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Research Paper

A multi-model evaluation of Enhanced Tunicate Swarm Optimization for parameter identification

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A R T I C L E I N F O

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A B S T R A C T

Parameter identification for a proton exchange membrane fuel cell (PEMFC) entails employing optimisation techniques to discover the best unknown parameter values required to generate an accurate fuel cell performance prediction model. This technique, known as parameter identification, is important since manufacturers' datasheets do not usually disclose these values. To address this, the manuscript examines five optimisation strategies, including the suggested algorithm, Enhanced Tunicate Swarm Optimizer (ETSO), for predicting these parameters in PEMFCs. Each technique uses the six unknown parameters as decision variables, aiming to reduce the sum squared error (SSE) between anticipated and observed cell voltages. The data reveal that the suggested strategy outperforms existing approaches and cutting-edge optimizers. The two models are used to assess the dependability and performance of the PEMFC. The results are also compared to the non-parametric tests, and it is found that the suggested method outperforms the other algorithms in both suggested models.

1. Introduction

The future of energy distribution is increasingly focused on DC microgrids, thanks to their efficiency and stability. This shift is driven by the growing use of DC sources like renewable energy, battery storage, and fuel cells (FCs) in these microgrids (Hachana, 2022; El-Sharkh et al., 2006). Among these sources, FCs are particularly important. A key advancement is the integration of hydrogen and solar energy to create a reliable and eco-friendly storage system known as hydrogen energy. Hydrogen is abundant, existing in fossil fuels, water, and even microbes (Kirubakaran et al., 2009; Akinyele et al., 2020). However, despite its prevalence, free hydrogen gas is rarely found in large quantities naturally. The potential of hydrogen energy has sparked significant global interest. FCs are electrochemical devices that directly convert hydrogen's chemical energy into electricity. Their growing popularity in transportation, portable devices, and stationary applications is a testament to their benefits: high efficiency, quiet operation, and impressive power and energy densities. Various types of FCs exist (Mitra et al., 2023a), including microbial fuel cells, phosphoric acid fuel cells, and solid oxide FCs. However, Proton Exchange Membrane Fuel Cells (PEMFCs) stand out due to their advanced technology and widespread use. While PEMFCs offer a compelling solution, their high cost necessitates a closer look at their operational conditions. Mathematical modeling is crucial for optimizing PEMFC performance and reducing costs through improved modeling techniques. PEMFCs are complex systems influenced by multiple factors, exhibiting dynamic and non-linear behavior. Their operation is governed by a combination of ordinary and/or partial differential equations (Mitra et al., 2023b; Fathy et al., 2022; Wu et al., 2021).

Accurately modelling Proton Exchange Membrane Fuel Cells

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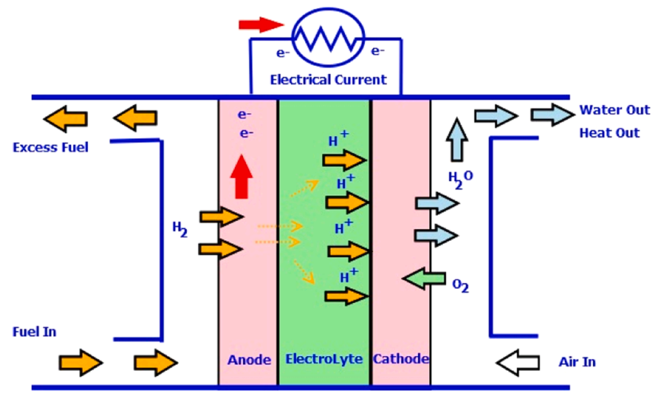

Fig. 1. Schematic representation of PEMFC.

(PEMFCs) is key to unlocking their inner workings. These models not only save time and effort but also optimize how fuel cells operate. A vital part of PEMFC modelling is the polarization curve. It shows the relationship between voltage output and current, essentially summarizing how the fuel cell behaves under various conditions (Shaheen et al., 2023; Wang, 2018). Despite ongoing research on creating accurate models for extracting PEMFC parameters, challenges remain. Manufacturer datasheets often lack sufficient information, leading to discrepancies between predicted and actual data (Rezk et al., 2022; Razmjooy, 2023). Estimating these parameters is a dynamic process, with the best solution found through specialized methods. Traditional optimization algorithms struggle with the non-linear nature of PEMFCs, resulting in lower accuracy and precision. Metaheuristic algorithms, in contrast, start with an initial guess and can converge towards a globally optimal solution, effectively tackling complex optimization problems (Yadav et al., 2024; Pandey et al., 2024; El-Fergany et al., 2019; Zaki Diab et al., 2020). Their adaptability allows them to handle the complexities of PEMFC parameter estimation. Researchers have developed a model using these algorithms to achieve high accuracy and efficiency. This model acts as a foundation for designing and integrating fuel cells, while also providing insights into the underlying physical phenomena. However, current PEMFC electrochemical models rely heavily on experimental data and empirical formulas. This highlights the need for more versatile modelling approaches that can accurately represent the dynamic nature of fuel cell operation (El-Fergany, 2018; Chen and Wang, 2019; Jia et al., 2009).

Modern advancements in optimization techniques are leading to more accurate and efficient PEMFC models. Researchers are increasingly using metaheuristic algorithms, which are powerful tools for finding good solutions to complex problems, to estimate the unknown parameters within these models (Zhang et al., 2023; Singla et al., 2021; Li et al., 2020). These algorithms offer significant advantages over traditional methods like genetic algorithms (GA) and particle swarm optimization (PSO) (Kandidayeni et al., 2019; Pratap Chandran et al., 2021; Holland, 1992; Shi and Eberhart, 1998). Traditional methods can be slow and struggle to find the absolute best solution, especially when starting conditions are unpredictable. A wide variety of metaheuristic algorithms have been applied to PEMFC parameter estimation. This includes bio-inspired algorithms like the shark smell algorithm, coyote optimization algorithm, and beluga whale optimization algorithm (Mohammad-Azari et al., 2018; Yuan et al., 2020; Premkumar et al., 2024a, 2024b; Mirjalili et al., 2014a; Mirjalili and Lewis, 2016). Other successful algorithms include the grey wolf optimizer, whale optimization algorithm, grasshopper optimization algorithm, moth flame optimizer, bald eagle search optimizer, and many more (Mirjalili and Lewis, 2016; Premkumar et al., 2024b; Meraihi et al., 2021a; Mirjalili, 2015; Alsaidan et al., 2022; Das and Pratihar, 2019; Sowmya et al., 2024; Chopra and Ansari, 2022; Hayyolalam and Pourhaji Kazem, 2020; Yousri et al., 2020). Researchers are constantly developing and improving these algorithms. Some studies combine multiple approaches, such as teaching-learning-based optimization with differential evolution (Abdel-Basset et al., 2023; Abdullah et al., 2021). Others focus on improving existing algorithms, like the work on enhanced differential evolution with better search efficiency (Singla et al., 2023). Even machine learning techniques are being explored. Some studies use a Bayesian regularized neural network alongside optimization algorithms for parameter estimation (Yang et al., 2020, 2021).

This continuous development in optimization techniques underscores the growing importance of optimizing PEMFC performance for real-world applications. From the literature survey, it is observed that world researchers are working on achieving the optimal optimization technique as well as algorithm in order to decreases the error and as well as small step towards increasing efficiency. It can also be deduced from the literature analysis that the researchers are keen in simplifying the algorithm to reduce the complexity as well as sufficient decrease in computational time. The key contributions of this work are:

- Tunicate Swarm Optimizer (ETSO) is enhanced to make it better at finding unknown settings (parameters) within PEMFC fuel cell stacks used in real-life situations.
- Validating the effectiveness of the ETSO on real-world PEMFC units by applying it to two specific models: Ballard Mark V and AVISTA SR-12.
- To demonstrate the superiority of the ETSO, it will be compared to established methods like Particle Swarm Optimizer (PSO), Grasshopper Optimization Algorithm (GOA), Political Optimizer (PO), Grey Wolf Optimizer (GWO), Tunicate Swarm Optimizer (TSO), and parental algorithm (ETSO).
- Ten Benchmark test function is also tested to verify the algorithm.

2. PEMFCs' modelling and problem formulation

PEMFC modeling uses mathematical equations and computer simulations to understand the chemical and electrical processes within the fuel cell. The PEMFC schematic representation is shown in Fig. 1.

PEMFCs experience voltage drops due to several factors:

- Activation losses: When the fuel cell starts operating (low load), slow initial reactions cause a rapid voltage drop.
- Ohmic losses: As the current increases, resistance to the flow of protons and electrons leads to a gradual voltage decline.
- Concentration losses: High power demands (heavy load) cause water buildup, reducing reactant concentration and leading to a significant voltage drop.

These voltage drops, collectively contributing to the overall voltage loss in the fuel cell, significantly impact the performance and efficiency of the system. Therefore, it is crucial to understand and minimize these voltage losses to enhance the performance of PEMFCs. Scientists and engineers employ various techniques to achieve this goal, such as catalyst development, improvements in flow field designs, and enhancements in reactant gas management.

Accordingly, Eq. 1 may be used to represent the PEMFC terminal voltage:

$$V_{FC} = E_{Nernest} - v_{act} - v_{ohm} - v_{conc} \tag{1}$$

For temperatures that operate below 100 °C, the reversible open-circuit voltage is represented by $E_{Nernest}$, which may be computed from Eq. 2.

$$E_{Nernest} = 1.229 - 8.5 \times 10^{-4} \times (T_{FC} - 298.15) + 4.3085 \times 10^{-5} \times T_{FC} \times \ln\left(P_{H_2}\sqrt{P_{O_2}}\right) \tag{2}$$

where T_{FC} is the cell temperature (K) and P_{H2} and P_{O2} denote the partial pressures of H_2 and O_2, correspondingly.

According to Eq. 3, the activation voltage loss (v_{act}) is approximated.

$$v_{act} = -\left[\xi_1 + (\xi_2 \times T_{FC}) + (\xi_3 \times T_{FC} \times \ln(C_{O_2})) + (\xi_4 \times T_{FC} \times \ln(I_{fc}))\right] \tag{3}$$

Where the FC current is defined as I_{FC}, and make use of the coefficients ξ_1 to ξ_4. C_{O2} and C_{H2} and indicate the oxygen concentration (mol/cm^3), which has the following definitions as shown in Eq. 4 and Eq. 5:

$$C_{O_2} = \frac{P_{O_2}}{5.08 \times 10^6} \times \exp^{\left(\frac{498}{T_{FC}}\right)} \tag{4}$$

$$C_{H_2} = \frac{P_{H_2}}{1.09 \times 10^6} \times \exp^{\left(\frac{-77}{T_{FC}}\right)} \tag{5}$$

The v_{ohm} is defined as follows and is calculated using the FC's equivalent resistance as shown in Eq. 6:

$$v_{ohm} = I_{FC} \times (R_m + R_c) \tag{6}$$

Where R_m and R_c stand for the membrane resistance and the contact resistance, accordingly. Eq. 7 and Eq. 8 can be used to determine the R_m.

$$R_m = \frac{\rho_m \times l}{M_A} \tag{7}$$

$$\rho_m = \frac{181.6 \times \left[1 + 0.03 \times J + 0.062 \times J^{2.5} \times (T_{FC}/303)^2\right]}{[\lambda - 0.634 - 3 \times J] \times \exp^{(4.18 \times (T_{FC} - 303)/T_{fc})}} \tag{8}$$

Where ρ_m, l, A_m, J and λ indicate, accordingly, the membrane's resistivity (Ω.cm), membrane thickness (cm), active area of the cell (cm^2), real current density (A/cm^2), and membrane water content.

The formula Eq. 9 can be utilized for estimating the v_{conc}.

$$v_{conc} = -\beta \times \ln(1 - J/J_{\max}) \tag{9}$$

Where β indicates the maximum current density (A/cm^2) and J_{max} signifies a constant coefficient.

The PEMFC stack is often made up of a series of cells (N_{cells}), and the stack voltage is determined (V_{stack}) as shown in Eq. 10:

$$V_{stack} = N_{cells} \times V_{FC} = N_{cells} \times (E_{Nernest} - v_{act} - v_{ohm} - v_{conc}) \tag{10}$$

By using the previously described equation while assuming that all of the cells behave uniformly and that the resistors that link them are disregarded.

Seven unknown variables (ξ1 to ξ4, λ, and β) need to be determined to fully define the mathematical model based on electrochemistry. An iterative process involving refinement, optimization, and validation is used to estimate these parameters in Mann's model (Kaur et al., 2020). To achieve accurate and dependable parameter values that reflect real-world PEMFC behavior, a combination of experimental data, computer modeling, and optimization techniques is crucial. This applies not only to Mann's model but also to any mathematical model. In essence, parameter optimization aims to find the values that minimize the gap between the model's predictions and actual experimental results.

2.1. Problem formulation

This paper proposes a method to improve the accuracy of a PEMFC model by aligning its predicted output voltage with real-world measurements. The model uses mathematical formulas and known parameters to predict the voltage for any given current density. To achieve better alignment, a proposed algorithm is employed. The effectiveness of this approach is evaluated by comparing the predicted voltage with measured voltage data using the Sum of Squared Error (SSE) metric. Eq. 11 details the objective function used in this evaluation.

$$\mathrm{SSE} = \mathrm{MIN}\left(\mathrm{F} = \sum_{\mathrm{i}=1}^{\mathrm{N}} (\mathrm{V}_{\mathrm{actual}} - \mathrm{V}_{\mathrm{i}})^2\right) \tag{11}$$

Where, actual experiment voltage is denoted by V_{actual}, computed model voltage is denoted by V_i, and N is denoted as the number of data points.

3. Proposed algorithm

3.1. Tunicate Swarm Optimization (TSO): A bio-inspired approach

This section introduces Tunicate Swarm Optimization (TSO), a nature-inspired technique for solving optimization problems (Gharehchopogh, 2022; Wang et al., 2018). TSO draws inspiration from the behavior of tunicates, marine animals known for their efficient food searching strategies.

Tunicates exhibit two key behaviors during food discovery:

- **Jet Propulsion (JP):** This behavior helps individual tunicates avoid crowding and move towards areas with potentially better food sources. Mathematically modeled equations ensure these movements minimize congestion and propel individuals towards promising locations.
- **Swarm Intelligence (SI):** Here, the entire group collectively adjusts the positions of individual members based on the location of the best food source found so far. Specific formulas govern how these adjustments occur, guiding the swarm towards the optimal solution. The following section will delve deeper into the mathematical formulas that model these behaviors in detail.

3.1.1. Preventing crowding during search

The Tunicate Swarm Optimization (TSO) algorithm uses a specific vector $\overrightarrow{T}$ to calculate the new position of each search element. This vector plays a crucial role in preventing overcrowding among search elements during the optimization process.

$$\overrightarrow{T} = \frac{\overrightarrow{G_h}}{\overrightarrow{G}_o} \tag{12}$$

$$\overrightarrow{G_h} = l_2 + l_3 - \overrightarrow{g} \tag{13}$$

$$\overrightarrow{g} = 2l_1 \tag{14}$$

The movement of search elements in Tunicate Swarm Optimization (TSO) is influenced by several factors:

- Horizontal water flow ($\overrightarrow{g}$): This term simulates the effect of currents on the movement of individual search elements.
- Randomness (l_1, l_2, l_3): These random values between zero and one introduce an element of chance, preventing the swarm from getting stuck in suboptimal solutions.
- Gravity ($\overrightarrow{G_h}$, $\overrightarrow{G}_o$): This term accounts for the gravitational pull acting on the search elements within the underwater environment.
- Interaction forces (Eq. 1): This component, defined in detail by Eq. (4), captures the attractive or repulsive forces between search elements. These forces guide the swarm towards promising areas and prevent crowding.

$$\overrightarrow{G_o} = \quad |l_1 Q_i + Q_m - Q_m| \tag{15}$$

Here, Q_i =4 and $Q_m = 1$ illustrate the highest and lowest velocities for providing interactions.

3.1.2. Following the path of the nearest neighbor

In Tunicate Swarm Optimization (TSO), when the crowding among

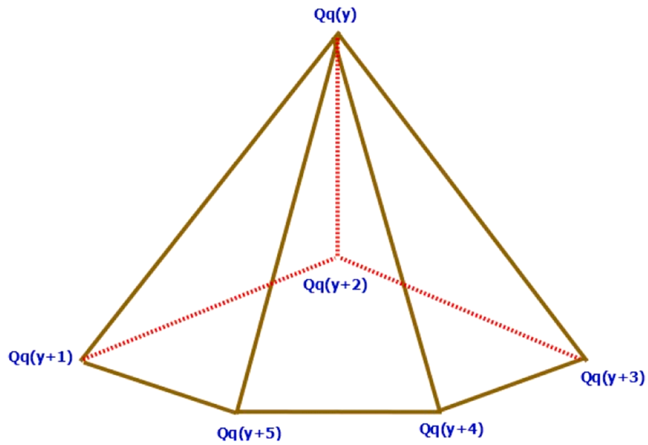

Fig. 2. Tunicate location vector.

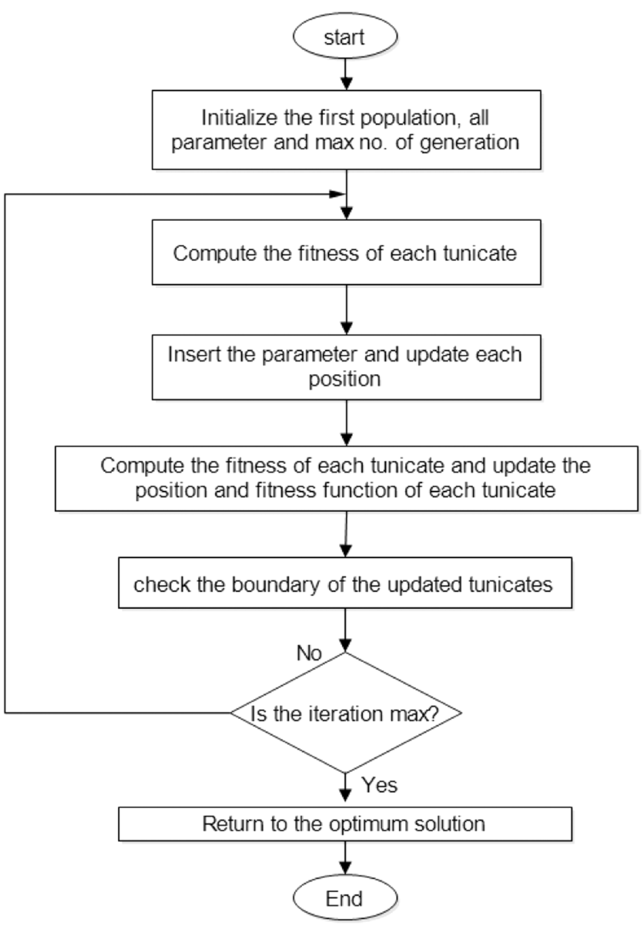

Fig. 3. flow chart of ETSO.

search elements is minimized, the movement of each element is influenced by the location of its best neighbor. This means individual elements tend to move closer to the element that has currently found the most promising solution.

$$\overrightarrow{E_m} = \left|\overrightarrow{GT} - L \times \overrightarrow{Q_q(y)}\right| \tag{16}$$

In the above equation, y signifies the number of the current epoch, and $\overrightarrow{E_m}$ illustrates the search individuals' gap with the sources of food. The food and tunicate situation are demonstrated by $\overrightarrow{GT}$ and $\overrightarrow{Q_q(y)}$, respectively, and L depicts a random amount from the interval of [0,1].

3.1.3. Convergence towards the best search candidate

Tunicate Swarm Optimization (TSO) leverages an "attraction behavior" where each element strives to be closer to the "best" element in the swarm. This behavior, akin to seeking the best food source, guides the swarm towards optimal solutions.

$$\overrightarrow{Q_q(y)} = \begin{cases} \overrightarrow{GT} + \overrightarrow{T} \bullet \overrightarrow{E_m}, & L \geq \frac{1}{2} \\ \overrightarrow{GT} - \overrightarrow{T} \bullet \overrightarrow{E_m}, & L < \frac{1}{2} \end{cases} \tag{17}$$

Here $\overrightarrow{Q_q(y)}$ does represent the adjusted position of tunicate with regard to the $\overrightarrow{GT}$.

3.1.4. Key aspects of swarm intelligence

Swarm Intelligence (SI) in Tunicate Swarm Optimization (TSO), the algorithm keeps track of the two best solutions found so far (often referred to as "epoch" in optimization problems). This information is then used to adjust the positions of other search elements, guiding them towards the locations of these top performers. This behavior can be mathematically expressed as:

$$Q_q(\vec{y}+1) = \frac{1}{l_1+2}\left(Q_q(\vec{y}+1) + \overrightarrow{Q_q(y)}\right) \tag{18}$$

Fig. 2 illustrates how the position of a search element is adjusted based on the best location found so far (represented by $\overrightarrow{Q_q(y)}$). Initially, the element occupies a random position within a cone-shaped or cylindrical area, determined by the current location of the tunicate.

Key Principles of TSO:

- Diversity: The random contributions of $\overrightarrow{T}$ and $\overrightarrow{g}$ within the search space help prevent crowding and maintain a diverse pool of potential solutions.
- Balance between Exploration and Exploitation: By adjusting the vectors $\overrightarrow{T}$, $\overrightarrow{g}$, and $\overrightarrow{G_h}$, TSO can strike a balance between exploring new areas and exploiting promising regions, leading to better overall performance.
- JP and SI: The combined behaviors of Jet Propulsion (JP) and Swarm Intelligence (SI) enable TSO to effectively navigate the search space and find optimal solutions.

3.2. Enhanced Tunicate Swarm Optimizer (ETSO)

Tunicate Swarm Optimization (TSO) is a powerful bio-inspired algorithm used for various optimization problems. However, research suggests that TSO can sometimes get stuck in suboptimal solutions (local optima) that aren't necessarily the best. This study addresses this limitation by introducing modifications to improve TSO's performance. The key issue lies in striking a balance between exploration (searching new areas) and exploitation (focusing on promising regions). To achieve this, we introduce a concept called "search mode." This technique leverages the core operators of TSO and combines them with a mutation operator from another well-known algorithm, Differential Evolution (DE) (Sun et al., 2021). TSO relies on two key components: exploration and exploitation. If $L < \lambda$, the exploring phase shifts the position of the predators. The term λ is achieved as follows:

$$\lambda = 1 - \frac{ju}{ju_{\max}} \tag{19}$$

The "search mode" concept promotes thorough exploration in the initial stages of the optimization process. As the algorithm progresses (time goes on), it gradually shifts towards exploitation, focusing on promising areas identified during exploration. This transition is facilitated by an "elitist" technique which prioritizes retaining the best

Table 1
Benchmark Test Function.

Name of Function	Function	Range	Dimension
f_1= Sphere	$f_1(y) = \sum_{j=1}^{m} y_j^2$	[−100,100]	m=50
f_2= Schwefel 2.22	$f_2(y) = \sum_{j=1}^{m} \lvert y_j \rvert + \prod_{j=1}^{m} \lvert y_j \rvert$	[−10,10]	m=50
f_3= Schwefel 1.2	$f_3(y) = \sum_{j=1}^{m} \left(\sum_{i=1}^{j} y_i \right)^2$	[−100,100]	m=50
f_4= Schwefel 2.21	$f_4(y) = \max_j \left\{ \lvert y_j \rvert, 1 \le j \le m \right\}$	[−100,100]	m=50
f_5= Rosen-brock	$f_5(y) = \sum_{j=1}^{m} 100\left(y_j + 1 - y_j^2\right)^2 + \left(y_j - 1\right)^2$	[−30,30]	m=50
f_6= Step	$f_6(y) = \sum_{j=1}^{m} \left(\left[y_j + 0.5 \right] \right)^2$	[−100,100]	m=50
f_7= Quartic	$f_7(y) = \sum_{j=1}^{m} j y_j^4 + randm[0,1]$	[−128,128]	m=50
f_8= Schwefel	$f_8(y) = \sum_{j=1}^{m} -y_j Sin\left(\sqrt{\lvert y_j \rvert} \right)$	[−500,500]	m=50
f_9= Rastrigin	$f_9(y) = \sum_{j=1}^{m} \left[y_j^2 - 10Cos\left(2\pi y_j\right) + 10 \right]$	[−5.12,5.12]	m=50
f_{10}= Ackley	$f_{10}(y) = -20\exp\left(-0.2\left(\frac{1}{m} \sum_{j=1}^{m} y_j^2 \right)^{\wedge} 0.5 \right) - \exp\left(\frac{1}{m} \sum_{j=1}^{m} Cos\left(2\pi y_j\right) \right) + 20 + e$	[−32,32]	m=50

Table 2
(a) Statistical Results of Benchmark Test Functions.

Algorithms		f_1	f_2	f_3	f_4	f_5
PSO	**MEAN**	5.96E+00	1.76E+01	1.94E+04	2.96E+01	4.74E +04
	SD	4.42E+00	3.26E+01	1.00E+04	1.67E+01	2.92E+04
GOA	**MEAN**	2.24E−03	2.86E−15	4.44E+03	1.19E+02	1.91E+03
	SD	7.57E−04	3.35E−15	4.27E+02	7.43E+01	1.95E+03
PO	**MEAN**	4.77E−23	2.69E−30	4.34E−21	2.10E−01	1.99E+00
	SD	3.08E−23	1.38E−30	3.35E−21	4.84E−01	7.19E−01
GWO	**MEAN**	3.76E−60	4.03E−50	3.47E−35	3.73E−21	2.12E+01
	SD	2.03E−60	2.29E−50	2.56E−35	2.26E−21	1.30E+01
TSO	**MEAN**	5.01E−180	2.81E−110	6.68E−155	3.13E−95	1.68E+01
	SD	0	2.7E−110	0	1.69E−95	3.77E−15
Proposed Algorithm	**MEAN**	0	6.61E−140	0	3.74E−127	4.64E−06
	SD	0	3.3E−140	0	0	2.40E−06

(b) Statistical Results of Benchmark Test Functions

Algorithms		f_6	f_7	f_8	f_9	f_{10}
PSO	**MEAN**	2.07E+01	4.34E−03	−4.23E+02	1.51E+02	1.27E+01
	SD	1.07E+01	2.42E−03	8.55E+01	1.10E+02	1.10E+01
GOA	**MEAN**	3.37E−03	4.69E−04	−3.85E+03	2.31E+02	2.17E+00
	SD	1.86E−03	2.44E−04	6.24E+02	2.92E+02	1.55E+00
PO	**MEAN**	5.30E−05	4.93E−05	−2.95E+04	1.18E+02	5.21E−15
	SD	2.83E−05	2.18E−05	9.37E+03	1.55E+02	2.16E−15
GWO	**MEAN**	3.32E−07	2.81E−06	−4.55E+03	2.65E+01	1.51E−17
	SD	2.72E−07	1.95E−06	2.38E+02	2.19E+00	0
TSO	**MEAN**	3.09E−10	4.70E−08	−3.73E+03	5.97E+00	8.88E−20
	SD	2.99E−10	2.08E−08	5.71E+02	7.31E−03	1.27E−35
Proposed Algorithm	**MEAN**	3.06E−40	4.70E−10	−1.36E+04	0	8.88E−24
	SD	1.44E−40	2.62E−10	6.07E−02	0	1.55E−39

Table 3
Parameter Search Range.

Parameter	Lower bound	Upper bound
ξ_1	−1.1997	−0.08532
$\xi_2 * 10^{-3}$	0.8	6.00
$\xi_3 * 10^{-5}$	3.60	9.80
$\xi_4 * 10^{-4}$	−2.60	−0.954
λ	10.00	24.00
$R_C * 10^{-4}$	1.00	8.00
b	0.0136	0.5

Table 4
Data sheet for the parameter estimation.

Model	Ballard Mark V	Avista SR-12
n	35	48
A [cm^2]	50.6	62.5
l [um]	178	25
J_{max} [A/cm^2]	1.5	0.672
P_{H2} [bar]	1	1.47628
P_{O2} [bar]	1	0.2095
Power [W]	1000	500
T [K]	343.15	323.15

solutions found so far.

A crucial aspect is ensuring all solutions remain feasible, meaning they adhere to the problem's constraints. When a proposed adjustment would cause a solution to fall outside these constraints (boundaries), the algorithm implements a specific correction mechanism. This mechanism involves:

$$Q_q(\vec{y}+1)^{new} = \begin{cases} \delta_o + \tau \times (\mu_o - \delta_o) if Q_q(\vec{y})^{new} < \delta_o \\ \mu_o - \tau \times (\mu_o - \delta_o) if Q_q(\vec{y})^{new} < \mu_o \end{cases} \tag{20}$$

where, τ defines a random amount varied from zero to one, δ_n and μ_n denote, in turn, the inferior and the superior limits of the dimension n.

Table 5
Parameter Estimation of PEMFC Model of Ballard Mark V.

Parameter/Algorithms	ξ_1	ξ_2	ξ_3	ξ_4	λ	R_C	b	SSE
PSO	−1.177	0.001	3.60E−05	−2.60E−04	11.589	0.0001	0.0136	1.69E−03
GOA	−1.066	0.001	2.63E−05	−2.02E−04	10	0.0001	0.0631	1.16E−04
PO	−1.197	0.001	2.60E−05	−2.03E−04	10.268	0.0002	0.0379	1.14E−05
GWO	−1.159	0.002	3.29E−05	−2.49E−04	10.353	0.0001	0.0587	1.06E−07
TSO	−1.129	0.0001	3.22E−05	−2.09E−04	9.285	0.0001	0.0121	1.18E−11
Proposed Algorithm	−1.086	0.0011	2.41E−05	−2.25E−04	10.540	0.0001	0.0418	2.56E−15

Table 6
Parameter Estimation of PEMFC Model of Avista SR-12.

Parameter/Algorithms	ξ_1	ξ_2	ξ_3	ξ_4	λ	R_C	b	SSE
PSO	−0.853	0.001	8.80E−05	−2.60E−04	9.854	0.0001	0.013	3.06E−03
GOA	−1.170	0.003	8.02E−05	−1.53E−04	11.420	0.0001	0.041	3.25E−04
PO	−0.988	0.001	9.02E−05	−2.22E−04	10.326	0.0001	0.141	8.97E−05
GWO	−0.971	0.001	9.14E−05	−1.19E−04	10.049	0.0001	0.018	8.32E−07
TSO	−0.894	0.001	8.70E−05	−2.60E−04	8.433	0.0001	0.217	5.15E−12
Proposed Algorithm	−1.114	0.0008	4.18E−05	−1.54E−04	11.547	0.0002	0.124	2.89E−14

Table 7
Statistical results of PEMFC Model of Ballard Mark V.

Algorithms	Minimum	Average	Maximum	Mean	S.D	Error
PSO	1.69E−03	1.91E−03	2.17E−03	1.69E−03	1.93E−04	SSE
GOA	1.16E−04	1.32E−04	1.62E−04	1.16E−04	1.86E−05	
PO	1.14E−05	5.38E−05	1.47E−04	1.14E−05	6.02E−05	
GWO	1.06E−07	1.69E−07	2.85E−07	1.06E−07	6.88E−08	
TSO	1.18E−11	1.7E−11	2.49E−11	1.18E−11	4.93E−12	
Proposed Algorithm	2.56E−15	4.56E−15	9.44E−15	2.56E−15	2.84E−15	

Table 8
Statistical results of PEMFC Model of Avista SR-12.

Algorithms	Minimum	Average	Maximum	Mean	S.D	Error
PSO	3.06E−03	3.38E−03	3.76E−03	3.06E−03	2.83E−04	SSE
GOA	3.25E−04	3.54E−04	3.68E−04	3.25E−04	1.98E−05	
PO	8.97E−05	9.37E−05	9.95E−05	8.97E−05	4.59E−06	
GWO	8.32E−07	9.24E−07	9.85E−07	8.32E−07	6.48E−08	
TSO	5.15E−12	6.26E−12	7.02E−12	5.15E−12	7.84E−13	
Proposed Algorithm	2.89E−14	3.76E−14	4.02E−14	2.89E−14	4.85E−15	

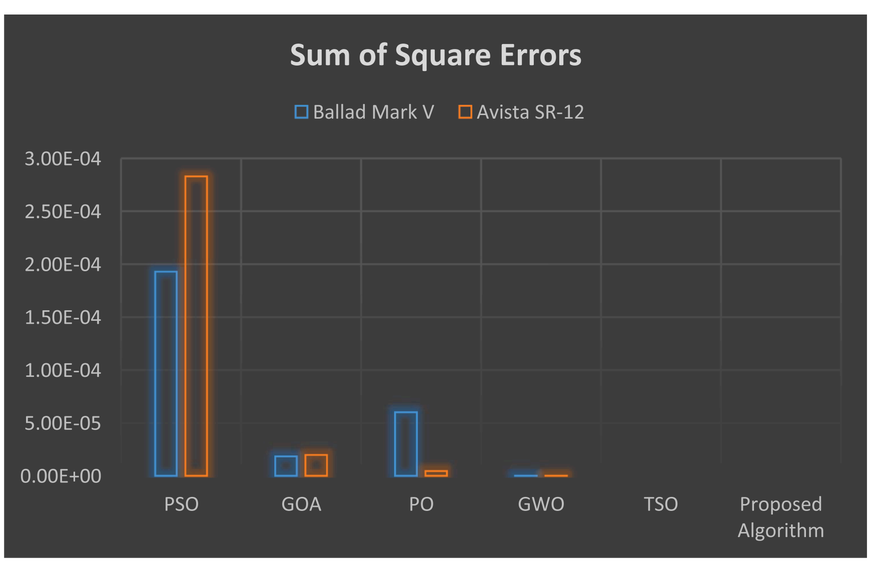

Fig. 4. SSE of both models.

Fig. 5. Multi-Axis Radar of Ballard Mark V.

To effectively navigate the search space and find optimal solutions, Tunicate Swarm Optimization (TSO) utilizes a dynamic "search mode" mechanism. This mechanism adjusts the balance between exploration (searching new areas) and exploitation (focusing on promising regions) based on the current results and population. Initially, Search Mode 1 prioritizes exploration, ensuring a thorough search even if the best solution (the "greatest predator") hasn't improved for a while. Once the solution quality starts to show improvement, the algorithm transitions to Search Mode 2. This mode emphasizes exploitation, leveraging the insights gained from exploration to refine promising regions and ultimately converge on the best solution. Fig. 3 shows the flow chart of ETSO.

4. Results and discussion

In this two section are there, in the first section benchmark test functions are tested and in the second section an engineering problem is tested. Both the sections are explained below:

4.1. Benchmark test functions

Ten benchmark functions were selected to evaluate the effectiveness of the new algorithm. These functions are detailed in Table 1. The first seven functions (f1-f7) represent problems with a single optimal solution (uni-modal), while the last three (f8-f10) are more challenging with multiple optimal solutions (multi-modal). All functions have 40 variables. To assess the new algorithm's performance, it was compared against established optimization algorithms: Particle Swarm

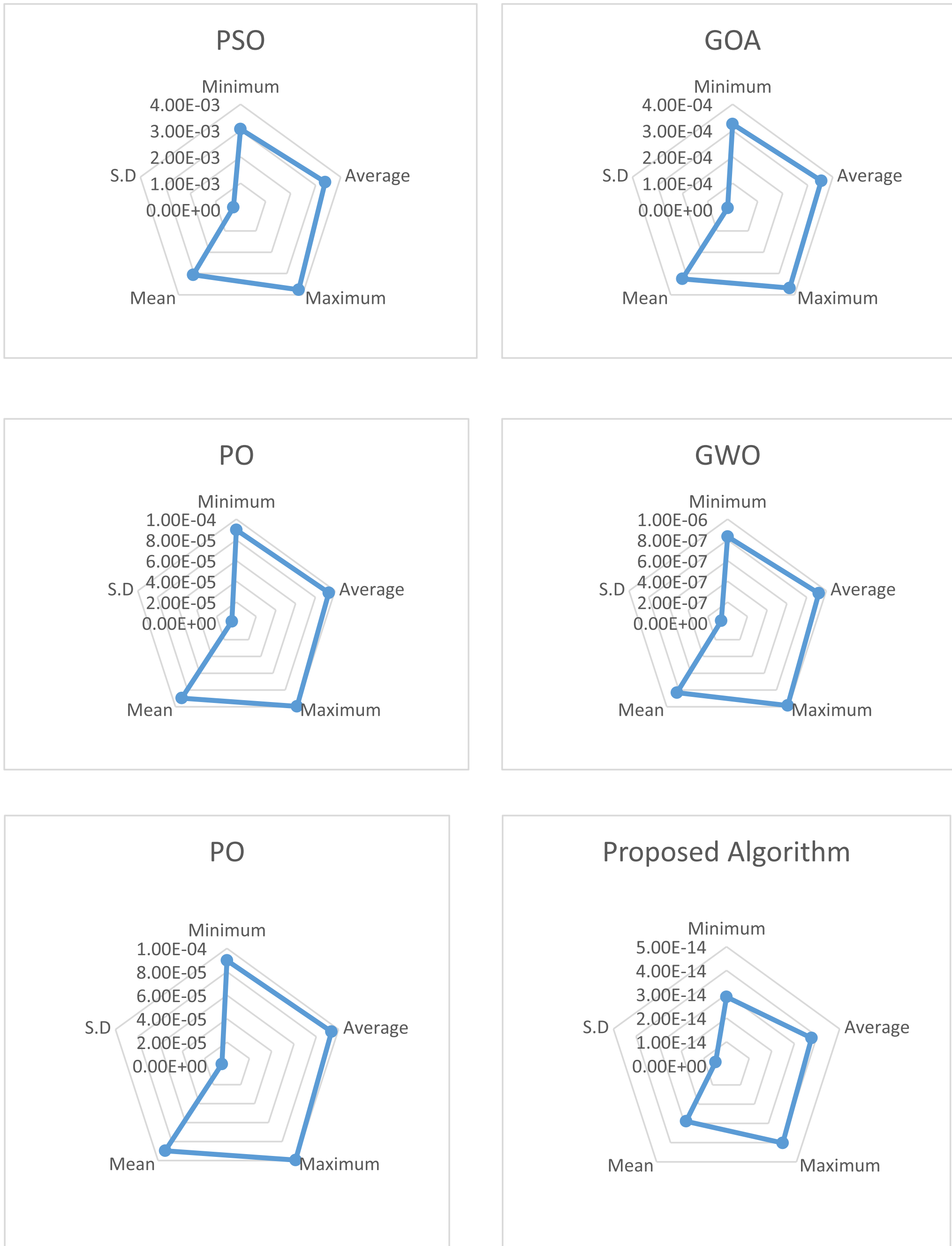

Fig. 6. Multi-Axis Radar of Avista SR-12.

Table 9
Computational time (Sec's) of both models.

Algorithms	Ballard Mark V	Avista SR-12	Statistical Analysis
PSO	3.187	3.245	Computational Time (Sec)
GOA	3.120	3.124	
PO	2.987	2.997	
GWO	2.187	2.547	
TSO	1.645	1.874	
Proposed Algorithm	1.011	1.015	

Optimization (PSO) (Meraihi et al., 2021b), Grasshopper Optimization Algorithm (GOA) (Askari et al., 2020), Political Optimizer (PO) (Mirjalili et al., 2014b), Tunicate Swarm Optimizer (TSO) (Gharehchopogh, 2022; Wang et al., 2018), and Grey Wolf Optimizer (GWO) (Mahato et al., 2020). All algorithms were run 50 times independently using the same number of function evaluations (Max NFEs = 1000) across the ten benchmark functions. For consistency, all codes were implemented in MATLAB 2018b.

The average performance (mean) and standard deviation (SD) of each algorithm on the ten benchmark functions are summarized in Table 2(a) and (b). These tables suggest that the proposed algorithm achieves superior performance compared to the established algorithms. This is because the proposed algorithm has consistently lower mean and standard deviation values across all ten test functions. Benchmark

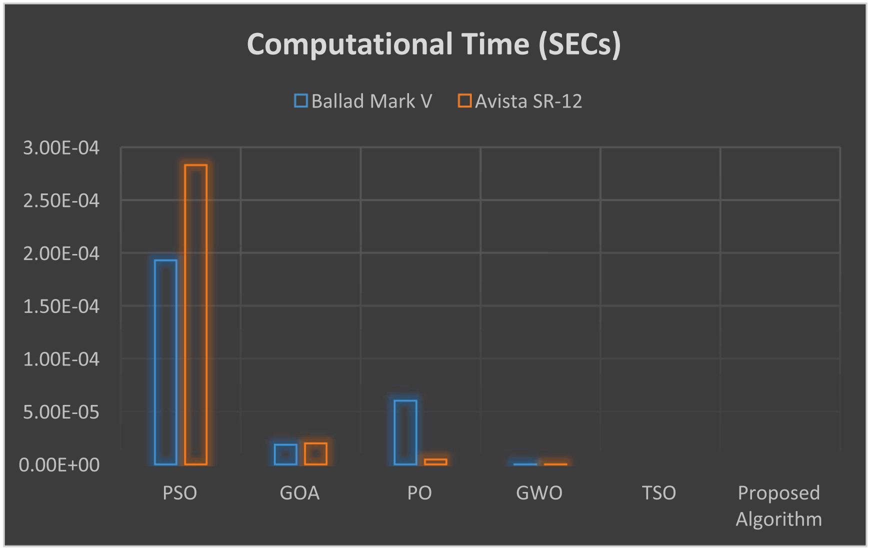

Fig. 7. Computational time of both models.

Table 10
Calculated Values of Voltage, Power and Absolute Error of Model Ballard Mark V.

Current Measured (A)	Voltage Measured (V)	Voltage Calculated (V)	Absolute Error (Voltage)	Power Measured (W)	Power Calculated (W)	Absolute Error (Power)
5.4	0.92	0.9203	3.00E−04	4.97	4.9696	3.80E−04
10.8	0.88	0.8797	3.00E−04	9.50	9.5007	7.60E−04
16.2	0.85	0.8497	3.00E−04	13.77	13.7651	4.86E−03
21.6	0.82	0.8202	2.00E−04	17.71	17.7163	6.32E−03
27.0	0.79	0.7897	3.00E−04	21.96	21.3219	6.38E−01
32.4	0.77	0.7695	5.00E−04	24.95	24.9318	1.82E−02
37.8	0.74	0.7402	2.00E−04	27.97	27.9795	9.56E−03
43.2	0.72	0.7180	2.00E−03	31.10	31.0176	8.24E−02
48.6	0.69	0.6899	1.00E−04	33.53	33.5291	8.60E−04
54.0	0.66	0.6601	1.00E−04	35.64	35.6454	5.40E−03
59.4	0.62	0.6199	1.00E−04	36.83	36.8220	7.94E−03
64.8	0.60	0.6205	2.05E−02	38.88	40.2084	1.33E+00
70.2	0.55	0.5502	2.00E−04	38.61	38.6240	1.40E−02
Sum of AE			2.51E−02			**2.12E+00**

Table 11
Calculated Values of Voltage, Power and Absolute Error of Model Avista SR-12.

Current Measured (A)	Voltage Measured (V)	Voltage Calculated (V)	Absolute Error (Voltage)	Power Measured (W)	Power Calculated (W)	Absolute Error (Power)
1.004	43.17	43.1699	1.00E−04	43.36	43.3425	1.74E−02
3.166	41.14	41.1399	1.00E−04	130.25	130.2489	1.08E−03
5.019	40.09	39.9995	9.05E−02	201.21	200.7574	4.53E−01
7.027	39.04	38.9999	4.01E−02	274.33	274.0523	2.78E−01
8.958	37.99	37.9795	1.05E−02	340.31	340.2203	8.96E−02
10.97	37.08	37.0745	5.50E−03	406.77	406.7072	6.27E−02
13.05	36.03	36.0298	2.00E−04	470.19	470.1888	1.11E−03
15.06	35.19	35.1897	3.00E−04	529.96	529.9568	3.12E−03
17.07	34.07	34.0654	4.60E−03	581.57	581.4963	7.36E−02
19.07	33.02	33.0154	4.60E−03	629.69	629.6036	8.63E−02
21.08	32.04	31.9999	4.01E−02	675.40	674.5578	8.42E−01
23.01	31.20	31.1984	1.60E−03	717.91	717.8751	3.48E−02
24.94	29.80	29.7899	1.01E−02	743.21	742.9601	2.50E−01
26.87	28.96	28.9587	1.30E−03	778.16	778.1202	3.97E−02
28.96	28.12	28.1189	1.10E−03	814.36	814.3233	3.67E−02
30.81	26.3	26.2996	4.00E−04	810.30	810.2906	9.32E−03
32.97	24.06	24.0599	1.00E−04	793.26	793.2549	5.10E−03
34.90	21.40	21.3989	1.10E−03	746.86	746.8216	3.84E−02
Sum of AE			2.12E−01			**2.32**

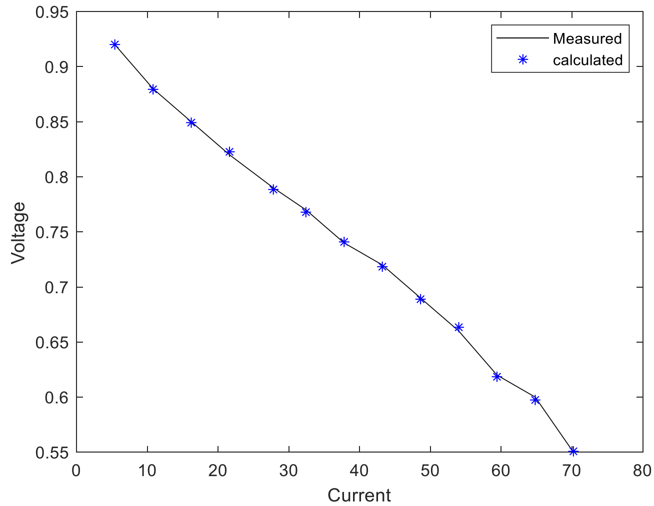

Fig. 8. Ballard Mark V V-I Characteristics Curve.

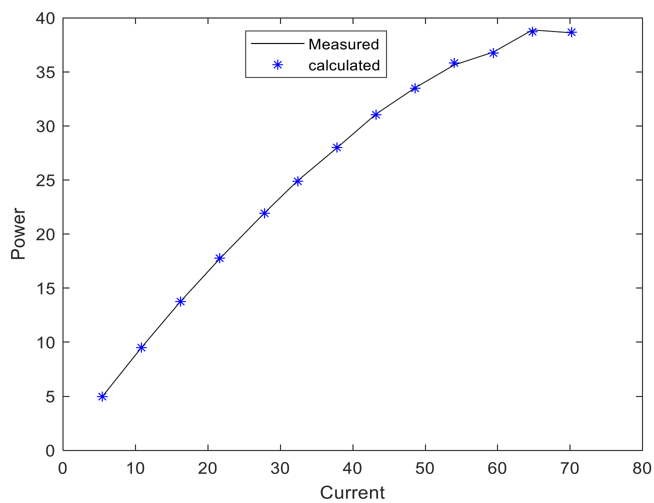

Fig. 9. Ballard Mark V P-I Characteristics Curve.

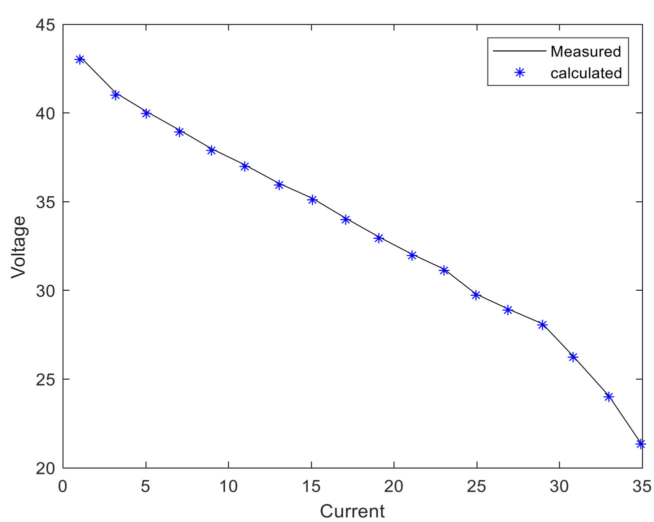

Fig. 10. Avista SR-12 V-I Characteristics Curve.

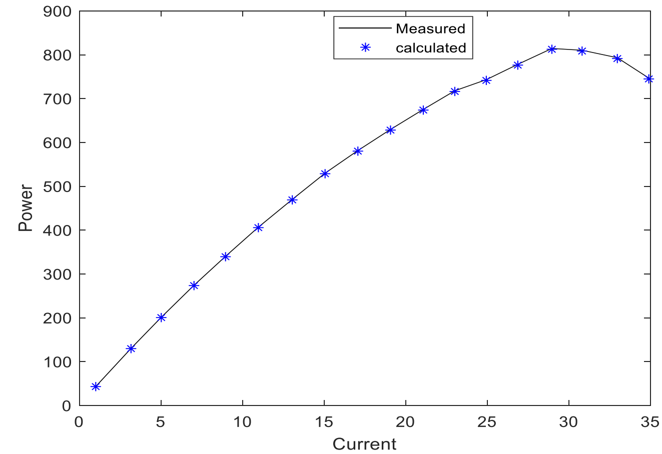

Fig. 11. Avista SR-12 P-I Characteristics Curve.

Table 12
Ballard Mark V Friedman Ranking Test.

Algorithms	Friedman Ranking
PSO	6
GOA	5
PO	4
GWO	3
TSO	2
Proposed Algorithm	1

Table 13
Avista SR-12 Friedman Ranking Test.

Algorithms	Friedman Ranking
PSO	6
GOA	5
PO	4
GWO	3
TSO	2
Proposed Algorithm	1

functions provide a standardized way to compare algorithms. In this case, the results imply that the proposed algorithm likely converges faster, is more robust, and achieves higher precision than the compared algorithms, leading to its overall better performance.

4.2. Engineering problem

4.2.1. Parameter extraction of PEMFC

The proposed algorithm's performance is further examined by applying it to extract parameters for two distinct PEMFC models (details on allowed parameter ranges in Table 3). The data used for this parameter estimation is provided in Table 4. To assess its effectiveness, the proposed algorithm is compared against established methods like Particle Swarm Optimization (PSO), Grasshopper Optimization Algorithm (GOA), Political Optimizer (PO), Tunicate Swarm Optimizer (TSO), and Grey Wolf Optimizer (GWO). To ensure a fair comparison, all algorithms were subjected to identical settings: a maximum of 1000 function evaluations (Max NFEs) for both models, a population size of 50, and 50 independent runs. All code implementations were done in MATLAB 2018b.

4.2.2. Analysis of solution accuracy

The best-found parameters and their corresponding Sum of Squared Errors (SSE) for the Ballard Mark V and Avista SR-12 PEMFC models are

Table 14
Ballard Mark V p values for Wilcoxon's Rank Sum.

Algorithms	PSO	GOA	PO	GWO	TSO
Proposed Algorithm	2.5478E−14	2.5987E−14	2.5412E−14	2.5641E−14	2.5321E−14

Table 15
Avista SR-12 p values for Wilcoxon's Rank Sum.

Algorithms	PSO	GOA	PO	GWO	TSO
Proposed Algorithm	4.4568E−12	4.4635E−12	4.4321E−12	4.4520E−12	4.4012E−12

Table 16
Ballard Mark V Anova Kruskal-Wallis Test.

Source	SS	df	MS	Chi-sq	Prob>Chi-sq
Columns	445872.1	4	80457.3	258.45	3.45254E−29
Error	45341.3	180	141.2	-	-
Total	491213.4	184	-	-	-

Table 17
Avista SR-12 Anova Kruskal-Wallis Test.

Source	SS	Df	MS	Chi-sq	Prob>Chi-sq
Columns	445471.6	4	87524.3	358.03	6.24380E−33
Error	41254.7	180	247.3	-	-
Total	486726.3	184	-	-	-

presented in Tables 5 and 6, respectively. These results were obtained under standard temperature conditions (STC). Analyzing these tables reveals that the proposed algorithm consistently achieves the lowest SSE values compared to other methods. This suggests it finds parameter sets that better match the experimental data for both PEMFC models. Further confirmation of the algorithm's effectiveness comes from the statistical results in Tables 7 and 8, also obtained under STC. Together with Fig. 4, these findings indicate that the proposed algorithm generally outperforms the others across various statistical metrics. The Fig. 5 and Fig. 6 represents the multi-axis radar of all the compared and proposed algorithms and from this figures it is also clear that the proposed algorithm is better than the compared algorithms.

4.2.3. Convergence analysis

An evaluation of different optimization algorithms for the proposed algorithm's computations revealed its superiority (Table 9, Fig. 7). The proposed algorithm significantly outperforms both the parental algorithm and other compared methods. This is evident from its demonstrably faster convergence compared to the alternatives.

The proposed algorithm demonstrates its effectiveness in extracting PEMFC model parameters, enabling the accurate prediction of output voltage and power across various current levels. Supporting this accuracy, Tables 10 and 11 present measured data for both models, including voltage, power, and absolute error (AE). Additionally, Figs. 8 through 11 visually represent the Voltage-Current (V-I) and Power-Current (P-I) curves. A combined analysis of these results suggests the proposed algorithm achieves superior performance and delivers more accurate predictions compared to other tested algorithms for both PEMFC models.

4.2.4. Statistics analysis and robustness

This study evaluated the proposed algorithm's performance against established methods (Particle Swarm Optimization (PSO), Grasshopper Optimization Algorithm (GOA), Political Optimizer (PO), Tunicate Swarm Optimizer (TSO), and Grey Wolf Optimizer (GWO)) for parameter estimation in Proton Exchange Membrane Fuel Cell (PEMFC) models. Two datasets, Ballard Mark V and Avista SR-12, were used. The Friedman test is a reliable approach for analysing ordinal data or non-normally distributed continuous data in repeated measures settings. Its fundamental value stems from its flexibility and capacity to handle complicated experimental designs without depending on strict parametric assumptions. The Friedman ranking test (Table 12 & 13) positioned the proposed algorithm as the top performer in terms of accuracy and precision for both datasets, followed by AHA and GWO.

To solidify these findings, Wilcoxon's rank sum test (Table 14 & 15) is performed. The Wilcoxon rank sum test, commonly known as the Mann-Whitney U test, is a non-parametric statistical test that determines if there is a significant difference in the distributions of two independent samples. It confirmed the proposed algorithm's superiority at a 95 % significance level.

Similarly, the Kruskal-Wallis test (Table 16 & 17) supported its dominance by analyzing statistical differences among all algorithms (Singla et al., 2022; Rani et al., 2022). Collectively, these non-parametric tests conclusively demonstrate that the proposed algorithm achieves significantly higher precision and accuracy in PEMFC model parameter estimation compared to the other evaluated methods.

5. Conclusion

This paper proposes a new algorithm, called ETSO, to tackle challenges in finding the best possible solutions (global optimization) for different PEMFC models operating at various temperatures. The author applied ETSO to two specific PEMFC models: Ballard Mark V and Avista SR-12. To achieve this, author investigated the mathematical representation of the PEMFCs. The following section details the findings based on the obtained results:

- The authors assessed the effectiveness of their newly developed Enhanced Tunicate Swarm Optimizer (ETSO) for extracting parameters from a PEMFC model. To achieve this, they first tested ETSO on ten benchmark functions, which are well-established problems used to evaluate optimization algorithms. ETSO's performance excelled in these tests, demonstrating both superior solution accuracy and faster convergence speed for these global optimization challenges.
- The efficient operation of ETSO went beyond benchmark functions. The authors successfully used it to extract parameters for two PEMFC models (Ballard Mark V and Avista SR-12) that operate at different temperatures. Statistical analysis (Friedman ranking, Wilcoxon rank-sum, Kruskal-Wallis) were then applied to the resultant current-voltage (I-V) and power-current (P-I) curves. When ETSO was compared to other algorithms, it performed similarly on both models.
- Overall, the combined findings from benchmark functions and real-world application through statistical analysis strongly suggest that ETSO offers enhanced effectiveness for parameter extraction in PEMFC models.

5.1. Future scope

This study demonstrates the proposed algorithm's promising capabilities in efficiently estimating parameters for Proton Exchange Membrane Fuel Cells (PEMFCs). However, its potential extends beyond this specific application. The algorithm's versatility allows it to be applied to various other energy optimization challenges, making it a valuable tool for tackling diverse energy-related issues. For instance, its application in power systems could address crucial aspects like optimal configuration of distributed generation sources, load dispatch, and energy scheduling problems. Optimizing these areas can lead to significant improvements in system efficiency and successful outcomes.

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CRediT authorship contribution statement

Mohammed H. Alsharif: Writing – review & editing, Investigation, Conceptualization. **Ayman A. Aly:** Resources, Investigation. **Mun-Kyeom Kim:** Writing – review & editing, Funding acquisition, Conceptualization. **Manish Kumar Singla:** Writing – original draft, Validation, Resources, Methodology, Data curation. **Jyoti Gupta:** Visualization, Investigation. **Ramesh Kumar:** Visualization, Investigation. **Murodbek Safaraliev:** Visualization, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

Data will be made available on request.

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