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PID-PSO CONTROLLER FOR PV PANEL SYSTEM IDENTIFICATION MODELS ON ANFIS AND NN-NARX SYSTEM

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Abstract

In this study, PID controller tuned by PSO technique on nonlinear system identification models for PV panel temperature has been presented well. Nonlinear system identification models have been generated in previous paper and consisted on: Neural Network (NN-NARX) based on the Nonlinear Auto-Regressive with External (Exogenous) Input and Adaptive Neuro-Fuzzy Inference System (ANFIS). This research is divided into three main parts: an experimental research that focused on Baghdad / Iraq environments to collect the input parameters (humidity, environmental temperature, irradiance and wind speed) and output parameters (temperature of the PV panel) in addition to generate identification models to predict the PV panel temperature. Finally, PID-PSO controller employed to keep the PV panel temperature within the permissible limits. As a result, PID-PSO controller succeeded to control the PV panel temperature at 30 °C for both models, but its performance was the best on NN-NARX model. Where, the MSE was 0.0371 using NN-NARX model and 0.1517 using ANFIS model. So, NN-NARX and ANFIS techniques have proven to be used experimentally in future control processes.

Keywords: Identification of nonlinear system, Particle swarm optimization, PID controller, PV panel system.

1. Introduction

Growing high-proficiency and low-emanation elective energy alternatives has happened to extraordinary significance with expanding worries about the petroleum product deficiency, high oil costs, a worldwide temperature alteration and ecological, and biodiversity hurt [1]. In this regard, solar photovoltaic is clean, renewable energy with long service life and high reliability [2]. In fact, more than 80% of the solar radiation falling on photovoltaic (PV) cells is not converted to electricity, but either reflected or converted to thermal energy. The photovoltaic temperature has a significant effect on the execution of photovoltaic, particularly when the climate is sweltering [3]. This problem must be fixed and the temperature of the photovoltaic panel reduced. Several cooling methods were attempted, many based on water and air refrigeration. In hot regions, air-cooling is not appropriate for extracting thermal energy from the photovoltaic absorber. In comparison, water cooling enables operating at much higher temperatures and makes more effective use of waste heat recovery. Hence, in many situations, air-cooling is a less desirable choice. In this work, water was used for refrigeration to reduce the temperature of the PV plate [4].

On the other hand, the models for foreseeing the PV panel temperature have been obtained from Hasan et al. [5]. The major aim of system identification is to locate approximate or accurate models of dynamics systems depend on observed inputs and outputs. A number of researchers have applied techniques to solve problems related to system identification. Several methods have been devised to find out models that describe the input-output behaviour of a system well [6]. Neural Network time series and Adaptive Neuro-Fuzzy Inference System (ANFIS) models represented as a method of system identification to predict PV panel temperature as a system output. Both verified modelling methods using mean square error (MSE). The efficacy of all methods was contrasted with the approach of knowing which is better. Lastly, the results obtained suggested that the ANFIS method registered the lowest MSE of 2.2627×10^{-7} compared to the NN-NARX method recording 5.078. Moreover, few intelligent controllers were employed in this work in order to control on temperature of the photovoltaic panel. A successful controller based on the ANFIS technique has managed to monitor the full initial cost of the device. The simulated results showed that the planned ANFIS succeeds in forcing the PV to produce maximum power by pushing the PV voltage to an optimal value determined by the qualified ANFIS system [7].

In many industrial applications, proportional integral and derivative (PID) controllers are used extensively to improve the transient of the system because of their simple structure, robustness, high performance, and easy maintenance [8]. The grid-connected PV/Wind hybrid network is modelled and configured using a Fuzzy-PSO algorithm. Comparison of PI and Fuzzy-PI approaches to monitor the current injected into the grid was rendered and implemented on the inverter. In simulation analysis, MATLAB/Simulink was used. Has tested the functionality and effectiveness of the proposed controller, the results showed that the PI controller delivers timely response and pictures less than the Fuzzy-PI power [9].

The optimum PID was compared for two hybrids wind-solar MPPT controllers with the optimum NPID controller. The simulation results showed that the proposed combination of nonlinearity and traditional NPID controller PID characteristics could boost the control performance [10]. Nonlinear device recognition Fuzzy-PID controller NN-NARX, NN-NAR, and ANFIS models for cylinder due to vortex induced vibration (VIV) were well described. The NAR model's lowest MSE is equivalent to 2.8452×10^{-9}. While the NN-NARX method's best model registered MSE = 1.2714×10^{-9}. Also, when the MF equals 2 for input and output, the lowest MES for the ANFIS model registered 2.5635×10^{-13}. For all models, but particularly for the ANFIS model, the Fuzzy-PID controller was effective in that the vortex induced vibration on the cylinder [11].

Building a schematic control has been done using traditional controller methods to obtain optimum power and current from the injected solar PV system into the grid and to output and dynamic response to the research device. For the 3-kW rated power PV system, MATLAB/Simulink was planned and simulated. The voltage and current control loops were designed to eliminate Total harmonic distortion from the current and changed power unit [12].

The aims of the current study are to decrease the temperature of the solar cell to increase the efficiency of the electrical conversion and generate models to predict the temperature of the PV panel. Eventually, the Proportional Integral Derivative - Particle Swarm Optimization (PID-PSO) controller used to keep the temperature of the PV panel within approved limits. This paper consisted of four main parts: firstly, data collection, the input (ambient temperature, humidity, irradiance, and wind speed), and output (PV module temperature). Secondly, system identification methods from Hasan et al. [5]. Thirdly, using PID- PSO controller on the models and finally discussion the results.

2. Experimental Work

The experimental set-up consists mainly of a photovoltaic panel and measuring devices (data logger with thermocouples, wind speed meter, solar power meter and multimeter) in order to collect the input (wind speed, humidity, environmental temperature and irradiance) and output (temperature of the PV panel) as shows in Fig. 1 and the solar panel specifications used can be seen in Table 1. The experimental test rig was installed with a 32° tilt angle to the south and the practical test was carried out from 09:00 a.m. to 13:30 p.m. for clear days at the site of Baghdad city located along the longitude 44.458 and latitude 33.272 ion29 February 2020.

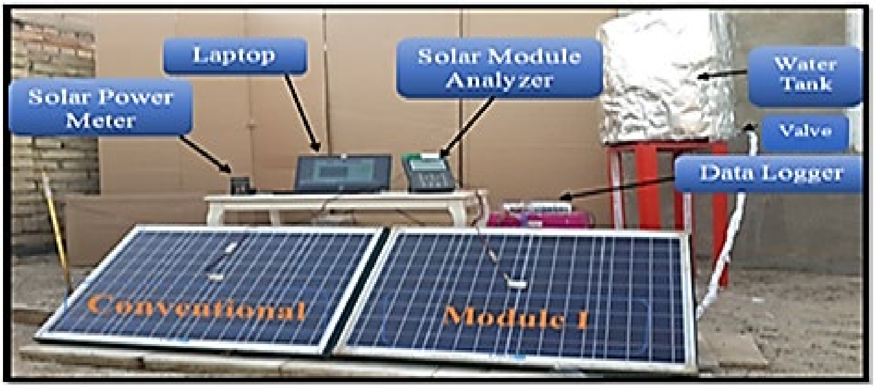


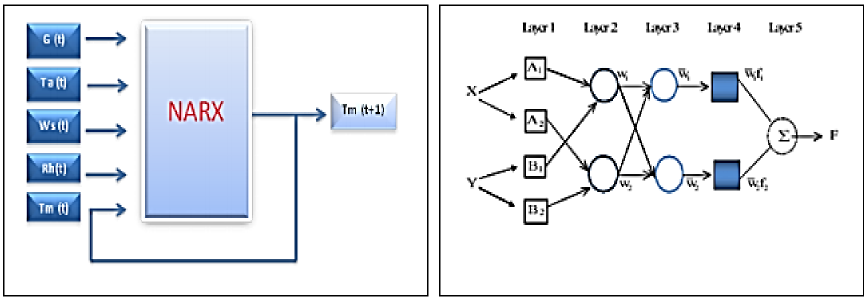
Fig. 1. Experimental setup system with measuring devices.

Table 1. PV-panel specification at STC (1000 W/ m^2, cell temperature 25 ºC).

Model	SR-100S
Maximum Power	111.2W
Short Circuit Current	8.031A
Peak Current	7.433A
Open Circuit Voltage	20.46V
Peak voltage	14.96V
Open Circuit Voltage Temperature Coefficient	-0.021V/°C
Short Circuit Current Temperature Coefficient	0.15A/°C
No. of Parallel Cells	1
No. of Serious Cells	32
Module Area	0.871m²

3.System Identification

System recognition use projected data to construct the transfer function or equivalent model for both the linear and nonlinear system [13]. In this work, system identification models have been obtained from Hasan et al. [5]. The nonlinear model consisted of two methods: Adaptive Neuro-Fuzzy Inference System (ANFIS) and Neural Network (NN-NARX) based on the Nonlinear Auto-Regressive with External (Exogenous) Input and Fig. 2 shows NN-NARX and ANFIS architectures.



A) NARX Structure B) ANFIS Structure

Fig. 2. Dynamic for predicting PV temperatures.

4. PID-PSO Controller

In industrial control systems, the proportional-integral-derivative controller (PID) is widely used to compare the desired and calculated values due to its health, economy and excellent efficiency. The parameters of the controllers (K_P, K_I, and K_D) are set to achieve optimal results. The name of the controller is related to the K_P, K_I and K_D values. This section focuses on the general PID controller type as shown in Fig. 3. One of the main challenges is to transform the PID controller from traditional to smart behaviour using smart optimization methods to change PID parameters [14]. PSO method was used to adjust PID parameters. The PID control can be expressed in continuous time as:

$$u(t) = K_P\, e(t) + K_I \int_0^t e(t)dt + K_D \quad (1)$$

where, K_P, K_I and K_D are the respective proportional, integral and derivative gains respectively, the controller output is $u(t)$, and the predicted error is $e(t)$, and the real output is. In the Laplace transform domain, the PID block structure can also be interpreted as:

$$u(s) = (K_P + \frac{K_I}{S} + K_D S)\ e(s) \tag{2}$$

The integral and derivative terms in Eq. (2) are converted in discrete time form to be:

$$\int_0^t e(t)dt\ \approx T\sum_{k=0}^{n} e(k) \tag{3}$$

$$\frac{de(t)}{dt} \approx \frac{e(k)-e(k-1)}{T}\ or \frac{\Delta e(k)}{T} \tag{4}$$

where, the k represents a discrete step at time t and Eq. (2) becomes:

$$u(t) = K_P\ e(K) +\ K_I\ \sum_{k=0}^{n} e(k) + K_D \Delta e(k) \tag{5}$$

The Laplace transform PID controller may be interpreted in discrete time as:

$$G(z) = [K_P + \frac{K_I}{1-z^{-1}} + K_D(1 - z^{-1})]e(z) \tag{6}$$

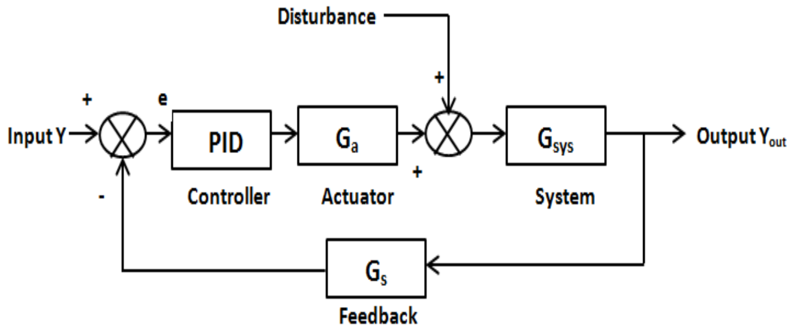


Fig. 3. Basic scheme of PID controller.

5. Results and Discussion

5.1. Experimental data and modelling results

In previous work [5], the results of the system were represented base on the nonlinear SI models and input-output data have been collected from the PV panel. Input data were represented in the system and consisted of 10286 data that sets over 4.5 hours with a sampling rate of sample per second as shown in Fig. 4. The same quantity of data was collected for the PV panel temperature as output for the system as shown in Fig. 5.

NN-NARX method used 10286 data sets for model creation. The data were divided into three parts: 1543 for validating, 1543 for testing, and 7200 for training. The process consisted of two parts to find the best model for system representation. Firstly, the lowest mean square error (MSE) was calculated when the number of delays (ND) was fixed at 2 and the NE ranged from 2-10. Secondly, the lowest MSE was calculated from the best ND ranged 2-10 for the LMSE of the NE obtained in the first step.

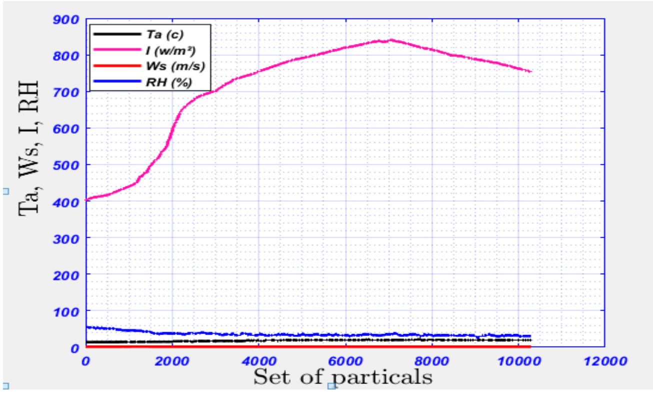


Fig. 4. Input data of the experimental setup.

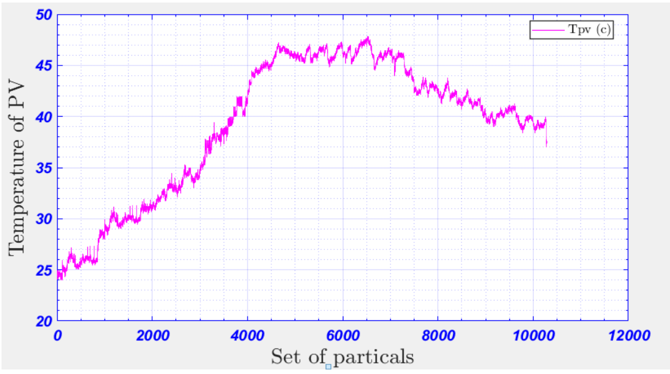


Fig. 5. Output data of the experimental setup.

The lowest MSE for the NN-NARX model was recorded as 5.6×10^{-2} when ND = 2 and NE = 6, while the lowest MSE recorded for the second part was 5.55×10^{-2} when ND = 9 and NE = 6. Figure 6 offers actual and predicted PV panel temperatures, while Fig. 7 displays predict the error.

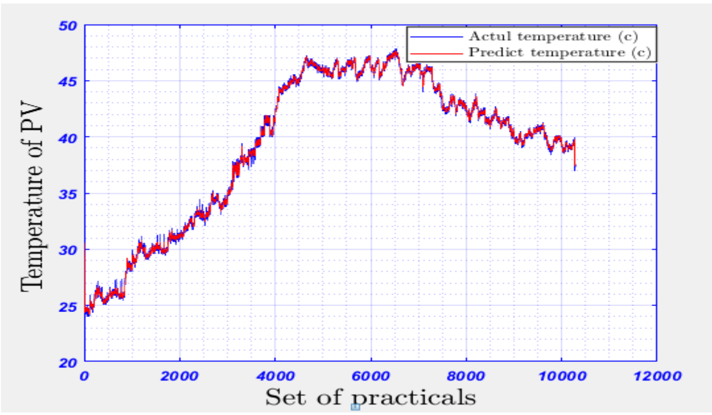


Fig. 6. Illustrate actual and predicted PV panel temperatures.

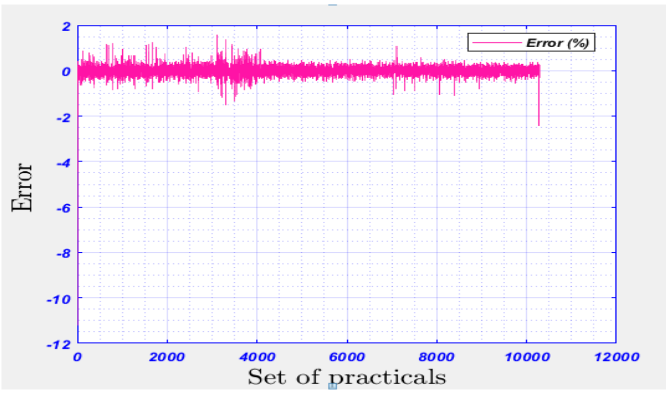


Fig. 7. Illustrate predict of the error.

To build the ANFIS model, two input variables (actual input *X* and actual output *Y*) were selected during the identification. The model used 5143 data for training and 5143 data for checking. The number of membership functions (MFs) including 2 then 3 for each input was specified. Next, the generalized bell shape was selected as the type of MF. This is considered an important step to create the FIS model. The step to generate the ANFIS model selected the epoch and tolerance values with equivalent iteration number and error value respectively. Finally, evaluation of the MF of the model and calculation of the MSE was performed. As shown in Table 2, the LMSE obtained using ANFIS identification was 2.9467×10^{-7} when MFs=2, and the LMSE was 0.0122 when the MFs =3. The intention was to adjust the MFs from 2 to 10, but it was found that when MFs increase, the error also increases, so that MFs=2 was the better option. Figure 8 displays actual and predicted PV panel temperatures at MFs = 2. While, Fig. 9 shows the predict error percentage at MFs equal to 2 and 3 respectively.

Table 2. Results of the ANFIS model.

Number of MFs	Minimal Training RMSE	Minimal Checking RMSE	Mean Squared Error	Number of nods	Number of fuzzy rules
2	10^{-6}	4.882×10^{-5}	2.946×10^{-7}	92	32
3	3.2×10^{-5}	4.864×10^{-2}	0.0122	524	243

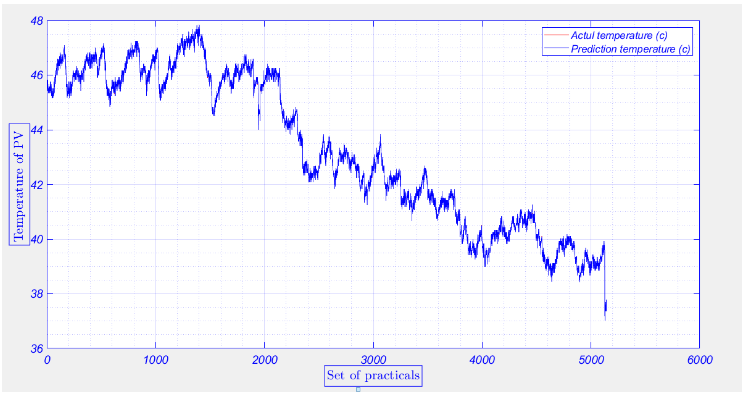
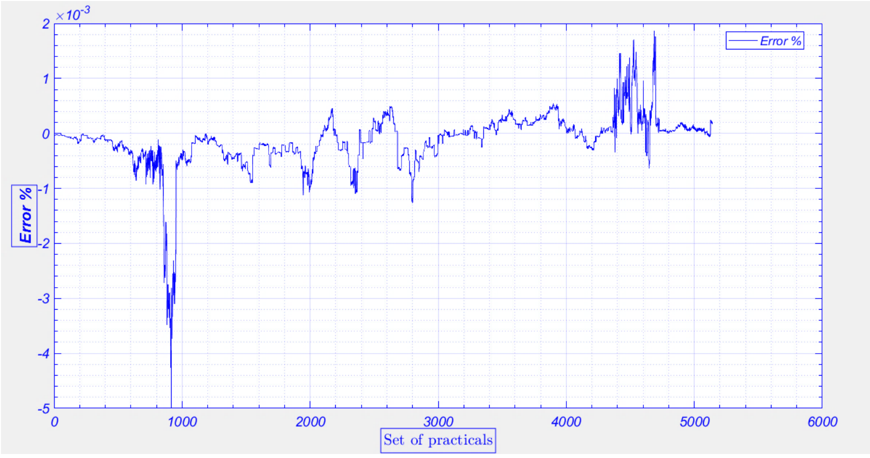
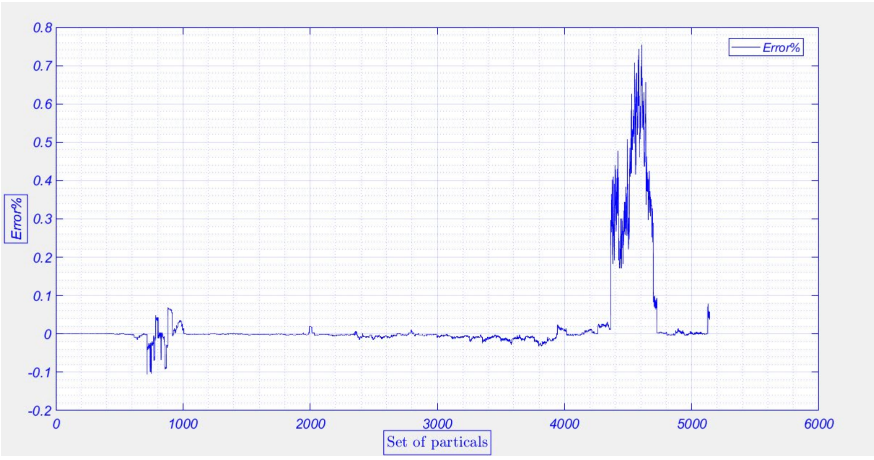


Fig. 8. Illustrate the actual and predicted PV panel temperatures at MFs=2.



(a) MFs=2.



(b) MFs=3.

Fig. 9. Predicted error.

5.2. PID controller results

In NN-NARX and ANFIS models the PID parameters were set during the heuristic method and consisted of finding the *P* gain value at the lowest MSE, then finding the *I* gain value at lowest MSE by fixing the *P* gain value found in the previous step and finally, finding the *D* gain value at the lowest MSE when the best values of *P* and *I* gain were fixed from the previous steps. Figure 10 shows PID controller system block diagram with NN-NARX model. After trying different values for PID gains, it was found that the lowest MSE equal to 0.0371 as the Table 3 shows that the PID controller with NARX model has succeeded in control on temperature of the photovoltaic panel as explains Fig. 11. The error under the PID-PSO controller based on the NN-NARX model illustrated by the Fig. 12.

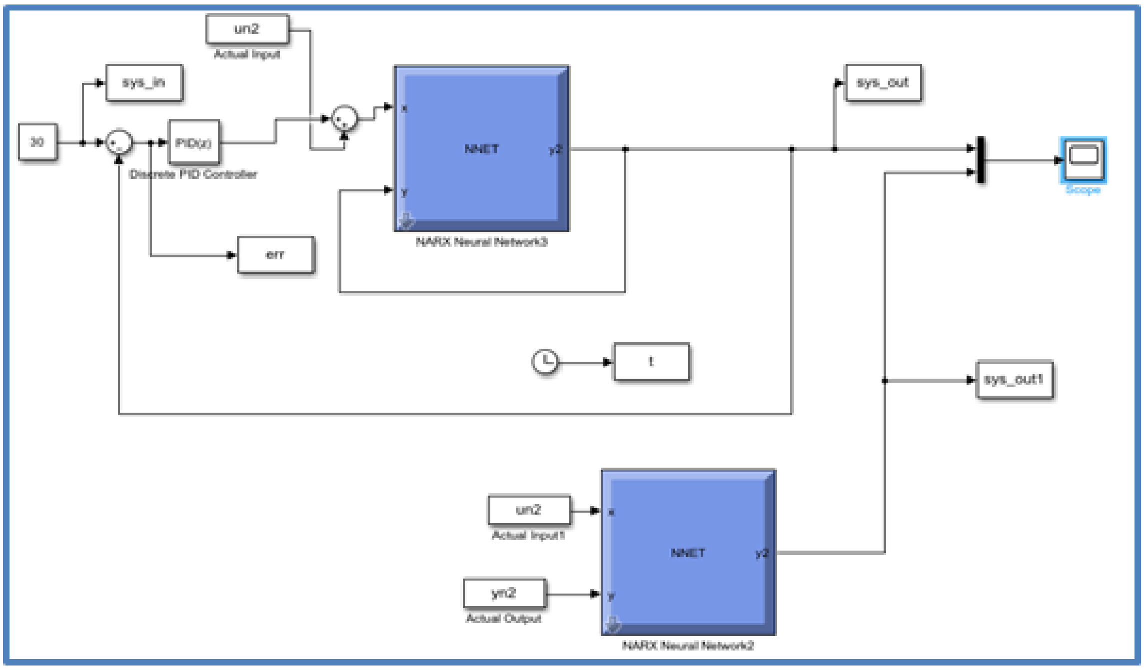


Fig. 10. PID controller system block diagram with NN-NARX model.

Table 3. PID-PSO parameters setting on the NN-NARX model.

Parameter	K_P	K_I	K_D	MSE
Value	-0.1	0	0	21.4833
	-0.1	-0.01	0	0.0374
	-0.1	-0.01	-0.01	0.0371

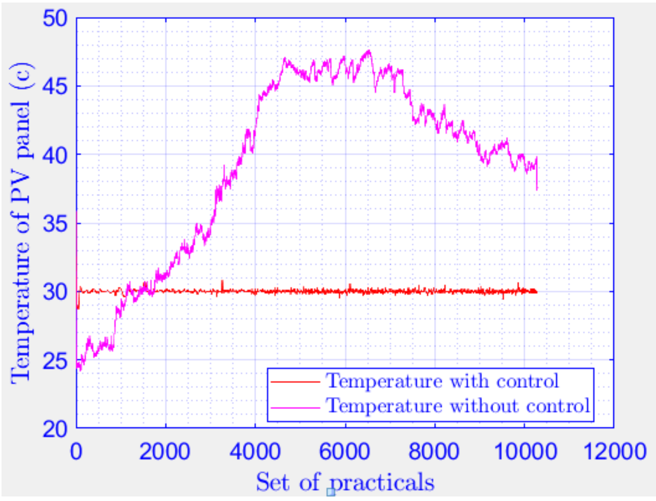


Fig. 11. Temperature of PV panel with\
without PID-PSO controller with NN-NARX model.

A PID controller system block diagram with ANFIS model was used as shown in Fig. 13. Table 4 shows the outcomes for PID gain values that recorded the lowest MSE equal to 0.1517. From Fig. 14, PID controller has succeeded in control on the temperature of the photovoltaic panel. A comparison was made between the temperature of PV panel with and without the controller. Figure 15 shows error under the PID-PSO controller based on the ANFIS model.

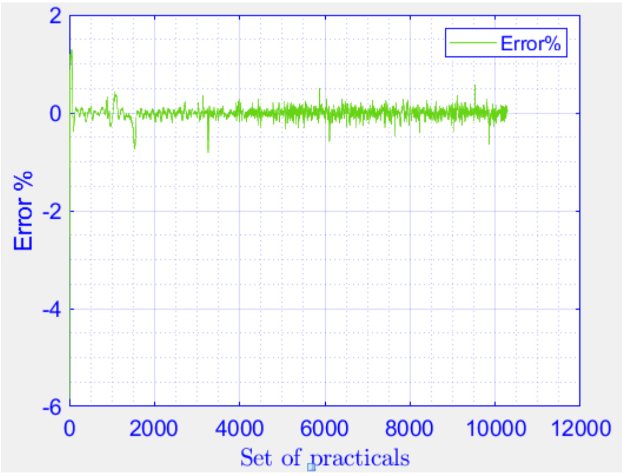


Fig. 12. Error under the PID-PSO controller with NN-NARX model.

Table 4. PID-PSO parameters setting on the ANFIS model.

Parameter	***K$_P$***	***K$_I$***	***K$_D$***	**MSE**
Value	0.9	0	0	0.1407
	0.9	0.8	0	0.1517
	0.9	0.8	0.7	0.1517

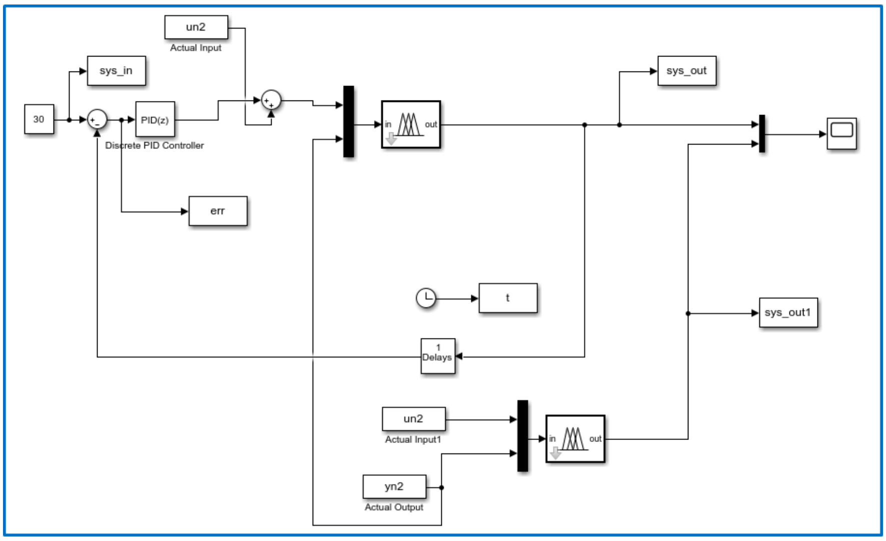


Fig. 13. PID controller system block diagram with ANFIS model.

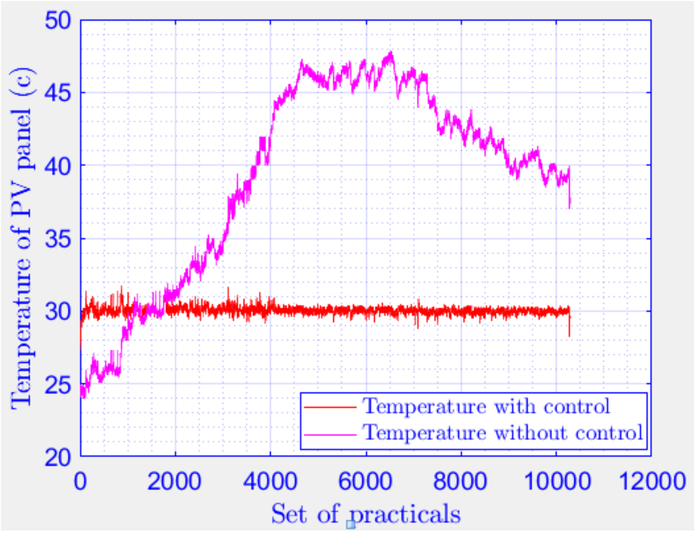


Fig. 14. Temperature of PV panel with\ without PID-PSO controller with ANFIS model.

Fig. 15. Error under the PID-PSO controller with ANFIS model.

6. Conclusions

Temperature is a significant factor affecting the efficiency of the PV module, particularly when the cell temperature rises, the ability of the PV module drops significantly. Subsequently, the thermal model used to predict PV module temperature is significant since the temperature of the module influences its capacity yield. The thermal model was utilized in anticipating the module temperature of the PV module working in Baghdad ecological conditions. A careful inquiry was conducted based on the information parameters considered to choose the arrangement of the ideal mix of data sources that has the most effect on PV temperature expectations. The NN-NARX and ANFIS models were constructed using 10286 databases composed of radiation intensity, relative humidity, ambient temperature, and wind speed to predict the temperature of the PV panel. In the first No. of the model, the neuron was changed from 2-10 to the lower MSE, the best result was fixed and the delay of 2-10 was changed. Whilst, the second model depended on selection the No. of MFs and membership function type. It can be very well understood from the results that in terms of predicting the ANFIS-based PV temperature the figure conveys better results when contrasted with the NN-NARX-based gauge, where the MSE was 5.55×10^{-2} by NN-NARX method and 2.946×10^{-7} by ANFIS method. Both NN-NARX and ANFIS models were used with the PID-PSO controller to control the solar panel temperature. The two models were successful in controlling the temperature where the MSE was 0.0371 with the NN-NARX model and 0.1517 with the ANFIS model.

Nomenclatures

de/dt	Derivative of error
$e(t)$	Error in continuous time
$e(z)$	Error in discrete time
G(z)	Transfer function
K_P	Proportional gain
K_I	Integral gain
K_D	Derivative gain
$u(t)$	Output signal

Abbreviations

ANFIS	Adaptive Neuro-Fuzzy Inference System
MFs	Membership function
MSE	Mean square error
ND	Number of delays
NE	Number of neurons
NN-NARX	Neural Network nonlinear Auto-Regressive with External (Exogenous) Input
PID	Proportional- Integral and Derivative
PSO	Particle swarm optimization
PV	Photovoltaic

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