adapt to changes in external factors. This makes them more flexible and efficient in the long term.

In a study by F. Granata & F. Di Nunno (2021), it was found that climatic conditions such as cloud cover and temperature significantly affect the performance of solar panels. Algorithms based on neural networks show high efficiency in changing weather conditions by quickly adjusting the system settings. This allows maintaining an optimal level of power generation even under unfavourable climatic conditions. These results support the above study, as neural networks have shown high adaptability to different operating conditions. Unlike traditional methods, they respond faster to environmental changes, which helps to minimize energy losses (Smyk & Arkhypova, 2023). In addition, their self-learning ability enhances system performance in the long term. Another significant finding was that the developed model showed robustness to changes in input parameters such as solar radiation intensity and operating temperature. This indicates the high adaptability of the model to different operating conditions and its ability to work correctly with different types of solar panels. Thus, the proposed system can be applied in a variety of climatic zones and scales of solar installations.

Of note is the work of J. Jasiūnas *et al.* (2021), who also found that neural networks allow the system to adapt to rapid changes in environmental parameters such as light level and temperature. Due to its ability to learn from a large amount of data, the system can adjust its performance in real time. This increases the stability of power generation and reduces the risks of efficiency degradation. In turn, S. Gorjian *et al.* (2021) concluded that the developed neural network-based models can be successfully applied to both residential and industrial solar installations. Their versatility allows systems to be customized for different scales and operating conditions. This makes them attractive to a wide range of users, from private homeowners to large energy companies.

These findings are consistent with the thesis in the previous section, where the flexibility and adaptability of neural networks were discussed. Models using such networks are not only better able to cope with environmental changes, but are also more versatile in their application. This confirms their relevance for different types of solar installations and a wide range of climatic conditions. Experimental results have also demonstrated that automating the maximum power point tracking processes using neural networks reduces the operation and maintenance costs of PV installations. This is achieved by minimizing the need for manual calibration and continuous monitoring. Reducing human intervention in system operation not only reduces operating costs but also improves system reliability and durability (Shahini *et al.*, 2024). M.S. Qureshi *et al.* (2024) also conducted a study, the results of which confirmed that the use of neural networks in solar panel control contributes to lower operating costs through more accurate prediction and optimized operation. The systems automatically adjust their operation, which reduces the need for regular maintenance. This reduces the cost of repairs and technical inspections, increasing cost efficiency. J.F. Derakhshandeh *et al.* (2021) also found that automating solar panel control processes using neural networks reduces the need for constant human monitoring. Algorithms are able to independently monitor and adjust system operating parameters in real time. This not only reduces the risks of human error, but also makes operation more convenient and efficient (Szafraniec *et al.*, 2021).

Comparing the data obtained in the course of research, there is a clear trend towards cost reduction and increased efficiency due to the automation of processes. Neural networks can minimize human involvement and optimize the operation of solar systems in the face of various external factors (Rexhaj, 2024). This emphasizes the importance of adopting such technologies to improve overall performance and reduce operating costs. In addition, the proposed mathematical model opens up opportunities for further research in the field of optimizing the performance of solar converters. This includes the development of methods for integrating weather forecasting and solar panel angle control to further improve the efficiency of power systems. Combining such approaches with neural network algorithms can significantly improve the management of energy resources.

G. Li *et al.* (2022) concluded that the field of solar energy continues to evolve, opening up opportunities for further research in optimizing panel performance and energy storage. One area of focus is improving neural network-based algorithms to improve their accuracy and responsiveness. Research into integrating solar systems with other renewable energy sources to create hybrid solutions is also relevant. S.U. Khan *et al.* (2023) revealed that integrating artificial (AI) intelligence with weather forecasting systems can improve real-time control of solar panels. AI can analyse weather data and adjust panel operating parameters to maximize energy generation. This enables more accurate and efficient utilization of solar energy, especially in regions with variable climatic conditions.

When analysing the results of the study, it is clear that integrating AI with weather forecasting significantly improves solar panel management. Such technologies not only improve the accuracy of the systems, but also allow them to adapt to rapidly changing climatic conditions. This opens new perspectives for a more efficient utilization of renewable energy sources and their integration into the energy networks of the future. In conclusion, the developed model shows significant potential for solar energy applications. The increased accuracy of maximum power prediction, reduced operating costs and improved system stability make this approach promising for widespread deployment in the renewable energy sector, especially under intermittent solar conditions.

CONCLUSIONS

As a result of the conducted study of mathematical modelling of solar electric power converters, several key conclusions have been reached, reflecting the efficiency and relevance of these technologies. The developed mathematical model based on the equivalent circuit of photovoltaic cells has demonstrated high accuracy in describing the basic electrical characteristics of solar modules. The model takes into account the influence of factors such as ambient temperature, light intensity and resistance, which allows a detailed analysis of the power output of the converters under different conditions.

The equations used to describe the photocurrent and saturation inverse current were the basis for creating an efficient simulation in the MATLAB/SIMULINK environment. This simulation provides the opportunity to investigate the behaviour of solar converters under different environmental conditions, which in turn improves the prediction of their performance and life cycle. The implementation of maximum power point tracking algorithms has had a significant impact on the performance of solar systems. The results of the study showed that the algorithms based on artificial neural networks provide more accurate and faster maximum power point detection compared to traditional methods such as lift-and-watch and incremental conductance. This significantly improves the overall performance of solar converters.

The results of the study highlight the importance of mathematical modelling and the application of advanced algorithms to optimize the performance of solar power converters. These findings offer new opportunities to improve their efficiency and incorporate them into sustainable energy supply systems, thereby promoting renewable energy development and reducing dependence on conventional energy resources. The limitations of this study are the focus on mathematical modelling of solar electric power converters without considering the actual operating conditions and environmental influences, which may affect the accuracy of the results obtained. It is necessary to study the impact of different materials and solar cell manufacturing technologies on their efficiency and durability, as well as to assess the economic feasibility of introducing innovative solutions into the mass production of solar electric power converters.

ACKNOWLEDGEMENTS

None.

CONFLICT OF INTEREST

None.

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Математичне моделювання сонячних перетворювачів електроенергії

Анотація. Дослідження було проведене для розробки математичної моделі фотоелектричних систем з використанням штучних нейронних мереж. Було створено математичну модель фотогальванічної системи, реалізовано процес симуляції з урахуванням ключових параметрів, а також застосовано метод відстеження максимальної точки потужності для підвищення ефективності роботи системи. Під час дослідження було розроблено та протестовано математичну модель фотоелектричної системи на основі штучних нейронних мереж, призначену для підвищення ефективності роботи сонячних панелей. Модель показала високу точність у прогнозуванні точки максимальної потужності за мінливих умов навколишнього середовища, таких як освітленість і температура. Аналіз отриманих даних продемонстрував, що використання нейронних мереж для відстеження максимальної потужності значно зменшує втрати енергії порівняно з традиційними методами відстеження. Експериментальні результати підтвердили, що запропонований підхід забезпечує більш стабільне і точне визначення точки максимальної потужності в реальному часі. Висновки показали, що впровадження такої системи може значно підвищити загальну продуктивність фотоелектричних установок, особливо в умовах непостійної сонячної активності, що робить її перспективною для застосування в різних кліматичних зонах. Крім того, модель показала стійкість до зміни параметрів вхідних даних, що робить її адаптивною до різних типів сонячних панелей і умов експлуатації. Також було виявлено, що система на основі нейронних мереж знижує витрати на експлуатацію та обслуговування фотоелектричних установок за рахунок мінімізації необхідності ручного калібрування і моніторингу. Отримана в результаті модель дасть змогу підвищити точність і ефективність відстеження максимальної потужності сонячних панелей за мінливих умов навколишнього середовища

Ключові слова: максимальна потужність; освітлення; температура; прогнозування; нейронні мережі