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Improving Parameter Estimation of Fuel Cell Using Honey Badger Optimization Algorithm

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In this study, we proposed an alternative method to determine the parameter of the proton exchange membrane fuel cell (PEMFC) since there are multiple variable quantities with diverse nonlinear characteristics included in the PEMFC design, which is specified correctly to ensure effective modeling. The distinctive model of FCs is critical in determining the effectiveness of the cells' inquiry. The design of FC has a significant influence on the simulation research of such methods, which have been used in a variety of applications. The developed method depends on using the honey badger algorithm (HBA) as a new identification approach for identifying the parameters of the PEMFC. In the presented method, the minimal value of the sum square error (SSE) is applied to determine the optimal fitness function. A set of experimental series has been conducted utilizing three datasets entitled 250-W stack, BCS 500-W, and NedStack PS6 to justify the usage of the HBA to determine the PEMFC's parameters. The results of the competitive algorithms are assessed using SSE and standard deviation metrics after numerous independent runs. The findings revealed that the presented approach produced promising results and outperformed the other comparison approaches.

Keywords: parameter extracting, fuel cells, optimization, proton exchange membrane fuel cell, honey badger optimization algorithm

1 INTRODUCTION

The technology of the fuel cell (FC) is an essential energy exporter due to its extraordinary production and reduced carbon effects. Also, in contrast to wind and photovoltaic power origins, the production of power from the FC is autonomous of the climatologic conditions. Thus, it can be used for perpetual power generation. Different models of the FC are revealed; their system is carried out based on the characteristics of the electrolyte applied. Among the numerous types of FCs are the chemical-based FC approach (CFC) (McLean et al., 2002), PEMFC (Eisman, 1989), solid-based oxide FC (SOFC) (Kawada et al., 1990), etc. One of the most well-known types of FCs is the PEMFC. Their active start is recognized because of their economic temperature and yield ranging between 30 and 60%. The PEMFCs are utilized in different disciplines (Messaoud et al.,

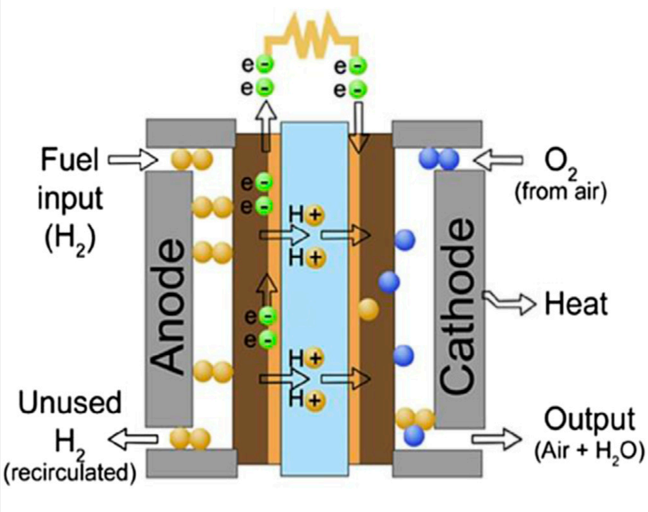

FIGURE 1 | PEMFC arrangement (Famouri and Gemmen, 2003).

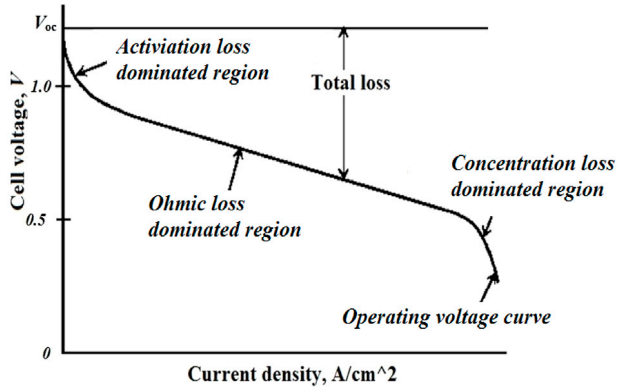

FIGURE 2 | Polarization curve of the PEMFC system (Famouri and Gemmen, 2003) showing the regions dominated by activation loss, ohmic loss, and concentration loss using HBA.

2021). The escalating cost of human energy has a hazardous impression on the atmosphere. Electricity requirements contribute primarily to ecological degeneration while consuming nonrenewable supplies (Nain et al., 2021). The portion of renewable electricity from the universal energy production is 26% approximately. Various varieties of power references for providing hydrogen exist. Now, most of the hydrogen composition is generated by solar power (37%) and comes behind conventional fossil fuel (26%), as shown in **Figure 1** (Fathy et al., 2020b). These H2 results guide to reasonable prices and more critical appropriate solutions via hydrogen in the real world (Kayfeci et al., 2019).

FC-based energy production methods can meet the anticipations of very low emanations and comparatively high conductivity (Mo et al., 2006). FC is characterized by more economical contamination and more extraordinary performance than traditional power origins; however, they have an excellent dynamic reaction, sound balance, and moderate noise (Ramos-Paja et al., 2010). Between several systems of FCs, because of their approximately low running temperature, quick reaction, small volume, high popular mass, no loss, and in case of explicit hydrogen zero emission is generated, PEMFC can be an excellent option for energy-producing origins in the future, particularly in the automation applications, shared power production, and transferable photoelectric applicability (Askarzadeh and Rezazadeh, 2011).

Despite substantial advancements in the previous few years, the financial performance of PEMFCs is still a point of contention among support and opposition (Alizadeh and Torabi, 2021). The improvement of PEMFC performance is critical for the marketing of the technology and achieving significant market adoption (Kahraman and Orhan, 2017). Generally, the performance of the FC is regarded as the essential aspect of end-user acceptability (J. Wang et al., 2018). Many published articles show that numerous structural and operational factors (parameters) highly influence the performance of the PEMFC. The most efficient methods that have successfully proved their ability to extract the parameters are the optimization methods (Eid et al., 2021; Hassan et al., 2021; Wang et al., 2021). This field still needs further investigation to find a more efficient approach to tackle this problem.

As presented in the relevant studies, Priya et al. (2015) presented a unique presentation for the efficient estimation of FC parameters. The parameters' values of FC were determined based on the genetic algorithm, and the obtained results proved its ability to find better results than several other methods in this domain. İnci and Caliskan (2020) proposed a new enhanced energy extraction-based optimization method to tackle the FC parameters. The presented technique is based on using an improved cuckoo optimizer. The proposed technique achieved better convergence acceleration than traditional techniques. Kandidayeni et al. (2019) used several optimization techniques to solve PEMFC. The proposed method reduced squared errors among the included and measured voltage for two possible test cases. The proposed SFLA method got better results in terms of precision and repeatability than the other comparative methods. Fathy et al. (2020a) introduced a hybrid of differential evolution and vortex search algorithms for determining the optimum parameters of the FC, called VSADE. The achieved results established the superiority of the introduced VSADE method. This study aimed to provide a new, simpler, and accurate model of the proton electrolyte membrane FC (Seleem et al., 2021). The suggested approach drastically lowers the number of unknown factors in such models, resulting in a more straightforward model. It discloses just four design factors within the model in this regard. This model's great effectiveness is tested both in steady-state and dynamic operating situations. It is possible to build a highly exact PEMFC model using the suggested approach. Menesy et al. (2020) suggested an enhanced artificial ecosystem optimizer to determine the problem of the FC parameters. According to the results, it is proved that the presented optimizer has high performance in obtaining the optimal parameters compared with the other comparative methods.

As mentioned before, metaheuristic optimization algorithms proved their ability to deal with various problems such as bioinformatics (Issa, 2021a; Issa and Abd Elaziz, 2020; Issa and Hassanien, 2017; Issa et al., 2018a; Issa et al., 2018b; Issa and Helmi, 2021; Issa et al., 2022), control engineering (Issa, 2021b; Issa et al., 2019), passive suspension system (Issa and Samn, 2022), and digital watermarking (Abualigah and Diabat, 2021; Issa, 2018). To estimate the model parameters of the PEMFC, an efficient method compared to the existing method is needed. This research work proposed a new parameter extraction technique to deal with the FC modeling optimization problem. The proposed method is based on the honey badger algorithm (HBA), a technique recently proposed by Hashim et al.(2021) inspired by the creative foraging habits of the honey badger in real life. The mathematical modeling of the HBA is produced using efficient search operators to deal with highly complicated problems which motivate to use it for the parameter estimation of PEMFCs. The balancing between diversification and intensification of the search space of the HBA is the main merit and motivation to use it in this work. The primary fitness function that is used in the proposed method is to minimize the integral squared errors. The high effectiveness of the presented technique is verified using dynamic and steady-state operating conditions. The results illustrated that the presented method using the HBA achieved promising results in comparison with several relevant study parameter extraction methods used in the literature.

The main contributions and novelties of this study are concluded as following:

1. The optimal values of the PEMFC model parameters were adjusted based on the HBA.
2. Three PEMFC datasets (NedStack PS6, 250 W, and BCS 500 W) were used in the experimental tests.
3. The results of the developed method were compared with well-known methods.

The remaining sections of this article are organized as follows: **Section 2** proposes the background of the used optimization methods. **Section 3** shows the procedure of the proposed FC parameter extraction using the honey badger algorithm. In **Section 4**, experiments and results are given. Finally, **Section 5** presents the conclusions and future potential works.

2 BACKGROUND

In this part, the primary mathematical representation of the PEMFC design is explained. It includes a cathode, negative charges, charged anode, and electrolyte, as described in **Figure 1**. In the PEMFC system, the hydrogen data are divided into two main parts utilizing a catalyst: protons and electrons. Moreover, the cathode pulls the protons, and the electrons produce the output charge by moving along the exterior circuit. The mathematical notations of the chemical stability produced in the FC are presented as follows (Alizadeh and Torabi, 2021):

$$H_2 \rightarrow 2H^{+} + 2e^{-}, \tag{1}$$

$$O_2 + 4e^{-} \rightarrow 2O^{-2}, \tag{2}$$

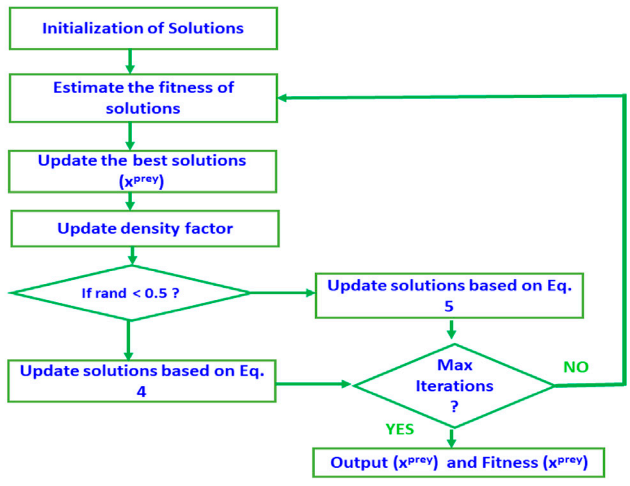

FIGURE 3 | Flowchart of HBA (Hashim et al., 2022).

$$H_2 + \frac{1}{2}O_2 \rightarrow H_2O + electrical\, energy + Heat. \tag{3}$$

In the PEMFC system, three drops normally happen during the voltage process, called activation (V_{act}), ohmic (V_{ohm}), and concentration (V_{con}). Thus, **Eq. 4** is used to calculate the FC terminal voltage.

$$V_{FC} = E_{Nernest} - V_{act} - V_{ohm} - V_{con}, \tag{4}$$

where $E_{Nernest}$ is the double-faced open circuit charge voltage, which is calculated as follows (Yuan et al., 2020):

$$E_{Nernest} = 1.229 - 8.5 \times 10^{-4}(T - 298.15) + 4.385 \times 10^{-5} T\, ln(P_{H2} + 0.5\, ln\, P_{O2}), \tag{5}$$

where RP_{O2} presents the pressure of the O2, RP_{H2} presents the pressure of H_2, and T represents the cell temperature value used in this research. The activation voltage loss value (V_{act}) is calculated as follows:

$$V_{act} = -[\xi_1 + \xi_2 T + \xi_3 T \ln(C_{02}) + \xi_4 T \ln(I_{FC})], \tag{6}$$

where I_{FC} is the present value of the FC and ξ_1, ξ_2, ξ_3, and ξ_4 denote the coefficient values. C_{O2} presents the condensation value of oxygen (mol/cm^3) calculated as follows:

$$C_{O2} = \frac{P_{O2}}{5.08^{*}10^{6*}e^{\left(\frac{-498}{T}\right)}}. \tag{7}$$

The V_{ohm} is calculated using **Eq. 8**, which is resulted from the equivalent resistance of the FC value.

$$V_{ohm} = I_{FC}(R_M + R_C), \tag{8}$$

where R_C presents the connection resistance and R_M presents the membrane resistances calculated as follows:

$$R_M = \frac{\rho_M . l}{A}, \tag{9}$$

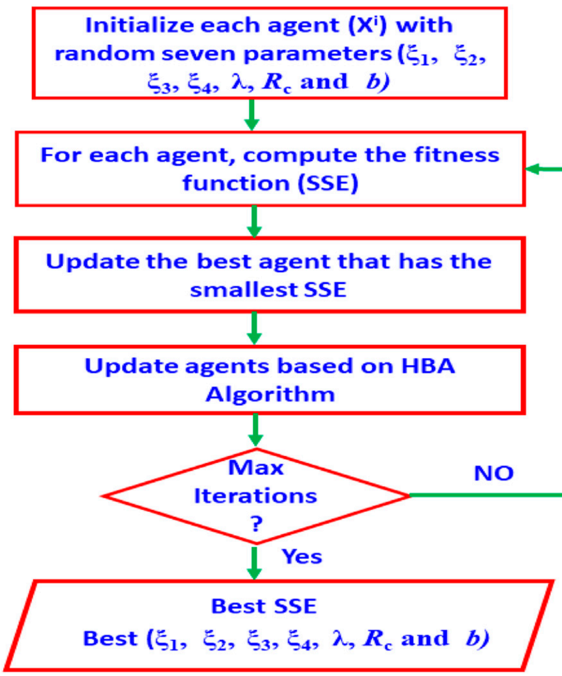

FIGURE 4 | PEMFC model parameter estimation based on HBA.

TABLE 1 | PEMFC dataset's electrical specifications.

Specification	BCS 500-W [2]	250-W [33], [34]	PS6 [33]
$cells_{nb}$	32	24	65
L (μm)	178	127	178
A_m (cm^2)	64	27	240
CD_{max} ($\frac{mA}{cm^2}$)	469	860	1125
TM_c (K)	333	343	343
PR_{H2} (atm)	1	1	1
PR_{O2} (atm)	0.2095	1	1

$$\rho_M = \frac{181.6\left[1 + 0.03\left(\frac{I_{FC}}{A}\right) + 0.0062\left(\frac{T}{303}\right)\left(\frac{I_{FC}}{A}\right)^{2.5}\right]}{\left[\lambda_m - 0.634 - 3\left(\frac{I_{FC}}{A}\right)\right] exp\left[4.18\left(\frac{T-303}{T}\right)\right]}, \tag{10}$$

where ρ_M presents the measure of the resisting power of the membrane (Ω.cm), l presents the density value of the membrane (cm), A presents the effective range of the cell (cm^2), and λ_m presents the membrane water fulfilled. The V_{con} value is calculated using **Eq. 11**.

$$V_{con} = -b \ln\left\{1 - \frac{\left(\frac{I_{FC}}{A}\right)}{I_{max}}\right\}, \tag{11}$$

where b presents a constant value and I_{max} is the present maximum destiny value. So, the stack includes a series value of n FCs, and the stack voltage value is calculated as follows.

$$V_{stack} = n.V_{FC} = n.(E_{Nernest} - V_{act} - V_{ohm} - V_{con}). \tag{12}$$

TABLE 2 | Two parameter ranges of PEMFC parameters.

Parameter	Lower limit	Upper limit
ξ_1	−1.1997	−0.8532
ξ_2	0.80E-3	6.00E-3
ξ_3	3.60E-5	9.80E-5
ξ_4	−26.00E-5	−9.54E-5
λ	13	23
R_c (Ω)	0.1E-3	0.8E-3
b (V)	0.0136	0.5000

TABLE 3 | Estimated BSC 500 W's parameters.

	HBA	HGS	HHO	SCA	GWO
ξ_1	**−0.952**	−0.9510	−1.093	−0.947	−0.948
ξ_2	**3.2E-03**	3.3E-03	3.3E-03	3.3E-03	3.3E-03
ξ_3	**7.40E-05**	−9.2E-05	−1.89E-04	−7.1E-5	−8.0E-5
ξ_4	**−7.24E-05**	−9.21E-5	−1.89E-4	−7.1E-5	−8.0E-5
λ	**2.01E+01**	14.00	2.00E+01	19.569	18.599
Rc	**5.43E-04**	1.4E-04	2.26E-04	4.1E-04	3.2E-04
b	**1.60E-02**	1.7E-02	1.51E-02	2.9E-02	3.01E-2
SSE	**0.0118**	2.113	0.0149	8.726	1.918

TABLE 4 | Estimated 250 W's parameters.

Parameter	HBA	HGS	HHO	SCA	GWO
ξ_1	−0.9486	−0.945	−1.1097	−0.9487	−0.9478
ξ_2	3.25E-03	3.00E-03	3.46E-03	3.23E-3	3.22E-3
ξ_3	7.80E-5	7.8E-05	8.32E-05	7.69E-5	7.69E-5
ξ_4	−1.73E-4	−1.0E-04	−1.52E-4	−1.8E-4	−1.8E-4
λ	1.7E+01	17.993	2.29E+1	18.395	18.231
R_c (Ω)	8.0E-04	5.8E-04	3.83E-04	2.8E-04	3.5E-04
b	1.60E-02	1.6E-02	5.42E-02	1.8E-02	1.8E-02
SSE	0.354	0.3576	6.46–01	0.546	0.3680

Figure 2 presents the FC polarization detour.

2.1 Honey Badger Algorithm

The HBA mimicked the locating of prey operation of the honey badger that lives in rainforests and semideserts of Southwest Asia, the Indian subcontinent, and Africa. For locating a prey, it depends on its smelling skills and moving.

- Digging phase: In this phase, the honey badger depends on its smelling sense for locating the prey and the suitable place to catch it.
- Honey phase: In this phase, the honey badger tracks the honey bird for locating the beehive.

The HBA starts with the initialization of the solutions within the lower boundary (lb) and upper boundary (ub) according to **Eq. (13)**.

$$x^i = lb_i + r_1 * (ub_i - lb_i), \tag{13}$$

where (x^i) represents the solution of the honey badger agent (i) where (i = 1:N) and (r_1) is a random number within (0,1). For balancing between the exploration and exploitation of the HBA, a density factor (α) is defined in **Eq. (14)**.

TABLE 5 | Estimated Nedstack PS6's parameters.

	HBA	HGS	HHO	SCA	GWO
ξ_1	**−0.952**	−0.945	−0.9525	−0.948	−0/949
ξ_2	**3.29E-03**	3.23E-03	2.91E-03	3.2E-03	3.2E-03
ξ_3	**7.40E-05**	7.80E-05	5.18E-05	7.5E-05	7.5E-05
ξ_4	**−7.24E-05**	−1.9E-04	−0.95E-05	−1.9E-4	−1.9E-4
λ	**2.01E+1**	19.273	1.26E+1	20.81	21.65
Rc	**5.43E-04**	1.00E-04	1.00E-04	1.3E-02	2.9E-04
b	**1.60E-02**	1.6E-02	1.36E-02	1.8E-02	1.6E-02
SSE	**1.59E-02**	4.6E-02	2.07	0.662	0.038

TABLE 6 | Statistical values for each method.

	—	Std	Worst	Best	Mean
BCS 500 W	HBA	**0.037**	**0.0119**	**0.0117**	**0.0118**
	HGS	0.934	4.5797	1.3265	2.11380
	HHO	0.490	1.824	0.0901	1.49E-02
	SCA	3.338	19.31522	5.150285	8.72860
	GWO	0.595	3.806807	1.357709	1.91880
250 W	HBA	**0.030**	**0.4275**	**0.3377**	**3.54E-01**
	HGS	0.018	0.3985	0.3377	0.34700
	HHO	0.155	0.955	0.422	6.46E-01
	SCA	0.155	0.955228	0.422466	0.54636
	GWO	0.021	0.408939	0.341183	0.36809
NedStack PS6	HBA	**0.2158**	**1.86**	**1.3196**	**1.59**
	HGS	4.75E-02	0.145	0.0118	0.04620
	HHO	0.5955	3.806	1.3577	2.07E+00
	SCA	0.49033211	1.824527	0.090154	0.66195
	GWO	0.05954205	0.266837	0.01197	0.03821

TABLE 7 | *p*-value for comparison between HBA and other methods.

	250 W	NedStack	BCS 500 W
HGS	5.32E-04	3.45E-04	2.13E-05
HHO	6.73E-07	1.15E-07	3.96E-06
SCA	2.34E-05	8.12E-05	4.87E-05
GWO	1.27E-04	9.12E-04	4.21E-06

$$a = C * exp^{\left(-\frac{t}{T}\right)}, \tag{14}$$

where C represents a constant with a value more than (1), T represents the total number of iterations, and t represents the current iteration.

In the HBA, there are two phases for updating the movements of solutions.

- Digging phase: In this phase, the movements are updated according to a cardioid shape [2], which is represented in **Eq. (15)**.

$$x^{new} = x^{prey} + F*\beta*I*x^{prey} + F*\alpha*d^{i}*r_3*|\cos(2\pi r_4)*[1 - \cos(2\pi r_5)]|, \tag{15}$$

where x^{new} is the new updated value of x^i; x^{prey} is the best-founded solution; (F) controls the direction of the search according to **Eq. (16)**; r_3, r_4, r_5, and r_6 are uniformly generated random numbers within the range (0,1); (B) is a constant number having a value greater than (1); and (I) is the smell intensity of the prey, which expresses the remoteness between the prey and the honey badger.

It was estimated according to **Eq. (17)** and **(18)**, where (d_i) represents the remoteness between the prey and the honey badger and (S) expresses the source strength.

$$F = \begin{cases} 1 & If\,(r_6 \le 0.5) \\ -1 & Else \end{cases}, \tag{16}$$

$$I_i = r_2 \frac{S}{4\,\pi d_i^2}, \tag{17}$$

$$S = \left(x^i - x^{i+1}\right)^2, \quad d_i = x^{prey} - x_i\,. \tag{18}$$

- Honey Phase: This phase simulates the tracking of the honey badger for the honey guide bird to find the beehive, and this operation is simulated as in **Eq. (19)**.

$$x^{new} = x^{prey} + F * r_7 * \alpha * d_i, \tag{19}$$

where r_7 is a uniform random number within the range (0,1). The procedure of the HBA is expressed as in algorithm (1). **Figure 3** shows the flowchart of HBA. HBA's time complexity is $O\,(T\ x\ N\ x\ C_{cost})$, where T is the total number of iterations, N represents the population size, and C_{cost} is the needed execution time for updating solutions.

Algorithm 1. HBA procedure

```
Set (β), (T), (C) and (N)
Initialization of the population size randomly
  (x^i, i= 1, 2, 3, …… N)
Estimate the fitness for the population (x^i)
While ( t <= T )
  Update a based on Eq. 13
  For k = 1 : N
    IF ( rand < 0.5) then
      Update the population (x^i) based on Eq. 15
    Else
      Update the population (x^i) based on Eq. 19
    End IF
    Update x^prey as the best solution founded.
  End For
  t=t+1
End While
Return x^prey
```

The balancing between diversification and intensification of the search space of the HBA is the main merit and motivation to use it in this work. The balancing is performed through three main parameters:

1 - Intensity (I)**:** It controls the transfer between exploration to exploitation and the reverse through the distance between the prey and the other solutions, which may be increased or decreased. In addition, there is another issue that controls the exploration/exploitation process that is the distance between two neighbors of solutions. These interactions increase the possibility of escaping from local minima.

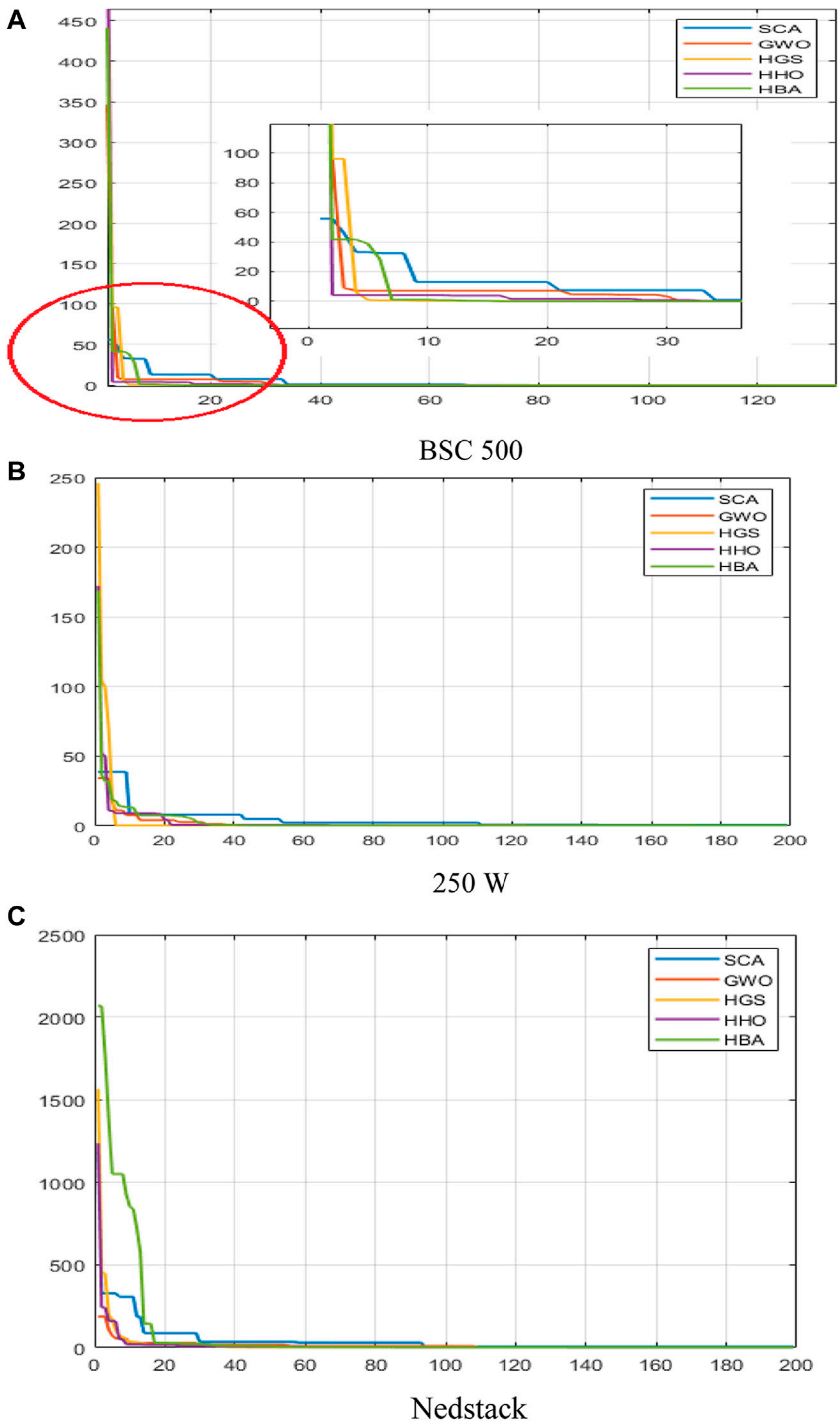

FIGURE 5 | Convergence curve of SSE of datasets. **(A)** BSC 500, **(B)** 250 W, and **(C)** Nedstack.

2 - Density factor (α): This parameter decreases with time, which achieves the trade-off between diversification and intensification of the search space.
3 - Flag (F): It controls the direction of the movements of the solutions, which increase the diversity of the generated solutions, which enhance the exploration.

3 PEMFC MODEL PARAMETER ESTIMATIONS BASED ON HBA

The HBA was used for tuning the best parameters' values of PEMFCs where each agent has a total of the seven parameters (λ, Rc, ξ_1, ξ_2, ξ_3, ξ_4, and b), and the best agent is the agent that

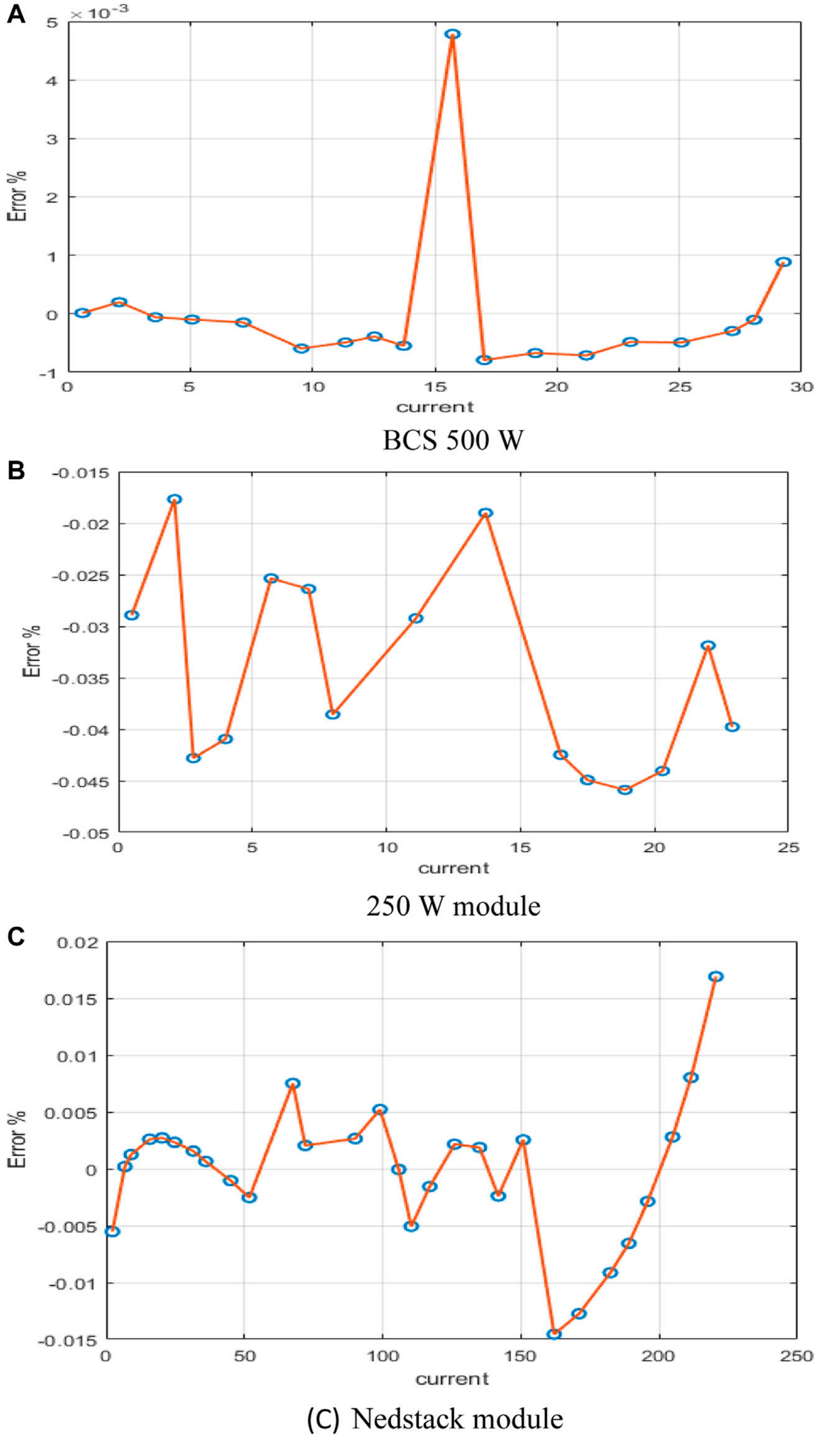

FIGURE 6 | Error % of datasets: **(A)** BCS 500 W, **(B)** 250 W module, and **(C)** Nedstack module.

produces the best fitness. The fitness function used to evaluate the search is the sum square error (SSE) function, which represents the integral square of the subtraction between experimental and estimated voltages. The representation of the SSE function as proposed in **Eq. (20)**, where Vexp and Vest represent the experimental and estimated voltages, respectively.

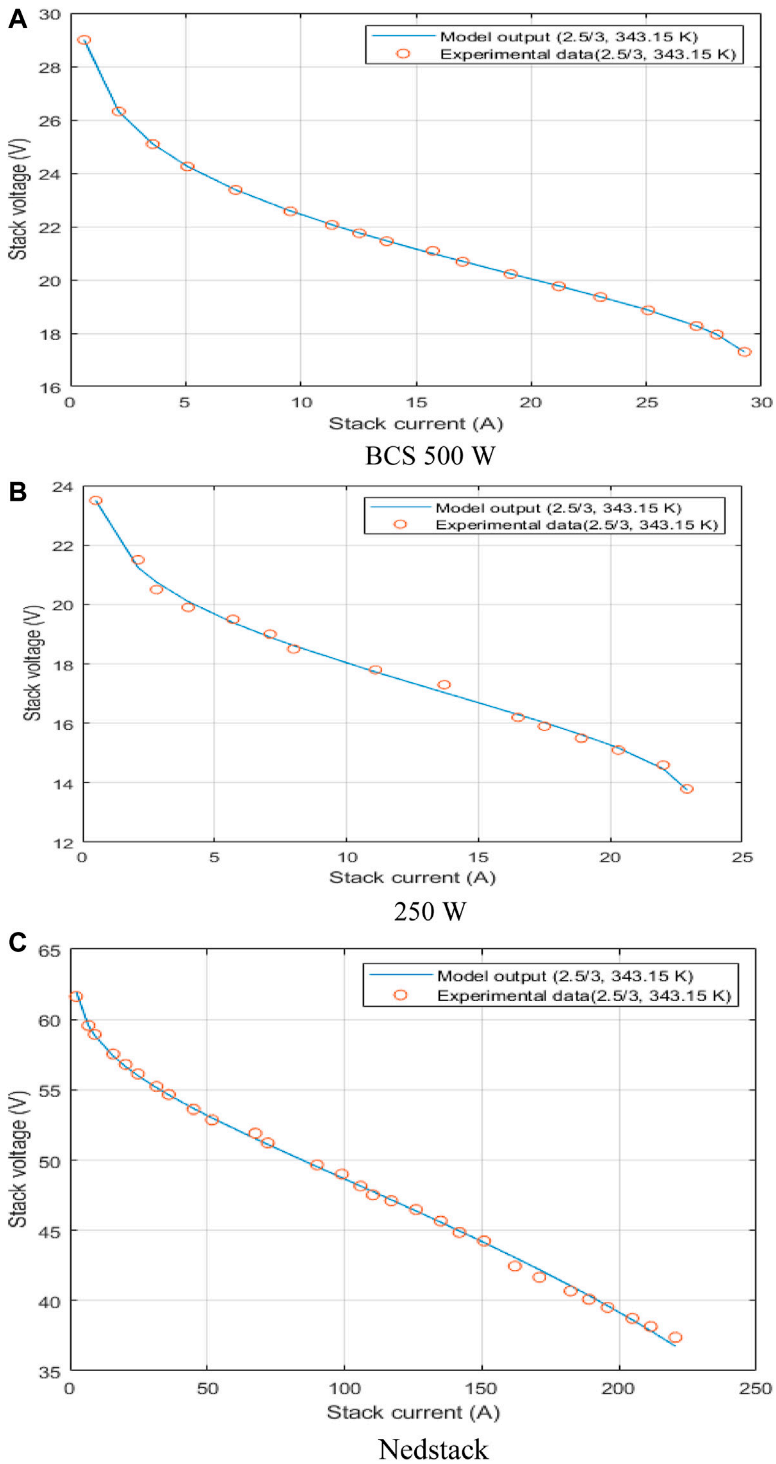

FIGURE 7 | I-V curves of datasets: **(A)** BCS 500 W, **(B)** 250 W, and **(C)** Nedstack.

$$SSE = \left(V_{exp} - V_{est}\right)^2. \tag{20}$$

Figure 4 shows the flowchart of parameter estimation of PEMFCs based on the HBA. The initial random solutions are initialized according to satisfying conditions and input into the HBA's block. The output of the HBA is the best solution found that achieves the smallest SSE.

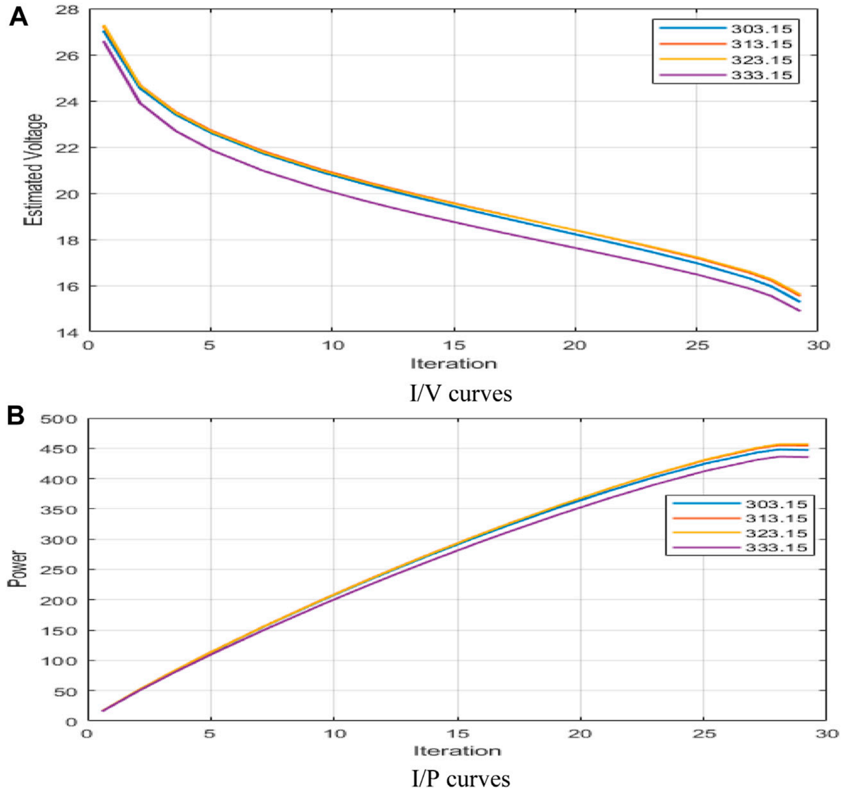

FIGURE 8 | Curves under different temperatures for BCS 500 W using HBA. **(A)** I/V curves and **(B)** I/P curves.

4 NUMERICAL ANALYSIS

The efficiency of the created HBA used for estimating PEMFC model parameters is assessed in this part using three datasets: PEMFC 250-W stack, NedStack PS6, and BCS 500-W, and their electrical specification are listed in **Table 1**. In addition, **Table 2** presents the parameters' boundaries (lower bound and higher bound) (Zhang and Liu, 2010).

The HBA is compared to other MH techniques such as grey wolf optimization (GWO) (Ali et al., 2017; Mirjalili et al., 2014), Hunger Games Search (HGS) (Yang et al., 2021), sine cosine algorithm (SCA) (Mirjalili, 2016), and Harris hawk optimization (HHO) (Heidari et al., 2019) to demonstrate its capability. The values of each algorithm's parameters are assigned depending on the algorithm's original implementation. The conventional settings for the number of populations and iterations are 50 and 500, respectively.

Tables 3–7 and **Figures 5–9** using the three datasets show the comparison between the HBA and other approaches. **Table 3** shows the estimated parameters derived by each algorithm and their SSE values in general. The performance of the HBA in terms of SSE is superior to other MH approaches among the datasets studied, as can be seen from these results. HBA's SSE value with BCS 500-W, 250-W, and NedStack PS6 is, for example, 0.0118, 0.3378, and 1.38E+00, respectively.

Furthermore, the values of SSE over the iterations for SCA, GWO, HGS, HHO, and HBA are presented in **Figure 5** among the three datasets for SCA, GWO, HGS, and HBA to justify the produced HBA's convergence rate. These charts show that the HBA has a higher convergence rate than other approaches, especially in the NedStack PS6 dataset. **Figure 6** also displays the voltage and measured I/V polarization percentage errors, where the percentage error was estimated as the difference between estimated and measured voltage relative to the measured voltage. The percentage error of the HBA is nearly -0.9E-3 to 4.8E-3 for BCS 500 W and from -0.012 to.015 for 250 W module, according to these curves. Finally, the percentage errors for the NedStack PS6 range from -0.012 to +0.012.

The obtained results in **Figure 8A,B** depict the effect of the three temperature values on the I/V and I/P polarization curves, respectively. The pressures RP_O2 and RP_H2 were set to justify the effect of temperature on the performance of the PEMFC stack as shown in **Figure 9A,B**.

Various statistical parameters such as mean, standard deviation, best, and worst of the SSE are calculated to further examine the effectiveness of HBA as a PEMFC model, as shown in **Table 6**. From these metrics, it is clear that the HBA is better at finding optimal settings than other approaches, as evidenced by the examined datasets. We also utilized the Wilcoxon nonparametric test to see if there was a significant difference between the HBA and other approaches. **Table 7** shows the Wilcoxon test p-value at a significance level of 0.05. These results show that there is a considerable difference in overall datasets between the HBA and other approaches.

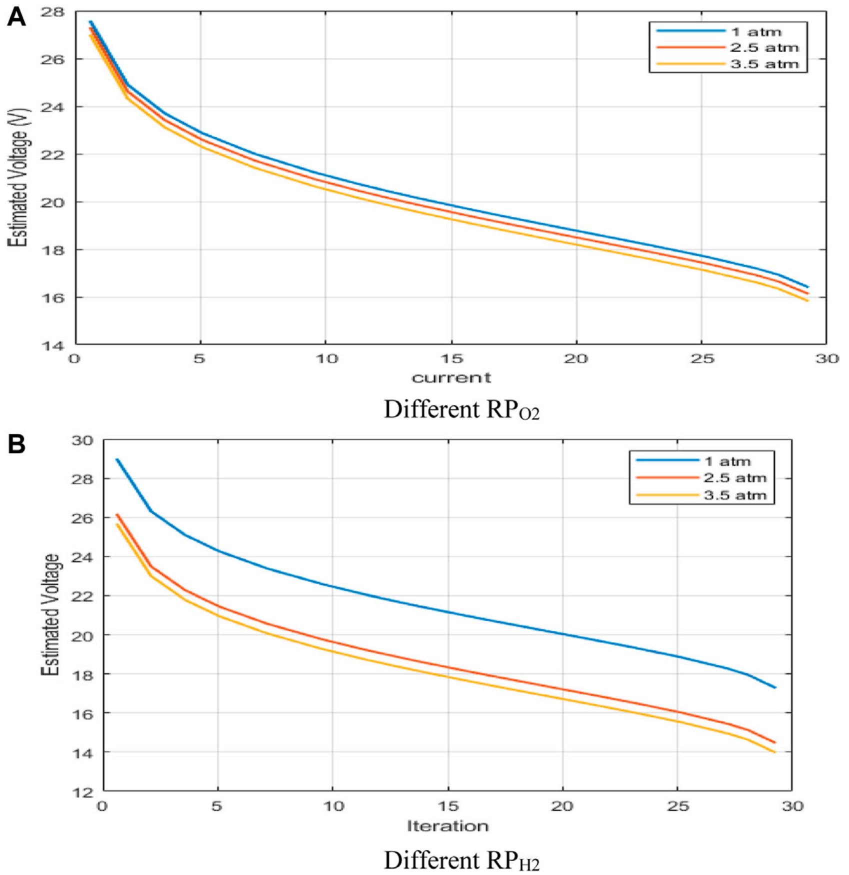

FIGURE 9 | Different RP_{H2} and RP_{O2} for BCS 500 W using HBA. **(A)** Different RP_{O2}. **(B)** Different RP_{H2}.

5 CONCLUSION

In this study, an alternative approach for estimating the model parameters of a PEMFC under various operating conditions is described. This method is based on the HBA. This algorithm has proven its efficacy in a variety of applications, which prompted us to use it. The main motivation for using the HBA for estimating the PEMFC's parameters is the advantage of balance between exploration and exploitation of the search space, which avoids trapping in local minima. A set of experimental series has been conducted utilizing three datasets entitled 250-W stack, BCS 500-W, and NedStack PS6 to justify the usage of the HBA to determine the PEMFC's parameters (i.e., λ, Rc, ξ_1, ξ_2, ξ_3, ξ_4, and b). HBA's results have also been compared to those of other metaheuristic techniques such as HGS and SCA. In terms of performance measures, the results showed that the HBA outperformed other MH approaches. The findings revealed that the presented approach produced promising results and outperformed the other pproaches. The main limitation of using the HBA for estimating the parameters of PEMFCs is it was tested on three modules only. More modules are needed to be used in the experimental tests for efficient verification of the performance of the HBA. Apart from the findings generated by the HBA, it may be employed in a variety of applications, such as PV parameter estimation, mechanical engineering, and other challenges such as cloud computing and picture segmentation.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding author.

AUTHOR CONTRIBUTIONS

All the authors have made a substantial, direct, and intellectual contribution to the work and approved it for publication.

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