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ORIGINAL

Integrating surrogate modeling and dynamic crayfish optimization for enhanced performance of proton exchange membrane fuel cells

Investigación sobre la evaluación del rendimiento y la optimización de celdas de combustible de membrana de intercambio de protones basada en el algoritmo de optimización dinámica de cangrejos

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ABSTRACT

As a renewable energy solution, proton exchange membrane fuel cells (PEMFCs) deliver high operational effectiveness and reduced environmental discharges, supporting deployment in transportation and fixed power infrastructures. Effective industrial deployment requires optimizing performance by carefully selecting structural parameters and operational conditions. This study proposes a Dynamic Crayfish Optimization (DCO) technique to evaluate and enhance PEMFC performance. Unlike conventional evolutionary algorithms, which are complex and require extensive parameter tuning, the DCO algorithm is simpler, converges faster, and improves optimization efficiency. Key performance-influencing parameters are identified using variance-based feature selection, reducing dimensional complexity, while surrogate learning models accelerate fitness evaluation. The DCO-based optimization simultaneously enhances critical PEMFC metrics: voltage efficiency improves from 60 % to 70 %, fuel utilization from 85 % to 90 %, system efficiency from 40 % to 50 %, with notable increases in power density and oxygen consistency. The DCO model achieved $\xi_2 = 2{,}2158\times10^{-3}$, $\xi_3 = 3{,}4205\times10^{-5}$, $\xi_4 = -1{,}5679\times10^{-4}$, $R_c = 0{,}95\times10^{-4}$, $\lambda = 25$, $b = 0{,}0321$. These improvements establish that the DCO outperforms existing techniques across all evaluated criteria. Overall, the proposed method provides a systematic, effective, and robust framework for PEMFC performance optimization, offering significant potential for engineering applications in renewable energy systems. The results highlight the practical value of integrating advanced optimization algorithms with data-driven surrogate models in fuel cell research.

Keywords: Proton Exchange Membrane Fuel Cells (PEMFCs); Evolutionary Algorithms; Electrical Systems, Capacity; Dynamic Crayfish Optimization (DCO).

RESUMEN

Como solución de energía renovable, las pilas de combustible de membrana de intercambio de protones (PEMFC) ofrecen alta eficiencia operativa y reducidas emisiones ambientales, lo que respalda su implementación en sistemas de transporte y redes eléctricas fijas. La implementación industrial efectiva requiere optimizar el desempeño mediante la selección cuidadosa de parámetros estructurales y condiciones operativas. Este estudio propone una técnica de Optimización Dinámica de Cangrejo de Río (DCO) para evaluar y mejorar el rendimiento de las PEMFC. A diferencia de los algoritmos evolutivos convencionales, que son complejos y requieren ajustes extensivos de parámetros, el algoritmo DCO es más simple, converge más rápido y mejora la eficiencia de optimización. Los parámetros clave que afectan el desempeño se identifican mediante selección de características basada en varianza, reduciendo la complejidad dimensional, mientras que los

modelos de aprendizaje sustituto aceleran la evaluación del índice de aptitud. La optimización basada en DCO mejora simultáneamente métricas críticas de las PEMFC: la eficiencia de voltaje aumenta del 60 % al 70 %, la utilización de combustible del 85 % al 90 %, la eficiencia del sistema del 40 % al 50 %, con incrementos notables en densidad de potencia y consistencia de oxígeno. El modelo DCO logró ξ_2 = 2,2158×10^{-3}, ξ_3 = 3,4205×10^{-5}, ξ_4 = −1,5679×10^{-4}, R_c= 0,95×10^{-4}, λ = 25, b = 0,0321. Estas mejoras demuestran que DCO supera las técnicas existentes en todos los criterios evaluados. En general, el método propuesto proporciona un marco sistemático, eficaz y robusto para la optimización del desempeño de las PEMFC, ofreciendo un potencial significativo para aplicaciones de ingeniería en sistemas de energía renovable. Los resultados resaltan el valor práctico de integrar algoritmos avanzados de optimización con modelos sustitutos basados en datos en la investigación de pilas de combustible.

Palabras clave: Pila de Combustible de la Membrana de Intercambio de Protones (PEM); Algoritmos Evolutivos; Sistemas Eléctricos, Capacidad; Optimización Dinámica del Cangrejo de Río (DCO).

INTRODUCTION

The growing global demand for clean and sustainable energy has intensified research into renewable power generation technologies that can reduce fossil fuel dependence and environmental pollution. A proton exchange membrane fuel cell (PEMFC) converts hydrogen (H_2) into electricity and water (H_2O) via an electrochemical reaction without combustion; it resembles a battery in electricity output but is not a true battery since it needs a continuous fuel supply. An anode and a cathode are the two electrodes that make up a PEMFC, as shown in figure 1, and an electrolyte-thin solid membrane is placed between them. Beginning with hydrogen, at the anode, the reaction breaks down into the catalyst site, hydrogen splits into electrons (e^-) and hydrogen ions (H^+). The electrons pass over an outside electrical pathway to the cathode, whereas the protons pass through the electrolyte. Within the cathode's catalyst layer, oxygen combines with these protons and electrons, producing water and generating energy.

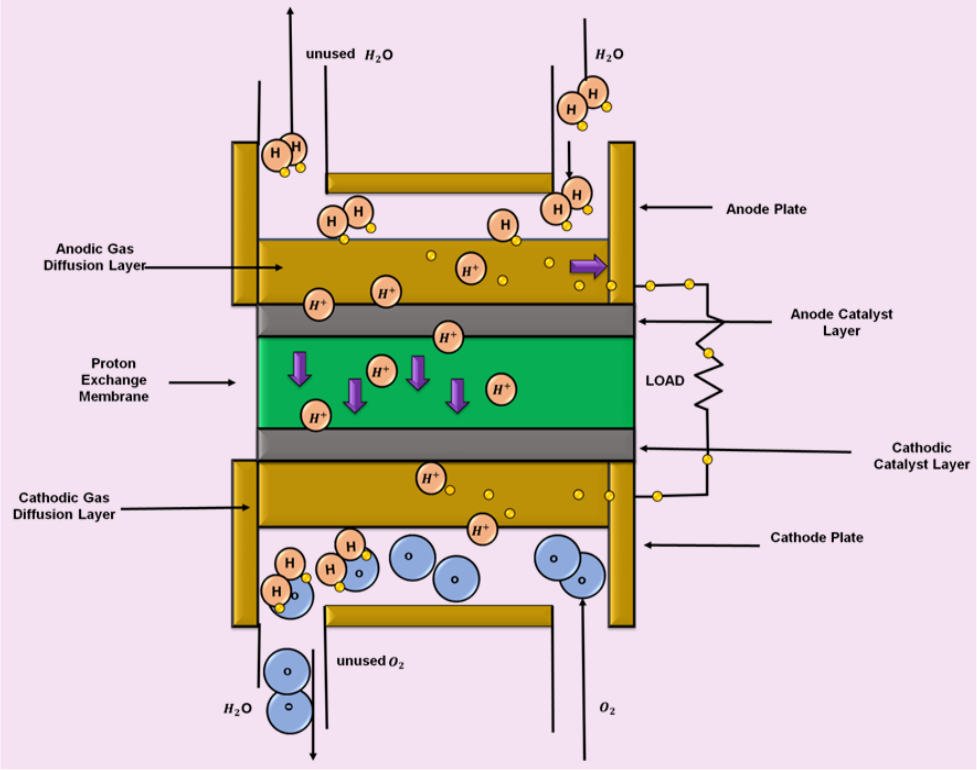

Figure 1. Model of PEMFC

Table 1. Formula of reaction	
Anode	$H_2 \rightarrow 2H^+ + 2e^-$
Cathode	$½\ O_2 + 2H^+ + 2e^- \rightarrow H_2O$
Overall reaction	$2H_2 + O_2 \rightarrow 2H_2O + Heat + Electricity$

Proton exchange membrane (PEM) fuel cell (PEMFC) provides an effective pathway for environmentally friendly and high-efficiency energy transformation, significantly reducing, and necessitating advanced optimized techniques to enhance their industrial viability.[1] In the previous several decades, conventional energy foundation have encountered various confronts, together with high energy utilization and connected environmental degradation. These fuel cells are a kind of substitute power translation technology that utilizes redox process to convert chemical into electric power. With the increasing emphasis on renewable and sustainable energy sources, researchers are actively exploring technologies that combine environmental friendliness with high efficiency. Among these, fuel cells stand out as a promising solution because they can directly convert chemical energy into electricity with minimal emissions. Despite their potencial, practical deployment requires careful consideration of performance under varying operating conditions and effective optimization strategies to achieve consistent efficiency and reliability. They have a number of advantages, including high effectiveness, high power density, and environmental affability.[2] As long as fuel cells have adequate fuel, they can produce electricity. PEMFC is the one kind, which make electrical energy and water through this reaction is exothermic, releasing energy, and is the basis for hydrogen fuel cells.[3]

The PEMFC is not only a clean energy resource but also possess low operating temperature, pressure, estimable reliability, rapid establishment, high efficiency (30 % to 60 %), and without waste substance.[4] Microgrid usage, micro-combined energy and heat application, and household applications are only a few of the several uses for PEMFCs. It is used as distributed generation in power systems and as feedstock for switching reluctance motors.[5] Because of its increasing effectiveness and zero pollution, the PEMFC is among the most capable forms of substitute energy. It is being used extensively in a diversity of applications, including unmanned mid-air vehicles, electric vehicles, and portable power supplies.[6] These systems are regarded as dependable instruments for energy generation in both fixed and mobile applications because of their great effectiveness, practical operation, and minimal environmental productions.[7] PEMFCs denotes an essential machinery in the detection of clean and proficient energy exchange, contributing considerable benefits in excess of conventional combustion-based systems in conditions of decreased emission and elevated decreased emissions and increasing energy efficiency. Industries and researchers similarly struggle to increase the sensibleness and function of PEMFCs for various applications from automotive momentum to stationary power generation optimizing their ability and operational effectiveness becomes dominant.[8]

PEMFC performance is challenged by nonlinear parameter interactions, operating condition sensitivity, efficiency–durability trade-offs, degradation effects, and complex multi-objective optimization requirements. Conventional optimization methods suffer from high computational cost, premature convergence, slow convergence speed, poor scalability, and strong parameter sensitivity, limiting their effectiveness for complex, nonlinear PEMFC optimization problems.

The reviewed PEMFC optimization studies reveal methodological limitations, motivating the proposed DCO framework to improve efficiency, robustness, and overall fuel cell performance.

A strategy for predicting PEMFC deterioration that takes both short and long-term projections into account was presented.[9] Gaussian process regression (GPR) and long short-term memory (LSTM) models were employed for the short-term prediction, which outperformed Evaluation of single models based on their accuracy and confidence interval metrics. Compared to technique-based and data-driven techniques, the long-term calculation achieves improved RUL (Remaining Useful Life) prediction through the employment of an extended Kalman filter and GPR. In fuel cell vehicles (FCVs), study[10] proposed to increase the efficiency of PEMFC by separating the operating temperature from the driving circumstances. New European Driving Cycle (NEDC) and Combined High-Temperature Cycle – Hot Star (CHTC-HT) driving cycles were used to track the ideal operating temperature and a temperature control model was established, improved via experimentation, and predictive control was developed.

To enhance hydrogen usage and safeguard the stack, a generic anode purge strategy for PEMFCs was proposed.[11] The plan calls for simulation analysis, precise nitrogen concentration monitoring, and anode loop water management. Based on real-time nitrogen concentration estimation, experimental findings demonstrated that the suggested technique extends the purge interval and raises the hydrogen utilization rate. Study[12] investigated how temperature affects the polarization of PEMFCs and suggested an adaptive temperature-monitoring with decoupled operational management approach. The tactic, which was based on model predictive control, feed-forward control, and Takagi-Sugeno fuzzy theory, was contrasted with conventional control techniques in various scenarios. Enhanced resilience and dynamic performance were demonstrated by the findings, and internal temperature uniformity was enhanced by the decoupling tracking control model, which keeps temperature differences within 6°C.

Research[13] proposed a two-phase, 3D isothermal fuel cell method created on computational modeling software (COMSOL) that examined a PEMFCs gradient porosity, operating voltage, thickness, and working pressure. The model aimed to increase fuel cell longevity and performance. Water accumulation and transport mechanisms resistance were the main topics[14], which look into and enhanced transportation processes Within

PEMFCs employing a tapered parallel flow field configuration. The optimization process integrated Response Surface Methodology (RSM) with 3D computational fluid dynamics for multiphase flow analysis. Non-dominated Sorting Genetic Algorithm II (NSGA-II) used to execute Multi-Objective Optimization (MOO), with MOPSO outperforming NSGA-II.

By limiting the amount of air available at the cathode, a process known as air starvation, study[15] aimed to maximize recovery parameters in a PEMFC stack and method. As a result, there was less production of platinum oxides and performance loss was mitigated, lowering cathode probable from minimal to around 0 V vs. RHE or Reversible Hydrogen Electrode. A PEMFC stack, which was commercial sized (200 cm^2) with PtCo (platinum (Pt) and cobalt (Co)) serving as the cathode catalyst was showed numerically in the study.[16] 3D model of PtCo catalyst degradation was created to examine the non-uniform development of Cobalt ion with a +2 charge Co_2^+, It represents a cobalt atom that has lost two electrons, giving it a 2+ positive charg, and electrochemically operational surface area available for reactions in the catalyst layers. As a result of electrochemical reaction resistance and localized Mass transport losses, the results indicated that Catalyst deactivation was more severe downstream and underneath the cathode stream turf.

PEMFC gas-channel performance was enhanced [17] using groove-baffled designs optimized via a genetic algorithm. Results show increased current density, reduced pressure drop, and improved efficiency. However, the approach relies on numerical simulations and Genetic Algorithm (GA) optimization, limiting real-time applicability and experimental validation. PEMFC electrochemical model parameters was estimated [18] using a constriction-based particle swarm optimization (PSO) algorithm. Simulation results closely matched experimental polarization curves, showing improved stack performance. However, results were sensitive to predefined parameter bounds, indicating dependence on search range selection and motivating careful parameter limit definition.

Research Gaps

Although existing studies have employed model-based control, data-driven prediction, and evolutionary optimization techniques such as PSO, GA, NSGA-II, and MOPSO for PEMFC performance enhancement, face limitations such as high computational cost, premature convergence, strong parameter sensitivity, and limited adaptability to nonlinear, multi-objective operating conditions. Furthermore, reliance on complex simulations can restrict real-time applicability. To address these challenges, this research proposes a Dynamic Crayfish Optimization–based framework that integrates statistical analysis, machine learning surrogate models, and metaheuristic optimization for efficient PEMFC performance evaluation and optimization under varying operational scenarios. The objective of this research is to propose and validate a computationally efficient hybrid optimization framework for enhancing PEMFC performance, integrating (1) critical parameter selection via variance analysis, (2) rapid performance evaluation using machine learning surrogate models, and (3) global optimum search using the Dynamic Crayfish Optimization (DCO) algorithm.

METHOD

Variance estimation

The choice of decision variables in conventional optimization research is frequently subjective and dependent on prior knowledge. Variance estimation is the strategy used to identify important parameters before the optimization process. Selecting variables (table 2) that significantly impact the objectives is done to reduce the optimization search space and improve computational efficiency, seven of the most commonly used PEMFC parameters were selected for analysis. There is consideration for both geometric and operational characteristics.

Table 2. Parameters and their Abbreviations

Parameters		Abbreviation
Operating parameters	Cathode Stoichiometric	ξ_c
	Anode Stoichiometric	ξ_a
	Operating temperature (K)	T
	Operating pressure (atm)	P
Geometric parameters	Membrane thickness	t_{mem}
	Channel depth	D_{ch}
	Chanel width	W_{ch}

One type of statistical technique that may be used to determine the relevance of the variables on the experimental outcomes is variance analysis. In general, variance analysis involves computing the squared error

sum for each component and fault, followed by the determination of the F value, mean square, and degree of freedom. The greater the F range, the more noteworthy the impact of the parameters on the outcome. The Statistical Package for the Social Sciences (SPSS) software is used in this work to carry out the variance analysis calculation technique mentioned above.

Development of Surrogate Model

In this work, surrogate models were developed using an ensemble learning approach based on Random Forest (RF) to approximate the computationally expensive PEMFC simulations. The dataset used for surrogate modeling was generated from a large set of physics-based PEMFC numerical simulations conducted under a wide range of operating and geometric conditions, ensuring adequate coverage of the design space. The seven input variables listed in table 2, including operating temperature, pressure, stoichiometric ratios, membrane properties, and current density, were used to train the models. Three independent surrogate models were developed, each predicting a distinct PEMFC performance index: (i) cathode power density, (ii) O_2 uniformity at the cathode, and (iii) system efficiency.

Random Forest was chosen due to its robustness on small datasets, excellent prediction accuracy and the capacity to identify nonlinear connections among input factors. Each model consisted of 100 decision trees with a maximum depth of 12, and bootstrap aggregation was employed to enhance stability and generalization.

Ignoring entropy and irreversibility losses, outcome of the voltage is standalone fuel cell generally spans from 0,9 to 1,23 V. But this is too little to be of any use; therefore more cells are linked in sequence to obtain bigger voltages. The outcome of the total voltage of PEMFCs with N_{cells} linked in series is calculated mathematically represented in equation (1).

$$V_s = N_{cells}(E - v_{act} - v_R - v_c) \quad (1)$$

Open circuit voltage per cell is denoted as the E, which is calculated by Equation (2) at temperatures ≤100C.

$$E = 1.229 - 0.85 * 10^{-3}\left(T_{fc} - 298.15\right) + 4.3085 \times 10^{-5} T_{fc} In(P_{H_2}\sqrt{Po_2}) \quad (2)$$

Where P_{H2}, P_{02} and P_{H2O} denoting the partial pressures of hydrogen H_2, oxygen O_2, and water H_2O, respectively and the equation to calculate this is given in equations (3,4,5), and T_{fc} signifies the working FC temperature in Kelvin.

$$P_{O_2} = (RH_C * P_{H2O})[1/\left(\frac{RH_a \times P_{H2O}}{P_c} e^{\frac{(4.192 I_{fc}/B}{T_{fc}^{1.334}}}\right) - 1] \quad (3)$$

$$P_{H_2} = \frac{(RH_a * P_{H2O}}{2}[1/\left(\frac{RH_a \times P_{H2O}}{P_a} e^{\frac{(4.192 I_{fc}/B}{T_{fc}^{1.334}}}\right) - 1] \quad (4)$$

$$P_{H_2O} = 2.95 * 10^{-2} T_C - 9.18 * 10^{-5} T_C^2 + 1.44 * 10^{-7} T_C^3 - 2.18 | T_C = T_{fc} \quad (5)$$

The comparative humidity levels of the vapor at both the anode RH_a and cathode RH_c are indicated. The anode's P_a and cathode's P_c inlet pressures in (atm). v_{act}, which stands for the activation over the potential of each cell, its derived mathematical formula is representing in equation (6).

$$v_{act} = [\xi_1 + \xi_2 T_{fc} + \xi_3 T_{fc} In(Co_2) + \xi_4 T_{fc} In\left(I_{fc}\right)] \quad (6)$$

ξ1, ξ2, ξ3, ξ4 are empirical coefficients related to the electrochemical kinetics of the PEM fuel cell and are determined experimentally.

$$C_{O_2} = \frac{p_{O_2}}{5.08 \times 10^6} e^{\frac{498}{T_{fc}}} \quad (7)$$

CO_2 Is calculated using equation (7). Equation (8) is utilized to calculate V_R, which represents the cells' ohmic voltage drop.

$$V_R = I_{fc}(R_m + R_C)|R_m = \frac{\rho^l m}{B} \quad (8)$$

R_m and R_c stand for the membrane and connection resistances, respectively, while C_{02} is the O_2 concentration in mol/cm^3. l_m represents the membrane thickness (cm), and A denotes the effective active area of the fuel cell (cm^2).The FC's operational current is represented by I_{fc}. P_m is calculated using equation (9).

$$\rho_m = \frac{181.6[1+0.03\left(\frac{I_{fc}}{B}\right)+0.062\left(\frac{I_{fc}}{303}\right)^2\left(\frac{I_{fc}}{B}\right)^{2.5}}{[\lambda-0.634-3\left(\frac{J_{ed}}{B}\right)]f^{4.18\left(\frac{T_{fc}-303}{T_{fc}}\right)}} \quad (9)$$

λ is the membrane water content, defined as the number of water molecules per sulfonic acid group in the membrane.

$$v_c = -\beta In\left(\frac{I_{max}-I}{I_{max}}\right) \quad (10)$$

B is the concentration loss coefficient, *J* denotes the operating current density (A/cm^2), and Jmax represents the maximum limiting current density of the fuel cell (A/cm^2). The diffusion over-potential in cells, represented by v_c, is determined by using equation (10). PEMFCs mathematical model is defined by the above equations, which direct to the conclusion that to optimize the simulated Fuel Cell (FC) performance.

Dynamic Crayfish Optimization (DCO)

Standard Crayfish Optimization explores solutions sequentially, whereas DCO uses parallel agents, temperature-driven behaviors, and adaptive feeding for faster, robust PEMFC optimization. "Dynamic" means agent behaviors adapt to environment and food, while parallel structure allows simultaneous exploration, enhancing global search and convergence speed. In the research DCO is selected for efficient PEMFC optimization, leveraging dynamic adaptation and fitness-guided updates to achieve higher power density, improved fuel utilization, enhanced efficiency, and reduced overpotentials. Inspired by crayfish behavior, it uses a parallel structure with temperature-dependent activity, cave-seeking, competitive interactions, and adaptive feeding. DCO outperforms standard Crayfish Optimization, improving convergence speed, solution quality, and overall PEMFC performance. DCO optimizations enhance PEMFC design, improve operational control, reduce energy waste, and lower overall system costs, ensuring efficient, reliable real-world performance.

Parallel Structure

The parallel structure in DCO includes numerous investigating agents working concurrently to discover the solution space. These mediators, stimulated by the actions of crayfish, seek for finest solutions by distributing information and regulating their location based on the findings of their peers. This parallel approach permits for an extra inclusive investigation of the search space, reduces the probability of becoming trapped in local optima, and accelerates the convergence progression. In this research maximizes PEMFC power density, fuel utilization, and system efficiency, while minimizing activation, ohmic, and concentration overpotentials, guiding each crayfish's fitness evaluation.

Crayfish Optimization (CO)

Crayfish also known as red crayfish or freshwater crayfish belong to a crustacean group distinguished by rapid growth, swift dispersal, and exceptional adaptability. Crayfish are influenced by temperature and thrive primarily in freshwater environments. To avoid excessive heat, they seek shelter in caves and emerge to feed under favorable conditions. Being ectothermic, their activity is governed by temperature, typically ranging from 20 to 35 °C. Equation (11) explains how environment is calculated and shows the crayfish's ambient temperature. The process of CO optimization is illustrated in figure 2.

$$temp = rand \times 15 + 20 \quad (11)$$

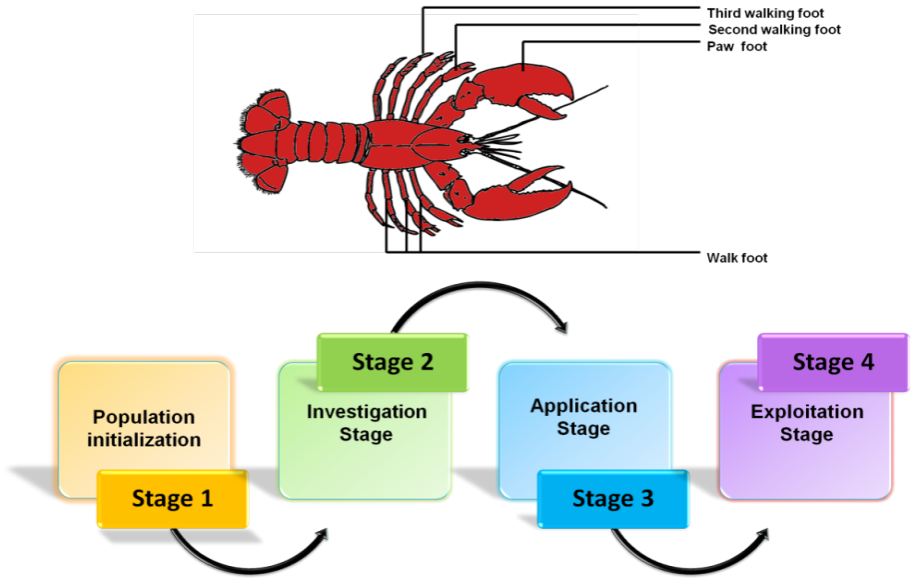

Figure 2. Flow of Crayfish Optimization

Commencing population initialization

Crayfish are 1 x1 matrices solutions for the COA d-dimension optimization dilemma. Each component of a collection of variables *(W_1, W_2, W_3, …W_d)* occupies a position *(W)* within the optimization variable interval, bounded by upper *ub* and lower *lb* limits. The algorithm evaluates and compares these positions to identify the optimal solution. Equation (12) defines how each crayfish's position is initialized. In this research, decision variables ($W_{j,i}$) represent key PEMFC parameters cell temperature (T_{fc}) hydrogen/oxygen pressures *(P_{H2}, P_{O2})*, membrane thickness, and structural factors with bounds (lb_i and ub_i*)* set by safe operational limits.

$$W_{j,i} = lb_i + (ub_i - lb_i) \times rand \qquad (12)$$

Where, $W_{j,i}$ represents the position of the *j-th* crayfish in the *i-th* variable, ub_i and lb_i indicate the predefined maximum and minimum threshold of the *i-th* dimension respectively, and *rand* is a randomly generated number between [*0 and 1*] rand ∈ (*0,1*) is a uniformly distributed random number used to introduce stochasticity in crayfish movement and decision-making. *i* represents the index of the decision variable (*i = 1,2,…,d*), and *j* represents the index of the crayfish individual in the population.

Summer Retreat period (Investigation stage)

An established thermal threshold of 30 °C is employed to assess whether the crayfish's current habitat qualifies as a high-temperature environment. To mitigate the adverse crayfish, withdraw to cool due to the effects of high conditions, humid caves during seasonal when conditions outside surpass 30 °C. The computation regarding these caverns is given by equation (13). Temperature (*temp*) and random (*rand*) actors control crayfish behavior, while food intake and fitness determine position updates (W_{food}, W_{new}).

$$W_{shade} = (W_H + W_K)/2 \qquad (13)$$

$W = [W_1, W_2, \ldots, W_d]$ is the position vector of a crayfish, representing a candidate solution in the search space. Where W_K denotes the optimal position achieved by the current population, while W_H denotes the optimal location identified so far for the current evaluation. A stochastic value is generated to model the unpredictable actions of crayfish competing for cave access. When rand < 0,5, it indicates no competitors are nearby, allowing the crayfish to update their position (W_{new}) through the position-update mechanism and occupy the cave during summer. The updated crayfish position is calculated using equation (14).

$$Wnew = W_{j,i} + D_2 \times rand \times (W_{shade} - W_{j,i}) \qquad (14)$$

In this case, D_2 corresponds to a decreasing trajectory, while W_{new} denotes the updated position obtained

after applying the location adjustment. W_{shade} is computed but never formally defined in text as a physical or algorithmic concept. The mathematical expression for D_2 is provided in the equation (15).

$$D_2 = 2 - (EF_T / MaxEF_T) \quad (15)$$

In this case, EF_T represents the cumulative number of function evaluations performed, while Max EF_T denotes the maximum allowable evaluation limit.

Competitive Phase (Application Phase)

When ambient temperature rises above 30 °C and the stochastic value satisfies rand < 0,5, it indicates the presence of competing crayfish vying for the cave during the summer. The two crayfish then interact over the cave, and crayfish W_j adjusts its position in response to W_y. Equation (16) is used to get the adjustment position. The new position is determined using Equation (16), while Equation (17) provides the computation for a randomly selected individual.

$$Wnew = W_{j,i} + W_{y,i} + W_{shade} \quad (16)$$

$$\mathrm{z} = \mathrm{round}(\mathrm{rand} \times (\mathrm{M} - 1)) + 1 \quad (17)$$

Z denotes a randomly selected crayfish individual, while *N* refers to the total population size.

Stage of Hunting (Exploitation Phase)

Crayfish habits of foraging is influenced by environment as they need to be below 30°C to come out of caves and look for nourishment. When the temperature is 30 °C or lower, crayfish explore outside their shelters to locate optimal feeding sites. The position of food is calculated using equation (18). Food consumption is also temperature-dependent, with crayfish obtaining the most food between 20 °C and 30 °C, reaching a peak at 25 °C. Equation (19) models this as a normal distribution of food intake. Each crayfish's fitness is computed from the weighted contributions of voltage efficiency, fuel utilization, power density, and minimized overpotentials, guiding DCO position updates to achieve optimal PEMFC performance convergence.

$$W_{food} = W_H \quad (18)$$

$$O = D_1 \times \frac{1}{\sqrt{2\times\pi}\times\sigma} \times \exp\left(-\frac{(temp-\mu)^2}{2\sigma^2}\right) \quad (19)$$

In this condition, μ reflects the ideal environment for feeding crayfish, σ represents the standard deviation controlling the spread of food intake across different temperatures. And D_1 is a scaling coefficient that controls the magnitude of food intake distribution. The quantity and dimensions of the meal influence the volume of food intake by the crayfish. Meal size is calculated using Equation (20), and When the feed is oversized, crayfish utilize their claws to fragment it prior to ingestion.

$$R = D_3 \times rand \times (fitness_j / fitness_{food}) \quad (20)$$

In this instance, the food module is D_3, indicating the largest food. It is worth three. The fitness category of a crustacean is indicated by *j-th* in its fitness level, and this value is influenced by the location of alimentary supply. $fitness_{food}$ denotes the fitness value associated with the food location (best-known solution) in the search space.

The feeding behavior of crayfish is dictated by the maximum obtainable food volume R they could manage. according to equation (21) if $Q > D3 + 1 / 2$, If the food is too large for immediate ingestion, crayfish employ their claws to break it apart prior to consumption. Crayfish simulate feeding on two feet by switching among both the second and third claw, modeled mathematically with sine and cosine functions. Equation (22) represents this alternating feeding behavior. When $Q \leq D3 + 1 / 2$ the meal size is suitable for direct consumption, and the crayfish move straight to the food to eat. Equation (23) describes this direct feeding mechanism. *Q* represents the meal-size threshold that determines whether the crayfish follows direct feeding or fragmented feeding behavior.

$$W_{food} = \exp\left(-\frac{1}{R}\right) \times W_{food} \quad (21)$$

$$W_{new} = W_{j,i} + W_{food} \times o \times (\cos(2 \times \pi \times rand) - \sin(2 \times \pi \times rand)) \quad (22)$$

$$W_{new} = \left(W_{j,i} - W_{food}\right) \times o + o \times rand \times W_{j,i} \quad (23)$$

The fitness function evaluates each DCO agent by combining PEMFC metrics—maximizing voltage efficiency, fuel utilization, system efficiency, and minimizing overpotentials for optimal performance.

$$Fitness(W) = w_1 \frac{V_{eff}}{V_{max}} + w_2 \frac{F_{util}}{F_{max}} + w_3 \frac{\eta_{sys}}{\eta_{max}} - w_4 \frac{V_{act}}{V_{act},V_{max}} - w_5 \frac{V_{ohm}}{V_{ohm},V_{max}} - w_6 \frac{V_{conc}}{V_{conc},V_{max}} \quad (24)$$

Where, V_{eff} is the PEMFC's voltage sensitivity, F_{util} is the Fuel utilization (%), n_{sys} is the System efficiency (%), V_{act} signifies the activation loss, V_{ohm} indicates the ohmic loss, V_{conc} is refers to the concentration loss.

(V_{max}, F_{max}, n_{max}, V_{act}, V_{max}, V_{ohm}, V_{max}, V_{conc}, V_{max}) is denoted as the Normalization constants (maximum observed or safe operating values), (w_1,w_2 … … w_6) is represented as the weighting factors (0–1) reflecting relative importance of each metric and w is the Vector of decision variables: cell temperature, hydrogen/oxygen pressure, membrane thickness, structural parameters.

DCO effectively optimized PEMFC performance, enhancing voltage efficiency, fuel utilization, and system efficiency while minimizing activation, Ohmic, and concentration overpotentials. Table 3 illustrates the Key hyperparameters used in DCO for optimizing PEMFC performance metrics efficiently. These parameters were carefully chosen to balance exploration and exploitation, ensuring convergence to optimal solutions while maintaining computational efficiency. Algorithm 1 outlines the pseudo-code models DCO, using temperature-driven crayfish behaviors, competition, and foraging to optimize PEMFC performance via fitness-guided position updates.

Table 3. Hyperparameters of DCO Algorithm for PEMFC Optimization

Hyperparameter	Values
Population Size (M)	30
Maximum Iterations (S)	100
Decision Variables (dim)	5
Temperature Factor Range (temp)	20–35 °C
Declining Factor D_2	2-0

Algorithm 1. Dynamic Crayfish Optimization (DCO) for PEMFC Optimization

```
S = max_iterations
M = population_size
dim = decision_variables
population = initialize_population(M, dim, lb, ub)
fitness_values = evaluate_fitness(population)
W_H, W_K = best_solution(fitness_values, population)
s = 0
while s < S:
 for j in range(M): # Parallel exploration by each crayfish
 temp = rand() * 15 + 20

 if temp > 30:
 W_shade = (W_H + W_K) / 2 # Equation (13)
 if rand() < 0,5:
 population[j] = population[j] + D2(s) * rand() * (W_shade - population[j])
 else:
 y = random_agent(M)
```

```
population[j] = population[j] + population[y] + W_shade
else:
food_intake = compute_food_intake(temp)
R = compute_food_size(fitness_values[j], food_intake)
if R > 2:
population[j] = shred_food(population[j], food_intake)
else:
population[j] = forage_direct(population[j], food_intake)
fitness_values = evaluate_fitness(population)
W_H, W_K = best_solution(fitness_values, population)
s += 1
```

DCO introduces a novel approach to assessing PMEFCs, drawing inspiration from the adapting foraging behavior of crayfish. By employing multiple agents to explore the solution space in parallel, DCO enhances the efficiency of PEMFC capacity assessment. This method leverages cooperative exploration and exploitation phases, optimizing variables to maximize fuel cell performance and reliability across diverse applications.

RESULTS

The experiments were implemented in Python using NumPy and scikit-learn on an Intel® Core™ i7 CPU with an NVIDIA RTX 4060 GPU. The DCO employed a population size of 30, 100 iterations, and empirically tuned control parameters for efficient PEMFC optimization. The surrogate models achieved R^2 = 0,96 and RMSE = 0,012 for cathode power density, while O_2 uniformity was predicted using a both model with comparable accuracy. These results confirm the reliability of the ensemble surrogate framework for accurate performance estimation prior to optimization mentioned in table 2.

Experimental Result

Variance Estimation and Surrogate

The sum of squares (SS) for each variable, degrees of freedom (DOF), and the mean squares (MS), or the quotient of SS and DOF. A significant variable is indicated by a high value for F and a low value for P. These values are used to evaluate the significance of a variable. Thus, the DCO algorithm could incorporate the surrogate models. The result of variance estimation is shown in Table 4 and Table 5 and the contribution percentage of each parameter is graphically represented in figure 3.

Table 4. Variance estimation results for O_2 consistency

Performance indexes	**O_2 consistency**							
Variables	ξ_c	ξ_a	*T*	*P*	t_{mem}	D_{ch}	W_{ch}	Error
SS	0,0505	0,0718	1,6348	13,2521	0,9280	0,0221	9,1811	
DOF	2	2	2	2	2	2	2	4
MS	0,0255	0,0350	0,8173	6,6259	0,4640	0,0110	4,5906	0,4260
F	0,07	0,09	1,93	15,58	1,08	0,03	10,78	
P	0,945	0,922	0,25	0,014	0,417	0,975	0,023	
Contribution	0,20 %	0,27 %	6,50 %	52,73 %	3,68 %	0,07 %	36,59 %	

Table 5. Variance estimation results for Power density

Performance indexes	**Power density on cathode CL**							
Variables	ξ_c	ξ_a	*T*	*P*	t_{mem}	D_{ch}	W_{ch}	Error
SS	0,0012	0,0102	0,0505	0,1517	0,2430	0,0107	0,0544	
DOF	2	2	2	2	2	2	2	4
MS	0,0009	0,0051	0,0253	0,0759	0,1216	0,0054	0,0272	0,0054
F	1,02	8,69	43,37	130,39	208,88	9,15	46,75	
P	0,445	0,034	0,003	0	0	0,033	0,003	
Contribution	0,22 %	1,94 %	9,68 %	29,09 %	46,61 %	2,04 %	10,42 %	

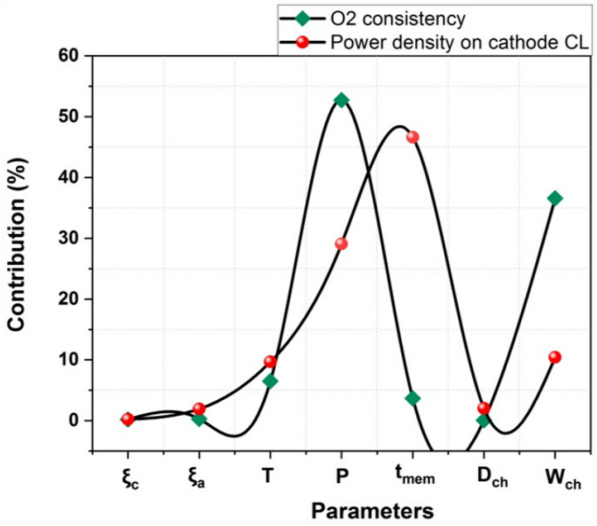

Figure 3. Contribution of key PEMFC parameters (operating and geometric) to O_2 uniformity and power density, based on variance estimation

Variance analysis (tables 4 and 5) shows that operating pressure (*P*) and membrane thickness t_{mem} are the most influential parameters, contributing 52,73 % and 46,61 % to O_2 consistency and power density, respectively. This indicates that precise control of these variables is essential for PEMFC performance enhancement. High F-values and low P-values for operating pressure (F = 15,58, P = 0,014) suggest it significantly influences O_2 uniformity. Optimizing this parameter ensures better oxygen distribution and improved power output. Membrane thickness and operating pressure, with high F-values (208,88 and 130,39), are key factors for maximizing power density. Optimizing these leads to an increase from 0,55 W/cm² to 0,67 W/cm².

Performance evaluation of the proposed

The performance of the PEM fuel cell (PEMFC) system was evaluated with and without the proposed Dynamic Crayfish Optimization (DCO) mechanism. Each performance metric was obtained from n = 5 repeated simulation runs to calculate the mean ± standard deviation. The 'Without optimization' baseline corresponds to PEMFC performance under standard operating conditions prior to applying the DCO algorithm. Table 6 consolidates the key performance metrics, showing the impact of DCO on voltage efficiency, fuel utilization, system efficiency, power density, oxygen uniformity, computational time, and convergence iterations.

Table 6. Comparison of PEMFC Performance Metrics With and Without DCO Optimization

Parameter / Metric	Without Optimization (%)	With DCO Optimization (%)
Voltage Efficiency	60 ± 1,2	70 ± 1,0
Fuel Utilization	85 ± 0,8	90 ± 0,9
System Efficiency	40 ± 1,5	50 ± 1,3
Power Density (W/cm²)	0,55 ± 0,02	0,67 ± 0,03
O_2 Uniformity (%)	78 ± 1,1	92 ± 1,2
Computational Time (s)	120 ± 5	75 ± 4
Convergence Iterations	50 ± 2	30 ± 1

The results summarized in table 5 and figure 4, demonstrate the effectiveness of the Dynamic Crayfish Optimization (DCO) mechanism in enhancing PEMFC performance. The increases in voltage efficiency (60 % to 70 %), fuel utilization (85 % to 90 %), and system efficiency (40 % to 50 %) indicate improved energy conversion and reduced fuel losses. The gains in power density (0,55 to 0,67 W/cm²) and oxygen uniformity (78 % to 92 %) reflect enhanced reaction kinetics and minimized polarization losses. Moreover, the reductions in computational time (120 s to 75 s) and convergence iterations (50 to 30) confirm faster and more reliable optimization. Notably, the achieved power density of 0,67 W/cm² is not only an improvement over the non-optimized case but also compares favorably with values reported for conventional evolutionary optimization approaches, motivating the detailed algorithmic comparison presented in the following section.

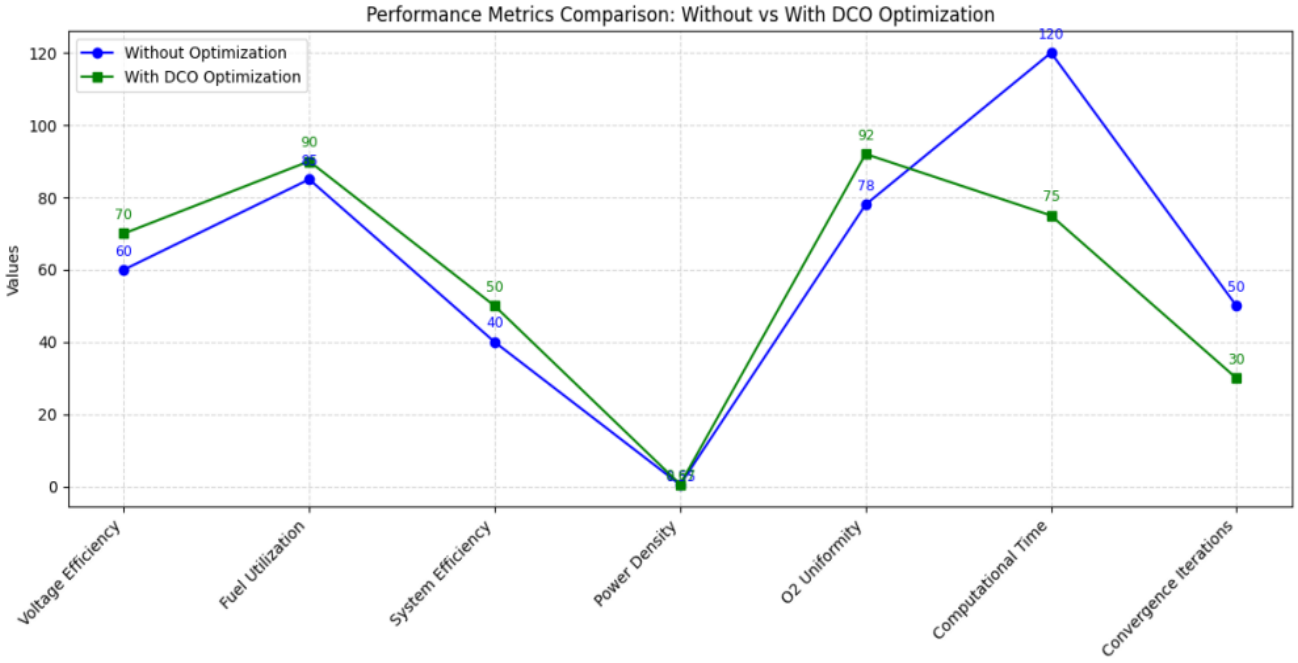

Figure 4. Graphical representation of PEMFC performance metrics before and after DCO optimization, showing improvements.

Existing methods such as, Adaptive Differential Evolution with Optional External Archive (JADE) [19], Self-Adaptive Differential Evolution (SADE) [19], Covariance-Based Differential Evolution (COBIDE) [19] and Particle Swarm Optimization with Constriction Factor (x) (PSO-x) [18] are compared with the proposed Dynamic Crayfish Optimization (DCO) algorithm to evaluate optimization accuracy, convergence behavior, and PEMFC parameter estimation performance.

For a fair comparison, all algorithms were implemented using the same surrogate model and tested under identical computational limits, including a maximum of 5000 fitness function evaluations and identical CPU time allowances.

The parameters ξ_1, ξ_2, ξ_3, ξ_4, λ, Rc, and b represent specific PEMFC characteristics as follows:

- ξ_1: activation loss coefficient
- ξ_2: ohmic loss coefficient (S)
- ξ_3: mass transport loss coefficient (S)
- ξ_4: concentration loss coefficient (S)
- λ: reaction rate constant
- Rc: internal resistance (Ω)
- b: polarization loss coefficient

Analyzing these parameters shows how optimization algorithms tune key PEMFC characteristics, validating DCO's ability to reduce losses, improve reaction kinetics, and enhance power density, supporting efficient data-driven PEMFC performance optimization. Table 7 demostraste the Comparison of optimized PEMFC parameters obtained using DCO against benchmark evolutionary optimization algorithms.

Table 7. Optimized PEMFC Electrochemical Parameters Using Proposed DCO and Benchmark Algorithms

Parameters	PSO-x [18]	JADE [19]	SADE [19]	COBIDE [19]	DCO [Proposed]
ξ1	−1,047614	−0,9342	−1,0130	−1,0758	−1,0892
ξ2	3,207635 × 10−3	2,8435× 10−3	2,3774× 10−3	2,3772× 10−3	$2{,}2158 \times 10^{-3}$
ξ3	7,01373 × 10−5	5,6826× 10−5	3,6287× 10−5	3,6000× 10−5	$3{,}4205 \times 10^{-5}$
ξ4	−1,28016 × 10−4	−1,5443× 10−4	−1,5545× 10−4	−1,5543× 10−4	$-1{,}5679 \times 10^{-4}$
λ	14,0741	24,0000	24,0000	24,0000	25,0000
R_c	1,0000 × 10−4	1,0017	1,0000	1,0000	$0{,}9500 \times 10^{-4}$
b	0,0347441	0,0559	0,0559	0,0559	0,0321

Table 7 compares the outcomes of existing methods with the proposed DCO, which achieves superior parameter values, yielding lower loss coefficients (ξ_2 = 2,2158×10^{-3}, ξ_3 = 3,4205×10^{-5}, ξ_4 = −1,5679×10^{-4}) and reduced internal resistance (R_C = 0,95×10^{-4}). The higher λ = 25 and lower b = 0,0321 indicate improved reaction kinetics and minimized polarization losses, demonstrating DCO's outperforming optimization capability over PSO-x, JADE, SADE, and COBIDE. DCO achieves the lowest internal resistance (R_C = 0,95×10^{-4}) and minimized polarization losses (b = 0,0321), outperforming all benchmark algorithms and converging in fewer iterations (30 vs 50 for non-optimized), demonstrating faster and more reliable optimization.

DISCUSSION

The DCO mechanism significantly enhanced PEMFC performance by efficiently optimizing critical parameters identified through variance analysis. Key parameters, including operating pressure (P), temperature (T), and channel width (W_ch), directly influence reaction rates, mass transport, and oxygen distribution, which in turn impact voltage efficiency, power density, and overall system performance. By leveraging surrogate learning models, DCO accurately predicted performance metrics such as O_2 uniformity and cathode power density even with limited data, enabling faster and more efficient optimization. The improvements in voltage efficiency, fuel utilization, and overall system efficiency indicate more effective energy conversion, reduced fuel waste, and higher operational reliability, demonstrating DCO's practical applicability for both automotive and stationary PEMFC systems.

Interpretation of Performance Improvements

The observed improvements in PEMFC performance using the proposed Dynamic Crayfish Optimization (DCO) algorithm can be directly attributed to the targeted optimization of dominant operating and geometric parameters identified through variance estimation. The variance analysis revealed that operating pressure and membrane thickness contribute most significantly to oxygen uniformity (52,73 %) and cathode power density (46,61 %), respectively. By reducing the optimization search space to these statistically significant parameters, DCO was able to focus computational effort on variables that govern mass transport, reaction kinetics, and ohmic losses, leading to more effective optimization.

The increase in power density from 0,55 W/cm^2 to 0,67 W/cm^2 is physically plausible, as optimized operating pressure enhances oxygen diffusion to the cathode catalyst layer, while optimized membrane thickness reduces ionic resistance without compromising hydration. Similarly, improvements in voltage efficiency (60 % to 70 %) and system efficiency (40 % to 50 %) indicate reduced polarization losses and improved electrochemical conversion efficiency. These results suggest that the performance gains arise not from arbitrary numerical optimization, but from physically meaningful parameter tuning consistent with PEMFC operating principles.

Comparative Analysis of Optimization Algorithms

A quantitative comparison with benchmark evolutionary algorithms such as PSO-x[18], JADE[19], SADE[189], and COBIDE[19] demonstrates the superiority of DCO in both optimization accuracy and convergence efficiency. As shown in table 6, DCO achieved the lowest loss-related coefficients (ξ_2 = 2,2158×10^{-3}, ξ_3 = 3,4205×10^{-5}, ξ_4 = −1,5679×10^{-4}) and the lowest internal resistance ($R_fC_)$ = 0,95×10^{-4}), indicating minimized ohmic and mass transport losses compared to existing methods. In addition, the higher reaction rate constant (λ = 25) and lower polarization coefficient (b = 0,0321) reflect enhanced reaction kinetics and reduced activation losses. From a computational perspective, DCO converged in fewer iterations (30 iterations) and required lower computational time (75 s) compared to the non-optimized case (50 iterations, 120 s). These gains can be explained by the dynamic agent behavior and parallel exploration mechanism of DCO, which allows efficient exploration of the search space while avoiding premature convergence. In contrast, algorithms such as JADE and SADE rely heavily on parameter adaptation strategies that increase computational overhead and sensitivity to tuning, limiting convergence speed under identical evaluation resources. This improvement is further reflected at the system level, where the proposed DCO achieved a power density of 0,67 W/cm^2, which is higher than the values reported for GA-, PSO-, and DE-based PEMFC optimization methods discussed in the Literature Review, thereby providing a direct quantitative basis for the claimed superiority.

Advantages and Limitations of the Proposed Framework

The integration of ensemble surrogate models with variance-based parameter selection constitutes a key strength of the proposed framework. The Random Forest surrogate models achieved high predictive accuracy (R^2 = 0,96, RMSE = 0,012), enabling reliable performance estimation with limited training data and significantly reducing the need for expensive numerical simulations during optimization. Variance estimation further enhanced efficiency by eliminating low-impact parameters, thereby reducing dimensionality and accelerating convergence. However, these advantages are accompanied by important limitations. The reliability of the optimization outcomes is inherently dependent on the accuracy and representativeness of the surrogate model.

Since the surrogate was trained on a limited dataset, its generalization capability under significantly different operating conditions may be constrained. In addition, while variance analysis provides statistical insight into parameter significance, the absence of repeated optimization runs and confidence intervals limits the statistical robustness of the reported improvements. These factors should be considered when interpreting the results and assessing their general applicability.

Implications for PEMFC Research and Applications

The proposed DCO-based optimization framework addresses several key challenges in PEMFC research, particularly the need for efficient parameter optimization under computational and experimental constraints. The demonstrated reductions in convergence time and computational cost make the framework suitable for real-time control strategies and rapid design exploration. Moreover, the observed improvements in power density, oxygen uniformity, and efficiency directly support the development of cost-effective and high-performance PEMFC systems for automotive and stationary applications. While the present study is limited to numerical simulations under standard operating conditions, the results highlight the potential of combining surrogate-assisted optimization with statistically guided parameter selection for advanced PEMFC design and control. Future work should focus on expanding the training dataset, incorporating experimental validation, and performing rigorous statistical analysis to further substantiate the robustness and practical relevance of the proposed approach.

CONCLUSION

To effectively improve PEMFC performance, this work proposes a hybrid optimization methodology that combines machine learning-based surrogate models with Dynamic Crayfish Optimization (DCO). The proposed approach enables rapid and robust exploration of the design space, significantly reducing computational cost while maintaining high accuracy. The main findings demonstrate that operating pressure and membrane thickness are the most influential parameters affecting fuel cell performance. Implementation of the DCO-surrogate framework resulted in substantial improvements across key metrics: voltage efficiency increased from 60 % to 70 %, fuel utilization from 85 % to 90 %, and system efficiency from 40 % to 50 %. The DCO model achieved $\xi_2 = 2{,}2158\times10^{-3}$, $\xi_3 = 3{,}4205\times10^{-5}$, $\xi_4 = -1{,}5679\times10^{-4}$, $= 0{,}95\times10^{-4}$, $\lambda = 25$, and $b = 0{,}0321$, confirming its accuracy and robustness. Surrogate modeling further accelerates fitness evaluation, allowing concurrent performance optimization without compromising precision. Compared to conventional evolutionary algorithms, DCO exhibits faster convergence, reduced parameter sensitivity, and more efficient identification of critical factors. These results provide a practical pathway toward real-time PEMFC design optimization and adaptive control, supporting dynamic operational scenarios in both automotive and stationary applications and demonstrating the value of systematic, computationally efficient optimization strategies.

Limitation and Future Scope

The DCO-based PEMFC optimization relies primarily on simulated data, which limits direct real-world validation. Additionally, the current study focuses on optimizing select performance metrics under steady-state conditions, not considering multi-objective optimization or dynamic operational scenarios. Future work can incorporate experimental testing, explore additional parameters such as membrane humidity and catalyst loading, integrate hybrid optimization techniques, and extend DCO applications to dynamic load conditions. These enhancements will improve robustness, computational efficiency, practical applicability, and broader adoption in automotive and stationary fuel cell systems.

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CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

AUTHORSHIP CONTRIBUTION

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Formal analysis: Songjie Wu.
Research: Yang Yang.
Methodology: YangYang.
Resources: Jipeng Mo.
Software: Jipeng Mo.
Drafting - original draft: Songjie Wu.
Writing - proofreading and editing: Songjie Wu.

APPENDIX

Table 8. Symbology

Symbol	Variable Name / Description	Symbol	Variable Name / Description
H_2	Hydrogen	E	Open-circuit voltage per cell
H^+	Hydrogen ion / Proton	v_{act}	Activation over potential
e^-	electron	v_R	Ohmic voltage drop
O_2	Oxygen	v_c	Concentration (diffusion) overpotential
H_2O	water	T_{fc}	Fuel cell operating temperature
V_s	Stack output voltage	P_{H2}	Partial pressure of hydrogen
N_{cells}	Number of cells in series	P_{O2}	Partial pressure of oxygen
P_{H20}	Partial pressure of water	RH_a	Relative humidity at anode
RH_c	Relative humidity at cathode	P_a	Anode inlet pressure
P_c	Cathode inlet pressure	I_{fc}	Fuel cell operational current
C_{O2}	Oxygen concentration/ Carbon dioxide	R_m	Membrane resistance
R_c	Connection resistance	P_m	Membrane resistivity
B	Fuel cell active area	λ	Membrane water content parameter
J_{ed}	Current density effect factor	f	Function factor in resistivity equation
ξ_1, ξ_2, ξ_3, ξ_4	Empirical coefficients in activation overpotential	B	Diffusion overpotential coefficient
I_{max}	Maximum operational current		