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Control of PV Panel System Temperature Using PID Cuckoo Search

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HIGHLIGHTS

- Produce the optimal power using PID-CSA controller by Cooling PV panel temperature.
- For this nonlinear system, NARX technique is the best modelling method based on MSE.
- The best values of the PID controller parameters are accomplished using MSE technique.

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ABSTRACT

In this study, the PV panel behavior as a nonlinear system had been studied well. The main contribution of this work was cooling the PV panel temperature to get the optimal power using a PID-CSA controller which was never employed previously in this application. In the beginning, the system has been modeled using three artificial neural network methods which are NARX, NAR and nonlinear input output based on MSE. Then, the PID controller with the intelligent cuckoo search algorithm technique had been studied to accustom PID controller parameters (K_P, K_I and K_D) based on MSE, ASE and IAE. The results exhibited that the best modeling method was NARX with 0.2255 MSE. On the other hand, all the controlling methods were effective and showed an excellent ability to control the system; however, the best method was based on MSE with an error equal to 2.578.

1. Introduction

Producing electrical energy from solar radiation is being done using Photovoltaic Panels (PV). There are many types of semiconductors that are used in solar cells manufacturing, and the common semiconductor is the mono crystal line silicon. Solar cell ideal efficiency is between 15% and 17%. PV panels comprise many solar cells connected together in parallel or series [1]. Solar energy has been relied on to produce electricity because it is clean energy, with high reliability and a long life service [2]. Heat is generated because over 80% of the solar irradiation that arrives to the PV panel surface is transformed into heat. Moreover, during producing electricity and due to the high ambient temperature in middle east countries, a spectacular increase in solar cells occurs, which led to an enormous reduction in PV panel efficiency. So that, cooling systems must be added to PV panels modules to improve the PV system efficiency and thus dramatizing the production power [3]. There are many types of cooling techniques that usually depend on air or water. In sweltering atmosphere countries, water cooling systems are more efficient than air cooling systems [4]. Many numerical models had been developed to predict the temperature of PV panels and the produced power. The preeminent prediction method is the Artificial Neural Network (ANN) because of its accuracy and faster processing time compared to other methods [5]. There are a lot of previous studies on PV panel's performance forecasting using ANN algorithms. For example, Hamdan et al. (2013) used three types of ANN (NARX, Elman and feed forward), and the best model for solar panel performance prediction was the feedforward [6]. Di Piazza et al. (2013) studied the prediction of solar radiation using feed forward time delay and NARX and both methods were suitable for the system [7]. Valerio et al. (2014) studied PV panel power output prediction using RNN, GM and MLP; the three models forecasted the output power efficiently in short time [8]. Mohammad et al. (2014) predicted the output power of PV panel using FFBP and GRNN; and the best method was FFBP [9]. Parmar (2015) predicted PV panel performance using feed-forward with LMBP; where the model was efficient for the system [10]. Shekher et al. (2017) predicted the PV system output power using three different input ways in FFBP method; and the three models were good to predict the system performance [11]. Khelil et al. (2017) studied PV panel performance by the MLP method, and the prediction was efficient. The commonly used controller in solar systems is the proportional-integral-derivative (PID) controller because it is economical and safe. This controller had taken its name from its parameters which are K_P, K_I *and* K_D. These parameters should be set to achieve the best

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results [12]. Cuckoo Search Algorithm (CSA) method is a very efficient way for intelligent controlling of solar applications. CSA was advanced by Suash Deb. and Xin-She Yang in 2009 inspired by the Cuckoo Birds way by placing their eggs in the other birds' types nests and depeniding on them to raise their young birds. This controlling method is very efficient in engineering problems optimization [13].

There are several previous studies on the cuckoo search intelligent controller such as: Sasidhar et al. (2016) studied the MPPT of the solar cell system using CSA and made a comparison with PSO, ABC and FA methods results, and the system was efficient [13]. Assis et al. (2016) studied PV panel optimum power tracking using CSA, and the model made a successful optimum power [14]. Shi et al. (2016) studied the MPPT of PV system, and the model was efficient [15]. Mosaad et al. (2019) trucked the MPPT of PV system using CSA and made a comparison with the results of Neural Network and incremental conductance methods, where CSA method was the best and the most efficient compared with the other methods [16]. Ibrahim et al. (2019) trucked CSA and conventional methods, and CSA was more efficient and correct than the conventional methods [17]. Abo-Elyousr et al. (2019) trucked the PV system MPPT using PSO and CSA, and CSA was much better than PSO [18]. Chang (2020) studied the performance of the inverter for the PV system using MPPT with CSA, where both the PV performance and the trucking speed were enhanced [19]. Based on pervious papers, many papers have used CSA algorithm to obtain the best performance by adjusting the PID parameters in different applications. Therefore, the main contribution of this work was cooling the PV panel temperature to get the optimal power using PID-CSA controller, which was never employed previously in this application. The study objectives are cooling a PV panel system using water with porous media to enhance the system efficiency and develop a model using three networks including NARX, NAR and Nonlinear Input/output ANN techniques to predict the PV panel temperature based on MSE. Finally, the intelligent PID-Cuckoo search controller is used to hold the PV panel temperature within the acceptable curb.

2. Experimental Setup

The experimental organization contains two indistinguishable PV panels of glass to glass type, made of mono crystalline solar cells, one panel is without a cooling system whereas the other one is cooled with water and porous media in a spiral shape made of pure aluminum; and measuring instruments such as: thermocouples connected to data logger, humidity meter, wind speed meter and solar meter. PV panels' specifications are shown in Table 1. The panels were set in Baghdad to the south direction with a tilt angle of 32.1°. The data were collected from 8am to 5pm for clear weather between 15th of April and 30 of June. Figure 1 below shows the PV panels' system setup.

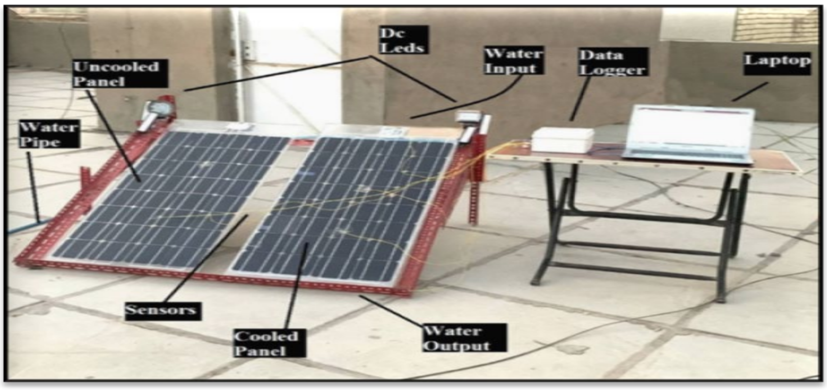

Figure 1: PV panel's system setup

Table 1: PV panels' specifications

STC Measurements	1000 W/m^2 , 25 ºC
Open circuit voltage (Voc)	21.05 V
Peak voltage (Vpm)	16.25 V
Short circuit current (Isc)	5.339 A
Peak current (Imp)	4.954 A
Maximum power (Pmp)	80.5 W
Voltage temperature coefficient (KV)	-2.10 mV/ cell/ ºC
Current temperature coefficient (KI)	15.00 µA/ cm 2 ºC
Cell efficiency	16.1%
Module efficiency	12.2 %
Cell area	156.25 cm^2
Module area	0.66 m^2
No. of parallel cells (Np)	1
No. of series cells (Ns)	32

3. Prediction Methods

Three ANN methods had been used in this work (NARX, NAR and Nonlinear Input/output) depending on the Mean Square Error (MSE). The input data were ambient temperature, wind speed, relative humidity and solar irradiance that are shown in Figure 2, while the output data are shown in Figure 3, representing the PV panel temperature.

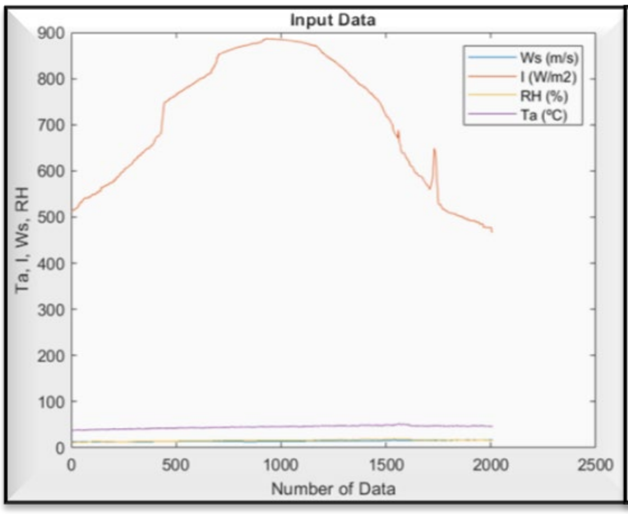

Figure 2: Input data

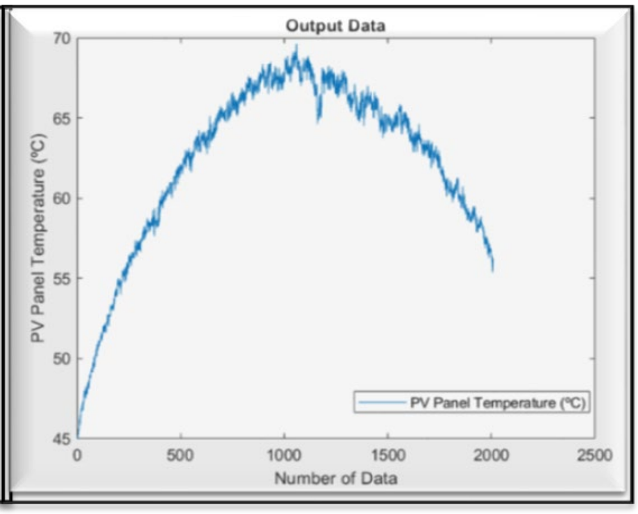

Figure 3: Output data

3.1 NARX modelling method

Prediction of the future data using old output data with external input is done by the NARX nonlinear system model [20]. Figure 4 presents the NARX model block diagram. The NARX model definition is illustrated in Eq. (1) below.

$$y(t) = f(x(t-1), x(t-2), ..., x(t-d), y(t-1), y(t-2), ..., y(t-d)) \quad (1)$$

Where
f: The function of the nonlinear system.
Y (t): The future forecasted data series.
X (t): External input data series.
D: The old data of x(t) and y(t).

3.2 NAR modeling method

Prediction of the future data using old output data only is done by the NAR nonlinear system model [21]. Figure 5 presents the NAR model block diagram. The NAR model definition is illustrated in Eq. (2).

$$Y(t) = f(y(t-1), y(t-2), ..., y(t-d)) \quad (2)$$

Where
f: The function of the nonlinear system.
Y (t): The future forecasted data series.
D: The old data of y (t).

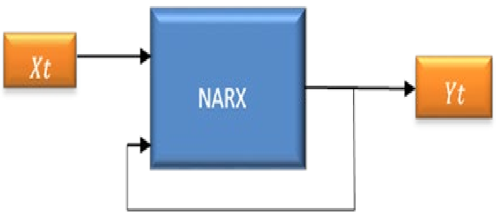

Figure 4: NARX model block diagram

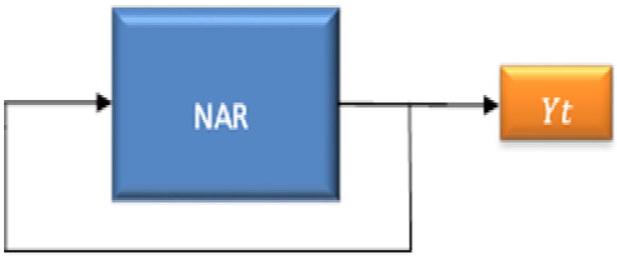

Figure 5: NAR model block diagram

3.3 Nonlinear input/ output method

Prediction of the future data using input data series and output data series without any old data is done by the nonlinear input/output system model [20]. Figure 6 presents the nonlinear input/output model block diagram. The NAR model definition is illustrated in Eq. (3).

$$Y(t) = f(x(t-1), x(t-2)\ldots x(t-d)) \tag{3}$$

Where:
f: The function of the nonlinear system.
Y (t): The future forecasted data series.
X (t): External input data series.
D: The old data of x (t).

Figure 6: Nonlinear input/ output model block diagram

4. Intelligent PID- Cuckoo Search Controller

The PID controller of the system can be defined as the deflection percentage ratio between the P, I and D forecasted output values and real input values. There is a real challenge in these days to convert the classic PID into an intelligent controller by many intelligent optimization techniques [12]. Figure 7 presents the PID controller scheme.

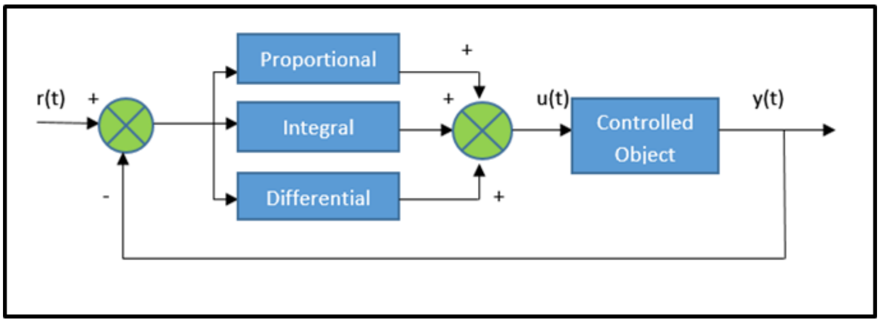

Figure 7: PID controller scheme [12]

The PID controller mathematical definition is shown in Eq. (4) below:

$$u(t) = K_P e(t) + K_I \int_0^t e(t)dt + K_D \frac{d\,e(t)}{dt} \tag{4}$$

Where;
U (t): The output of the controller.
K_P: Proportional parameter's gain.
K_I: Integral parameter's gain.
K_D: Derivative parameter's gain.
E (t): The real output and predictable error.

In Laplace domain transform, the PID controller can be written as in Eq. (5)

$$u(t) = \left(K_P + \frac{K_I}{S} + K_D S\right) e(S) \tag{5}$$

The integral and derivative terms in Eq. (5) can be converted into discrete time form as in Eq. (6) and Eq. (7).

$$\int_0^t e(t)dt \approx T\,\Sigma_{K=0}^{n}\, e(K) \tag{6}$$

$$\frac{de(t)}{dt} \approx \frac{e(k)-e(k-1)}{T} \;or\; \frac{\Delta e(k)}{T} \tag{7}$$

Where k is the phase discrete at time (t).
Thus, Eq. (4) becomes Eq. (8) below:

$$u(t) = K_P e(K) + K_I \Sigma_{K=0}^{n} e(K) + K_D \Delta e(k) \quad (8)$$

And in Laplace discrete transform, PID controller becomes Eq. (9):

$$G(z) = [K_P + \frac{K_I}{1-Z^{-1}} + K_D(1 - Z^{-1})]e(z) \quad (9)$$

CSA has shown very successful and efficient results for PID tuning in many control system applications. There are some parameters that CSA method depends on, such as:
G: the generation number.
N: the size of population.
D: the dimension of the problem.
A: the size of flight step.
Pa: alien eggs discovery rate.
LHC: boundary limits.
The first step is preparing population, so that D and N, the upper and lower ranges, are stated randomly by Eq. (10).

$$Pop_{ij} = L + (H - L) * rand\ (1.D) \quad (10)$$

Where:
$i = 1.\Lambda\Lambda$, D and $j = 1.\Lambda\Lambda$,N
The new generation is produced from the utilization of Levy flights by Eq. (11).

$$x_i(t+1) = x_i(t) + \alpha * step * (x_i(t) - bestnest) * randn(N) \quad (11)$$

Where,

$$step = \frac{u}{|v|^{(1/\beta)}} \quad (12)$$

$$u = randn(N) * \sigma \quad (13)$$

$$v = randn(N) \quad (14)$$

$$\sigma = (\frac{\Gamma(1+\beta) * \sin\left(Pi * \frac{\beta}{2}\right)}{\Gamma\left(1+\frac{\beta}{2}\right) * \beta * 2^{\left(\beta - \frac{1}{2}\right)}})^{(1/\beta)} \quad (15)$$

$x_i(t+1)$: New nest.
$x_i(t)$: The corresponding nest of the initial population.
(Xi (t) – best nest): Difference factor.
β= 1.5.
In this work, CSA optimization method was utilized to accustom PID controller parameters (K_P, K_I and K_D) depending on MSE, Integral Square Error (ISE), and Integral Absolute Error (IAE) to conclude which method is the best for this system.

5. Results and Discussion

5.1 ANN modelling results

The first step was collecting input and output data that were represented by ambient temperature, wind speed, relative humidity, solar irradiance and PV panel temperature to be applied in ANN time series modelling techniques. 2008 input data and the same number for output data had been collected. For the three methods, (NARX, NAR and Nonlinear input/ output) were modified as 50% of the collected data for the training range, 25% of the collected data for the validation range and 25% of the collected data for the testing range. Firstly, a fixed hidden neurons number (Nan) of 10 was taken, while the number of delays (ND) was changed from 2 to 12. Then, the number of hidden neurons (Nan) was changed starting from 2 and ending at 12, while fixing the number of delays at the delay number of the lowest MSE. The best MSE was for the NARX method with 0.2255 when Nan was 7 and ND was 3. Figure 8 below displays NARX PV panels' actual and predicted temperatures.

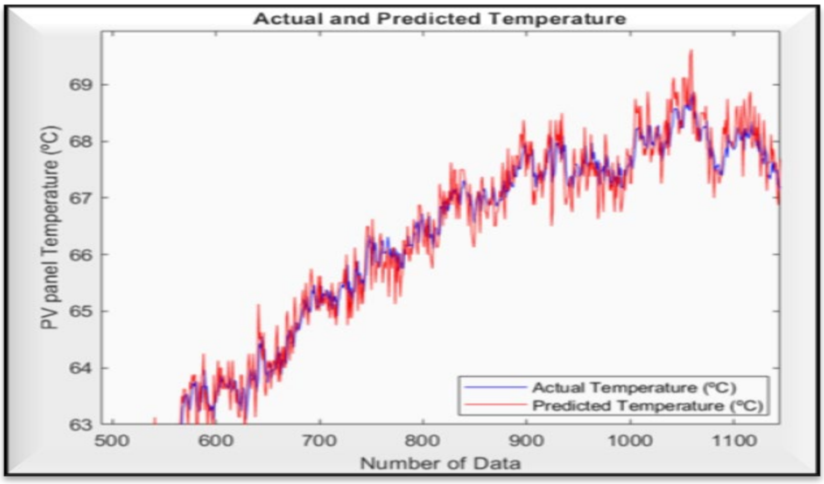

Figure 8: NARX PV Panel Actual and Predicted Temperatures

5.2 PID cuckoo search results

The next step was analyzing the PID cuckoo search using NARX results based on MSE, ISE and IAE. The PID controller with cuckoo search is presented in Figure 9, and Table 2 displays the $\boldsymbol{K_P, K_I}$ **and** $\boldsymbol{K_D}$ values based on MSE, ISE and IAE.

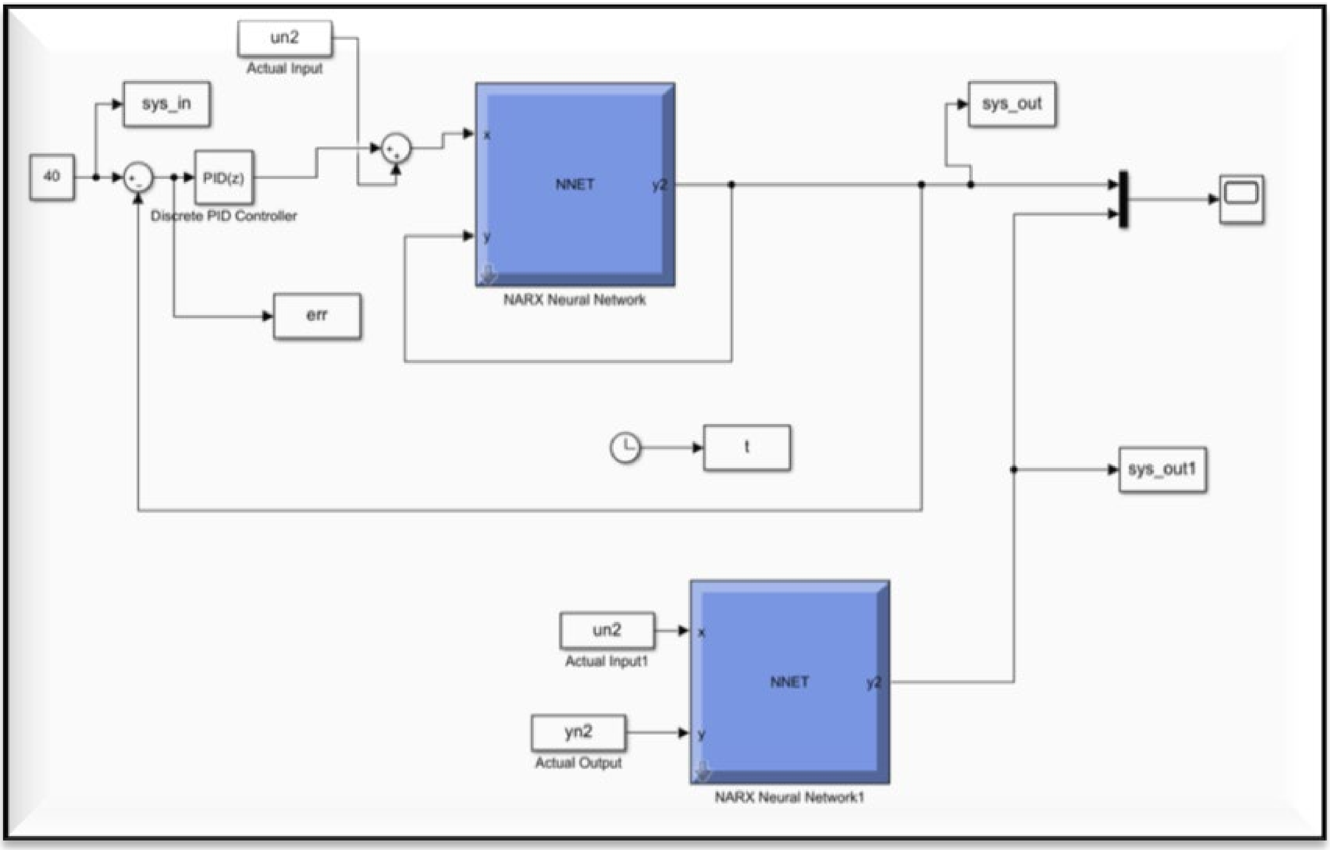

Figure 9: PID controller with cuckoo search block diagram

Table 2: K_P, K_I and K_D values based on MSE, ISE and IAE

K_P	K_I	K_D	MSE	ISE	IAE
80.639	88.037	11.1	2.578	-	-
23.733	23.479	0	-	4.703e+03	-
100	89.517	0	-	-	2.975e+03

Then, a comparison was made between the temperature of PV panel with and without the controller as shown in Figures 10, 11 and 12, respectively.

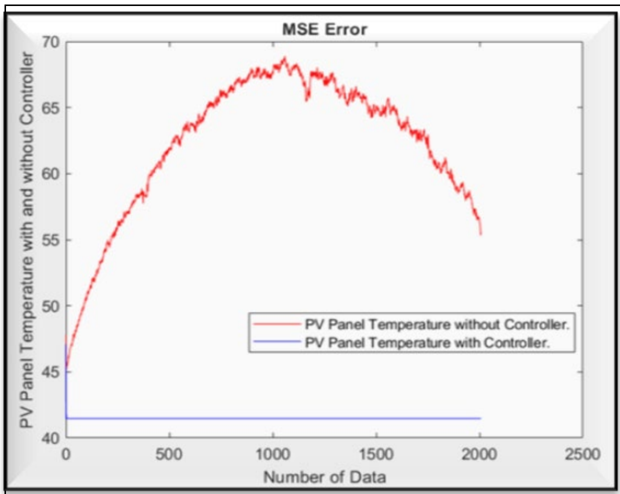

Figure 10: PV panel temperature with and without the controller based on MSE

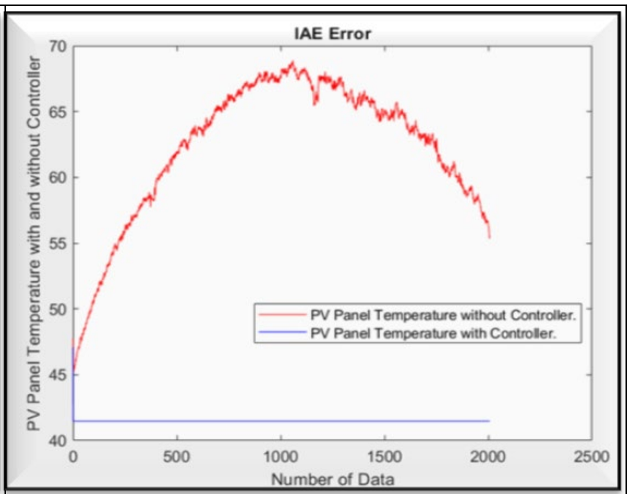

Figure 11: PV panel temperature with and without the controller based on IAE

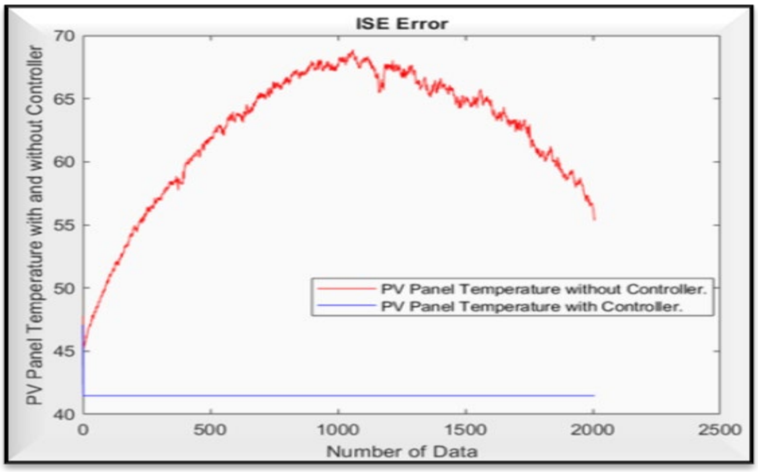

Figure 12: PV panel temperature with and without the controller based on ISE

6. Conclusions

The aim of this work is to control the temperature of the PV panel system using intelligent PID Cuckoo Search. Firstly, modeling of the system had been done using NARX, NAR and Nonlinear input/ output based on MSE. The best modeling method was the NARX technique due to its lowest MSE, which is 0.2255 while for NAR and nonlinear input/ output, the MSE were 0.2278 and 0.4239, respectively. Therefore, both NARX and NAR can be adopted in this system considering the slightly contrast between them. Finally, the PID Cuckoo Search intelligent controller had been added to the system to accustom PID controller parameters (K_P, K_I and K_D) based on MSE, ISE and IAE, which was never employed previously in this application. The three methods were effective and showed excellent ability to control the system, but the best method was based on MSE with an error equals to 2.578. As a future work, a fuzzy controller will be employed instead of the PID-CSA controller to control and cool the PV panel temperature in order to get the optimal performance of the system.

Author contribution

All authors contributed equally to this work.

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Data availability statement

The data that support the findings of this study are available on request from the corresponding author.

Conflicts of interest

The authors declare that there is no conflict of interest.

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