Design of Optimum SIMO-PID Neural Voltage-Tracking Controller for Non-Linear Fuel Cell System Based on a Comparative Study Of Various Intelligent Swarm Optimization Algorithms

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Abstract. This paper presents the enhancement of the output performance of a non-linear fuel cell (FC) system using a new design that comprises an adaptive SIMO-PID neural controller with different types of online swarm optimization algorithms. The work focuses on improving the use of single-input multi-output (SIMO) PID neural networks to control the non-linear FC system. The goal of the proposed adaptive SIMO-PID neural voltage-tracking controller is to rapidly and precisely identify the optimal hydrogen flow rate and oxygen flow rate control actions that are used to control the (FC) stack terminal output voltage. Three swarm optimization algorithms are used to find and tune the weights of the SIMO-PID neural controller: the Firefly algorithm, chaotic particle swarm optimization algorithm, and proposed hybrid Firefly-chaotic particle swarm optimization (F-CPSO) algorithm. Numerical simulation results show that the proposed controller using the (F-CPSO) algorithm is more accurate than with the FA or CPSO; the proposed SIMO-PID neural controller parameters are obtained more rapidly there is a high reduction in the number of function evolutions. Furthermore, the proposed controller's ability with the F-CPSO algorithm to generate a smooth flow rate control response for the non-linear (PEMFC) system without voltage oscillation in the output is determined by investigations under load variations.

Keywords. SIMO-PID neural, Voltage-tracking, Fuel cell system, Intelligent swarm, algorithms.

1. Introduction
Fuel cells (FCs) generate electrical power from a chemical reaction involving oxygen and hydrogen, and because of this electrochemical nature, they have been widely used in recent years. FCs have obtained the chemical compounds employed from nature, and this distinguishes them from other sources of electrical power generation (such as batteries and internal combustion engines). They also have many other advantages, such as producing low emissions (approaching zero), being a clean energy source, and operating quietly. FCs have two sides (a left side and a right side) known as the electrodes: the left side is the anode side, and it acts as the entrance for hydrogen gas, and the right side is the cathode where oxygen gas is input. A catalyst material covers the electrodes [1]. The other FC component is the electrolyte. The power generated from each cell is less than or equal to 1 V;
therefore, a group of cells is connected either sequentially or in a parallel form to generate an adequate amount of power. The group of FCs is then called a ‘stack.’ FCs can be classified into many different types according to the type of electrolyte: a direct methanol FC, alkaline FC, phosphoric acid FC, molten carbonate FC, solid oxide FC, reversible FC, and a proton exchange membrane FC (PEMFC) [2]. The PEMFC is of considerable interest because it provides many advantages; for example, it can be operated at room temperature. It requires only low pressure. It has a fast start-up, quiet operation, and is small in size and highly efficient [3], [4]. Many factors affect the work of FCs when they produce electrical power. To ensure that a high amount of energy is generated, several researchers have suggested the use of various control methods to track the output voltage of the FC stack when the load current is variable; for example, the use of a fuzzy logic controller [5], optimal PEMFC based hybrid learning [6], cascade control [7], robust neural network adaptive control [8], a support vector machine (SVM) algorithm [9], traditional sliding mode controller [10], the hybrid Taguchi method and genetic algorithm neural networks [11], a backtracking search algorithm combined with Burger's chaotic map (BSABCM) [12] and a second-order sliding mode [13]. Also, many types of intelligent algorithms have been employed to understand the implicated phenomena of FCs, such as the salp swarm optimizer (SSO) [14], particle swarm optimization [15], genetic algorithm [16], BIPOA [17], and grey wolf optimization [18]. This paper focuses on optimizing the dynamic responses of the PEMFC stack and stabilizing its power output, mainly when different loads are employed in mobile applications. However, representative modeling of the PEMFC system and control of the output voltage remain challenging issues. The highlight of achievements of this work is the following: an analysis of the PEMFC operating system concerning the effect of each variable input-output, such as hydrogen partial pressure, oxygen partial pressure, temperature, and the cell load current; a feedback SIMO-PID neural controller is newly designed for use in stabilizing and tracking the desired output voltage of the FC system in a transient state, in addition to obtaining optimal (or near-optimal) hydrogen and oxygen flow rates control action; the output voltage performance of the PEMFC system is stabilized and improved using online multi-objective performance index evaluation based on an online tuning control FA, CPSO and the proposed hybrid F-CPSO algorithm.

This paper is arranged as follows: Section 2 explains the modeling of the PEMFC system; Section 3 presents the SIMO-PID neural network controller using three swarm optimization algorithms; Section 4 discusses the numerical results of simulations conducted using the proposed controller, and Section 5 presents conclusions made concerning the proposed controller.

2. Modeling of PEMFCs

FCs have an important role in many applications, and they require careful manufacturing. As both the membrane and electrode are made of platinum, they are therefore expensive [6]. PEMFCs will be an important and eco-friendly source of future power generation [6], and the main concept behind their operation is shown in Fig. 1. H₂ gas enters the PEMFC from the left side (the anode) and then decays into two compounds: positive chemical compounds (protons) and negative chemical compounds (electrons) because of the presence of the platinum catalyst. The chemical reaction on the left side is

\[
2\text{H}_2 \rightarrow 4\text{H}^+ + 4e^-
\]  

(1)

Only the positive compounds pass from the left to the right side [6], [18], and the negative chemical compounds (electrons) are transported through the external electrical circuit to generate the electric signal. Positive and negative compounds react with oxygen from the air to produce water and energy due to the chemical reaction [6], [8]. The chemical reaction on the right side is

\[
4e^- + 4\text{H}^+ + \text{O}_2 \rightarrow 2\text{H}_2\text{O}
\]  

(2)

The water produced by the chemical reaction must be managed to maintain the PEMFC, as the water pool on the cathode side can lead to cell flooding and cell loss [3]. Every single cell produces energy ranging from 0.9 to 1 V. Since this amount of power is too low to operate any type of system, several researchers have proposed linking cells in a parallel or sequential group as a ‘stack.’ The operating temperature of these types of cells is around (50 to 80 °C) [5], [6], [8]. When modeling the system controllers and simulating a power state, a polarization curve is employed to represent the modules and show the relationship between the voltage and current (V-I).
A mathematical model of a PEMFC can be calculated using the following equations [6], [8], [18],

\[ V_{\text{cell}} = V_{\text{steady}} - V_{\text{transient}} \]  
(3)

\[ V_{\text{steady}} = E_N - V_{\text{ohm}} \]  
(4)

\[ V_{\text{transient}} = V_{\text{act}} + V_{\text{con}} \]  
(5)

where \( V_{\text{cell}} \) represents the output voltage of the FC; \( E_N \) represents the thermodynamic potential; \( V_{\text{act}} \) is low voltage due to interaction between the anode and cathode; \( V_{\text{con}} \) is the concentration overvoltage, and \( V_{\text{ohm}} \) represents a decline in voltage resulting from the impedance of proton conduction through the electrolyte and of the electrons through their path.

The thermodynamic potential \( E_N \) can be calculated using the following equation [19, 20, 21],

\[ E_N = 1.229 - 0.85 \times 10^{-3} \times (T - 298) + 4.3085 \times 10^{-5} \times T \times ((\ln(PH_2) + 0.5 \times \ln(PO_2)) \]  
(6)

where \( PH_2 \) is the partial pressure of hydrogen, \( PO_2 \) is the partial pressure of oxygen, and \( T \) is the temperature of the full cell. The model equations so far accept partial pressures of gases as inputs. To derive the perfect gas equation, a specific relation needs to be derived between the partial pressure and the fuel's input flow rate. The partial pressure of hydrogen and oxygen are given in Equations (7) and (8) [20 and 21] as follows,

\[ P_{H_2} = [(1 / k_{H_2})/(1 + \tau_{H_2}S)](Q_{H_2} - 2Ikr) \]  
(7)

\[ P_{O_2} = [(1 / k_{O_2})/(1 + \tau_{O_2}S)](Q_{O_2} - 1kr) \]  
(8)

where \( k_{H_2} \) is the valve molar constant for hydrogen; \( k_{O_2} \) is the valve molar constant for oxygen; \( \tau_{O_2} \) is the response time for oxygen; \( \tau_{H_2} \) is the response time for hydrogen; \( kr \) is the modeling parameter constant, and \( I \) is the cell load current.

The activation loss falls in voltage relating to activity between the anode and the cathode [19]. This type of loss can be calculated as

\[ V_{\text{act}} = \alpha_1 + \alpha_2 \times T + \alpha_3 \times T \times \ln(CO_2) + \alpha_4 \times T \times \ln(I) \]  
(9)

where \( CO_2 \) is the concentration of oxygen dissolved in the surface of the cathode ohm /cm\(^3\) and can be calculated using Henry law, as shown in the following Equation [19],

\[ CO_2 = \frac{P_{O_2}}{5.08 \times 10^6 \times \exp\left(-\frac{-498}{T}\right)} \]  
(10)

The voltage of ohmic loss can be determined by using [19], [22],

\[ V_{\text{ohm}} = I \times (R_e + R_m)R_a \]  
(11)

where \( R \) represents the constant value of proton resistance, and \( R_a \) represents the equivalent resistance of the electron flow and can be calculated as
where, \( \rho_m \) is the specific resistance of the membrane, which can be calculated as

\[
\rho_m = \frac{\rho_m L}{A}
\]

(12)

The concentration loss can be determined as [19], [22]

\[
V_{con} = -\beta \ln\left(1 - \frac{J}{J_{max}}\right)
\]

(14)

The total output voltage of the stack can be determined by the following equation [19], [22],

\[
V_{FC} = N_{cell} V_{cell},
\]

(16)

where \( N_{cell} \) represents the number of stacks.Finally, the equation below is used to determine the overall output power from the stack,

\[
P_{power_{FC}} = V_{FC} I_{FC}
\]

(17)

3. Controller design

Based on the characteristics of the PEMFC operating system, it has three outputs: the FC stack output voltage (VFC), temperature (T), and the load current (I_L), while the inputs of the PEMFC system (which control operation of the FC) are the hydrogen flow rate and the oxygen flow rate (which need to be controlled to provide suitable hydrogen and oxygen partial pressure values that are used to operate the FC). The controller proposed in this paper is a newly designed SIMO PID neural controller structure that combines a combined non-linear neural network with a PID controller. The traditional PID control module is characterized by simplicity, efficiency, effective learning capabilities, and an automatic adaptation to neural networks. However, neural networks require lengthy training times and many parameter settings [23], [24]. Therefore, this new control structure, which combines the features of traditional PID control and a neural network, provides high performance and acts as a strong and adaptive SIMO controller. Figure 2 shows the main structure of the non-linear SIMO-PID neural network. The non-linear SIMO-PID-NN is presented here in two parts: the first part relates to the non-linear SIMO-PID-NN structure, and the second part relates to online tuning algorithms.

![Figure 2. General block diagram of the fuel cell (FC) controller.](image-url)

Figure 3 explains the construction of the proposed PEMFC’s controller as the first part.
Figure 3. Proposed controller structure.

The proposed structure uses a multi-layer perceptron (MLP) neural network consisting of three layers. The input layer consists of $e(k)$ and $e(k-1)$, and there are six neurons in the hidden layer, which are the proportional, integral, and differential neurons for two non-linear PID controllers. After $kp_{1,2}$, $ki_{1,2}$, and $kd_{1,2}$ gains are calculated, a sigmoid function is used to calculate the weighted sum (representing the output of the hidden layer) as follows,

$$ net1(k) = kp_1 \times e(k) + ki_1 \times (e(k) + e(k-1)) + kd_1 \times (e(k) - e(k-1)) $$

$$ net2(k) = kp_2 \times e(k) + ki_2 \times (e(k) + e(k-1)) + kd_2 \times (e(k) - e(k-1)) $$

$$ h1(k) = \frac{1}{1 + \exp(-1 \times net1(k))} $$

$$ h2(k) = \frac{1}{1 + \exp(-1 \times net2(k))} $$

where $kp_{1,2}$, $ki_{1,2}$, and $kd_{1,2}$ are the proportional, integral, and derivative gains, respectively, and $e(k)$ is the tracking voltage error, which is defined as the difference between the desired output voltage ($V_{des}$) and the actual output voltage ($Vo$).

In the output layer, the proposed control law equations for hydrogen and oxygen flow rates are as follows,

$$ Q_{H2}(k) = h1(k) + \beta h2(k) $$

$$ Q_{O2}(k) = h2(k) + \alpha h1(k) $$

where $Q_{H2}(k)$ represents the hydrogen flow rate control effort, $Q_{O2}(k)$ represents the oxygen flow rate control effort, and $\alpha$ and $\beta$ are gain values from swarm algorithms.

The learning swarm algorithm is usually based on minimization (with respect to the neural network weights) of the proposed online multi-objective cost function,

$$ E = \frac{1}{p} \sum_{l=1}^{p} [V_{des}(k+1) - Vo(k+1))^2 + (ts_{des} - ts)^2 + (mp_{des} - mp)^2] $$

where $p$ represents the number of training points in the training set; $Vo(k+1)$ is the actual output voltage of the FC of each $k^{th}$ iteration; $V_{des}(k+1)$ represents the desired output voltage of every iteration; $ts_{des}$ is the desired settling time of the closed-loop control system; $ts$ is the actual settling time of the system; $mp_{des}$ is the desired overshoot of the closed-loop control system, and $mp$ is the actual overshoot of the system. The second part of the study relates to intelligent swarm optimization algorithms. Here, different intelligent algorithms are used to find and tune the SIMO-PID-NN controller’s best weights. Their effectiveness is shown in terms of the number of iterations employed,
evaluating the fitness function, and obtaining the minimum value for the multi-objective cost function. They are presented as follows.

3.1. The firefly algorithm

The firefly algorithm is a meta-heuristic algorithm, and its principle of operation is based on the flashing behavior of a firefly [25]. In general, the firefly algorithm formulation is based on three ideal rules: (1) that all fireflies are unisex; (2) that the firefly’s attractiveness ($\beta$) is proportional to its brightness ($I$), and if the brightness of two fireflies decreases, then the distance ($r$) between them is increased. Furthermore, (3) with firefly movement, those that are less bright will move toward brighter ones, and if there are no brighter fireflies, then the firefly moves randomly. The brightness is associated with the objective function. The relationship between the attractiveness of each firefly can be described by monotonically decreasing function of the distance between any two fireflies and is formulated as [25] and [26],

$$\beta = \beta_0 \exp^{-\gamma r^m}$$

(25)

where $\beta_0$ is equal to 1, and it represents maximum attractiveness (at $r = 0$); $\gamma$ is a factor with a range from 0.1 to 10, and it represents light absorption, and $m$ is more than 1.

The distance between any two fireflies (i) and (j) at positions $x_i$ and $x_j$ can be estimated using the distance formula as follows [25] and [26],

$$r_{ij} = \sqrt{\sum_{k=1}^{d}(x_{i,k} - x_{j,k})^2}$$

(26)

where $d$ is the number of dimensions and $x_{i,k}$ is the $k$th spatial coordinate element $x_i$ of the $i$th firefly.

The movement of firefly can be formulated using three terms: the first term represents the firefly’s current location; the second one represents the firefly’s attractiveness, and the final term denotes the random movement of the firefly (if there are no brighter fireflies) [25] and [26],

$$x_i = x_i + \beta_0 \exp^{-\gamma r^m} (x_i - x_j) + \alpha (\text{rand} - 0.5)$$

(27)

where $\alpha$ is a randomization variable between (0–1).

3.2. Particle swarm and chaotic particle swarm optimization algorithms.

One of the modern stochastic search algorithms employed is Particle Swarm Optimization (PSO), which is often employed because of its simple concept, ease of implementation, and quick convergence [27]. The particles in this technique start with a random initial particle (population of individuals), and each particle is led by internal interaction to provide a near-optimal solution by minimizing or maximizing a given objective function; this is achieved by flying through the search space. The movement of particle $x_i$, $x_i$, depends on its velocity, $V_i$, which is adjusted at each time step using the Global best position, $G_{\text{best}}$, and the Local best position, $L_{\text{best}}$, which have been already found.

Equation (28) represents the particle’s velocity update, and Equation (29) represents the particle’s position update [27] and [28],

$$\begin{align*}
(k + 1) &= w_i(k) + c_1 r_1 [L_{\text{best}} - x_i(k)] + c_2 r_2 [G_{\text{best}} - x_i(k)] \\
x_i(k + 1) &= x_i(k) + v_i(k + 1)
\end{align*}$$

(28)

(29)

where $c_1$ and $c_2$ are cognitive coefficients and $r_1$ and $r_2$ are two uniform random numbers (0 to 1).

The chaotic technique is employed to solve global optimization problems that use a large number of local minima; it has been employed in specific metaheuristic methods, and its numerical performance is generally superior to that of random operators when searching [29].

In this respect, the Chaotic Particle Swarm Optimization CPSO algorithm is proposed because it can improve global searches and reach an optimal solution using fewer iterations that depend on the probabilities of chaotic techniques [30] than stochastic techniques. The logistic equation employed for constructing the chaotic PSO is described as [29]

$$\beta(k + 1) = \mu \beta(k) [1 - \beta(k)]$$

(30)

where $\mu$ is equal to 4 (as the control parameter). Therefore: (0) $\notin \{0, 0.25, 0.5, 0.75, 1\}$.

Equations 30 and 31 are employed to calculate the new weight parameter, $w_{\text{new}}$, as follows,

$$w = w_{\text{max}} - \left( (w_{\text{max}} - w_{\text{min}}) \times \frac{\text{iteration} - 1}{\text{max.no.iteration}} \right)$$

(31)
To enhance the capability of PSO in global searching, new inertia weighting needs to be placed in the velocity update equation to become
\[ v_i(k+1) = w_{new} \cdot v_i(k) + c_1 r_1 [L_{best-i} - x_i(k)] + c_2 r_2 [G_{best} - x_i(k)] \] (33)

3.3. The proposed hybrid optimization algorithm

The proposed algorithm combines two optimization algorithms, namely the firefly and the CPSO, to optimize the order, increase learning speed, avoid filling in the local minimum, and reduce the number of fitness evaluations. The hybrid F-CPSO algorithm develops the movement of the firefly equation by converting the equation of distance forms into the distance between \( x_i \) and \( L_{best} \) in the Cartesian distance (as in Equation 34) and the distance between \( x_i \) and \( G_{best} \) in the Cartesian distance (as in Equation 35),

\[ r_{LX} = \sqrt{\sum_{j=1}^{d} (L_{best,j} - x_i,j)^2} \] (34)
\[ r_{GX} = \sqrt{\sum_{j=1}^{d} (G_{best,j} - x_i,j)^2} \] (35)

In addition, the new inertia weighting acquired in Equation (32) is added to the movement of the firefly equation, and the final proposed movement of a firefly is represented as

\[ x_i(k+1) = w_{new} \cdot x_i(k) + c_1 \exp^{-r_{LX}} \left( L_{best-i} - x_i(k) \right) + c_2 \exp^{-r_{GX}} \left( G_{best-i} - x_i(k) \right) + \alpha (rand - 0.5) \] (36)

The effectiveness of the proposed hybrid F-CPSO algorithm is evident throughout the entire population and each particle is randomly attracted towards the \( G_{best} \) position. A local search can be conducted in different regions using the modified attractiveness step of the proposed algorithm.

4. Simulation results

The proposed non-linear SIMO-PID neural network controller explained in Figure 2 was designed using the m.file MATLAB package 2018. The first stage in controller design was to study and analyze the dynamic characteristics of the PEMFC system that are taken from [19, 20, 21] and listed in Table 1.

| Parameters | Units          | Values |
|------------|----------------|--------|
| \( N_{cell} \) | cm\(^2\) | 32     |
| \( T \)    | Kelvin degree | 298    |
| \( A \)    | cm            | 64     |
| \( L \)    | cm\(^{-6}\)  | 178 \times 10^{-6} |
| \( PH_2 \) | Atm           | 1.5    |
| \( PO_2 \) | Atm           | 0.2    |
| \( R_0 \)  | \( \Omega \)  | 0.0003 |
| \( B \)    | V             | 0.0169 |
| \( \alpha_1 \) | --      | 0.948  |
| \( \alpha_2 \) | --        | -0.00312 |
| \( \alpha_3 \) | --       | -7.6 \times 10^{-5} |
| \( \alpha_4 \) | --     | 1.93 \times 10^{-4} |
| \( J \)    | mA/cm\(^2\)  | 0.0073 |
| \( J_{max} \) | mA/cm\(^2\) | 0.469  |
| \( \Phi \) | Sec           | 23     |
| \( \tau_{O2} \) | --      | 6.74   |
| \( \tau_{H2} \) | Sec    | 3.37   |
| \( k_{H2} \) | Kmol/(sec atm) | 4.22 \times 10^{-5} |
| \( k_{O2} \) | Kmol/(sec atm) | 2.11 \times 10^{-5} |
| \( K_r \)  | Kmol/(sec A)  | 1.0364 \times 10^{-5} |
The results are shown as a polarization curve of the output voltage and the stack output power of the FC in a normal operational state during a variable cell load current between 0 A and 30 A. The other parameters were as follows: hydrogen partial pressure at a constant value of 1.0 bar; oxygen partial pressure at a constant value of 0.2 bar and constant temperature of operation at 25°C, as shown in Figure 4-a and b. This model's maximum power is apparent, as the current is equal to 29 A. Figure 5 shows the polarization curve of the loss voltage in the FC system during a variable load current between 0 A and 30 A.

![Polarization Curve](image1)

**Figure 4.** a) Output voltage of FC against variable load current, b) Output power of FC against the variable current.

![Voltage Drop Curve](image2)

**Figure 5.** Voltage drop in FC system against variable load current.
The second step of the study determined the effect of hydrogen partial pressure (which changed from 0.1 bar to 5 bar) on the FC's output voltage with a variable load current from 0 A to 30 A. The other parameters were as follows: temperature of operation was constant at 25 °C, and oxygen partial pressure was constant at 0.2 bar. Figure 6 shows the output voltage of the FC, which increases with an increase in hydrogen partial pressure because the thermodynamic potential (EN) value of the PEMFC system, which is shown in Equation (6), has been improved and is increasing, thereby causing an improvement in the performance of the FC system. The third study is to show the effect of the oxygen partial pressure, which changes from 0.1 bar to 5 bar on the output voltage of the Fuel Cell operation during the load current of the fuel cell is variable from 0 A to 30 A, while the hydrogen partial pressure is constant at 1 bar and the temperature of the operation is constant at 25°C. Figure 7 shows the output voltage of fuel cell, which increases when the oxygen partial pressure increases too because the thermodynamic potential (EN) value of the PEMFC system as in Equation (6) has been improved toward increasing, which led to the improving the performance of the Fuel Cell system.

Figure 6. FC output voltage system against variable load current with a change in hydrogen partial pressure against variable load current.

Figure 7. FC output voltage against variable load current with a change in oxygen partial pressure against variable load current.
The fourth part of the study determined the effect of temperature, which changed from 25°C to 80°C, on the output voltage of FC operation during the variation in the FC load current from 0 A to 30 A, where the hydrogen and oxygen partial pressures were maintained at constant values of 1.0 bar and 0.2 bar, respectively. Figure 8 shows the output voltage of the FC, which increases with an increase in temperature. This occurs because the thermodynamic potential (EN) value of the PEMFC system has been increased and thus improved, and the impact values of the parameters have been reduced with respect to the loss voltage in the FC system, which ultimately leads to an improvement in the FC system performance. However, when the FC operation's temperature is increased, the humidity required for cell membranes is lost, which has a negative impact on the life of the FC.

To implement the proposed SIMO-PID-NN controller design, as shown in Figs. 2 and 3, several parameters based on the three swarm optimization algorithms were firstly defined, as listed in Table 2, before running the m.file program.

| Algorithm Type | Numbers of Particles | Numbers of Firefly | Particle weights | Firefly weights | $c_1$, $c_2$ | $r_1$, $r_2$ | Best iteration number |
|----------------|----------------------|--------------------|------------------|----------------|-------------|-------------|----------------------|
| CPSO           | 200                  | 8                  | -                | $[\beta, \gamma, \alpha, m]$ | 1.735       | -           | Random (0,1) 50 |
| F              | -                    | 200                | -                | $[1.5, 0.2, 2]$ | -           | -           | 50                   |
| F-CPSO         | -                    | 100                | 8                | $[-0.2, -]   $ | 1.735       | -           | 25                   |

There are eight controller parameters ($k_{p1,2}$, $k_{i1,2}$, $k_{d1,2}$, $\alpha$, and $\beta$); therefore, the particle weight is equal to eight. Figure 9 shows the five different step changes of the desired output voltage using five variable cell load current cases of 15, 10, 6, 15, and 10 A, as shown in Figure 10, where experiments were conducted using 125 samples with sampling time is equal to 0.1 sec. These results represent the PEMFC’s output voltage responses when the proposed SIMO-PID-NN controller is applied, and the three different types of tuning algorithms are used, respectively. It is clear that the proposed controller can track the desired output voltage when there is a variable cell load current. However, the controller's best performance is for the PEMFC model tuned using the F-CPSO algorithm, where the actual output voltage of the PEMFC is proficiently tracked, and there is no overshoot without oscillation in the output.
Figure 9. Actual PEMFC output voltage response.

Figure 10. The current variation of FC load.

Table 3 shows the FC system's dynamic characteristics after applying non-linear SIMO-PID-NN controllers at only the first step change concerning the rise time, settling time, overshoot, and steady-state error where the desired rise time is 0.3 sec and the desired settling time is 0.45 sec.

Table 3. Dynamic characteristics of FC output voltage based on different types of intelligent swarm algorithms.

| Algorithm type | Rise time (sec) | Settling time (sec) | Overshoot | Steady-state error (volt) |
|----------------|-----------------|---------------------|-----------|--------------------------|
| CPSO           | 0.39            | 0.58                | 0         | 0.023                    |
| F              | 0.58            | 0.71                | 0         | 0.098                    |
| F-CPSO         | 0.31            | 0.49                | 0         | 0.011                    |

The controller is more accurate when tuned with the F-CPSO algorithm than with the F and CPSO algorithms. The steady-state error is approximately equal to zero with a minimum online multi-objective performance index value shown in Figure 11.
Figure 11. The response of FC error voltage.

Figure 12 shows the online multi-objective performance index for the three different optimization algorithms during tuning of the controller's weighting parameters; this was conducted to track the desired output voltage of the FC.

Figure 12. On-line cost function (MSE).

Figures 13 and 14 show the hydrogen and oxygen flow rate control action, respectively, of the non-linear SIMO-PID-NN controller, where smooth action of the flow rate is used to track the desired output voltage and to make the error is approximately minimized to zero at steady state. Because the effectiveness of the local search of the proposed hybrid F-CPSO tuning control algorithm is modified attractiveness step that conducted in different regions that led to attracting each particle randomly towards the G_best position. Therefore, the control parameters' values are smooth optimal, or near-optimal generated that obtained minimal spike action without oscillation in the transient state.
Figure 13. Hydrogen flow rate control signal based on three different swarm algorithm types.

Figure 14. Oxygen flow rate control signal based on three different swarm algorithm types.

Figure 15 shows the hydrogen partial pressure response based on the SIMO-PID-NN controller using the three different swarm optimization algorithm types, where there is a small spike response of the partial pressure used to track the desired output voltage. The steady-state error is approximately minimized to zero when the hybrid F-CPSO swarm optimization is employed. Figure 16 shows the FC power response based on the SIMO-PID-NN controller with the three different types of swarm optimization algorithms; the power response is fast and smooth when the FC load current is changed.

Figure 15. Hydrogen partial pressure control signal based on three different types of swarm algorithms.
5. Conclusion
A proposed non-linear SIMO-PID-NN controller with the hybrid Firefly-Chaotic Particle Swarm Optimization (F-CPSO) is presented in this paper. The proposed algorithm is used to control the non-linear dynamic behavior of an FC system. The proposed control structure with the F-CPSO learning algorithm has higher capabilities rather than the Firefly algorithm and the Chaotic Particle Swarm Optimization algorithm because the proposed hybrid F-CPSO algorithm was evident throughout the entire swarm population, and each particle “control gain parameters” are randomly attracted towards the $G_{best}$ position and the local search could be conducted in different regions using the proposed algorithm's modified attractiveness step. Therefore, the results of this study show that:

(i) The proposed F-CPSO was a fast learning algorithm that can generate two control actions (hydrogen and oxygen flow rates) without an oscillation and spike response or a saturation state problem.

(ii) A minimum fitness evaluation was required to determine the optimal weight control parameters for the SIMO-PID-NN controller.

(iii) The strong, robust SIMO-PID-NN controller can track the desired output voltage of the PEMFC system during cell load current variations.

(iv) The actual output voltage of the PEMFC was proficiently tracked, and there was no overshoot and no oscillation in the output.

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