RASĀYAN J. Chem.
Vol. 17 | No. 2 |576-587| April - June | 2024
ISSN: 0974-1496 | e-ISSN: 0976-0083 | CODEN: RJCABP
http://www.rasayanjournal.com
http://www.rasayanjournal.co.in

A COMPERATIVE STUDY ON ARTIFICIAL NEURAL NETWORK-BASED MULTI-OBJECTIVE OPTIMIZATION FOR PROTON EXCHANGE MEMBRANE FUEL CELL

Sankhadeep Ghosh[1], Avijit Routh[1], Saikat Mondal[2], Mehabub Rahaman[1] and Avijit Ghosh[3,✉]

[1]Department of Chemical Engineering, Jadavpur University, Kolkata, India
[2]Department of Mechanical Engineering, Islampur Govt. Polytechnic, WB, India
[3]*Department of Chemical Engineering, Heritage Institute of Technology, Kolkata, India
✉Corresponding Author: avijit.ghosh@heritageit.edu

ABSTRACT

Proton exchange membrane fuel cells (PEMFCs) offer significant potential for conversion from chemical energy to electrical energy due to their significant low-temperature range, high power density, mobility, and increasing start-up. PEMFC design and applications have been simplified through the utilization of artificial neural network (ANN) based multi-objective optimization (ANN-MOO). This approach can be easily adjusted to consider multiple factors simultaneously, even when dealing with customized objective functions or new case scenarios. This study thoroughly examines the existing body of literature on the application of Artificial Neural Network-Multi-Objective Optimization in the Proton Exchange Membrane Fuel Cell industry. The original elucidation of ANN-MOO provided a full explanation of its definition, classifications, and structure. The study evaluates objectives, intelligence algorithms, and tradeoff methods in PEMFC, focusing on ANN-MOO's application in components, kinetics, control, performance, and hybrid systems.
The relevant issues, including the techniques, variables, objectives, and outcomes of optimization, were enumerated and discussed. The present review aimed to examine the existing limitations in the field of study and put up suggestions for future research.

Keywords: Multi-Objective Optimization (ANN-MOO), Proton Exchange Membrane Fuel Cells (PEMFCs), Membrane Electrode Assembly (MEA), Computer Intelligence Aided Design (CIAD), Artificial Neural Network (ANN)

RASĀYAN *J. Chem.*, Vol. 17, No.2, 2024

INTRODUCTION

The interest in the development of alternative energy generation devices is growing rapidly to overcome the challenges of global warming and environmental pollution due to the use of fossil fuels. Internal combustion (IC) engine enhances the generation of CO and CO_2.[1] To replace traditional fossil fuels and internal combustion engines, this has raised the demand for clean, renewable energy sources as well as alternative energy-producing technology. Due to its great thermodynamic efficiency and nearly negligible emissions, hydrogen is utilized as the fuel, and oxygen is used as the oxidant. So, fuel cells have drawn the attention of researchers and scientists as a potential replacement for internal combustion engines.[2,3] Proton exchange membrane fuel cells (PEMFC) have received a lot of research interest because they can run in low temperatures and utilization of hydrogen was done very effectively.[4] Without burning it or releasing any air pollutants, PEMFCs are exceptionally efficient electrochemical energy conversion technologies[5,6] that can convert hydrogen's chemical energy into electrical and thermal energy.[7] PEMFCs are adaptable and have a variety of uses, including as vehicle power sources because of their high-power density, quick start-up, low operating temperature, and mobility. The two most essential parts of a typical single PEMFC unit are the bipolar/end plates (BPs) and the membrane electrode assembly (MEA), which is shown in Fig.-1. The proton exchange membrane (PEM) is located in the center of the MEA. This structure consists of microporous layers (MPLs), gas diffusion layers (GDLs), and catalyst layers (CLs) on the anode and cathode sides, respectively. PEMs function as the medium for ion conductance between the anode and cathode in a fuel cell, while also acting as a barrier to prevent the mixing of fuels and oxidants.[8] Catalysts

http://doi.org/10.31788/RJC.2024.1728807

and chemical reactions take place at catalytic sites. The MPL and GDL are deployed ensuring that catalysts are uniformly distributed and enabling the circulation of gases. Along with the components in Fig.-1, additional critical auxiliaries including coolant channels and humidification units are needed.[9,10]

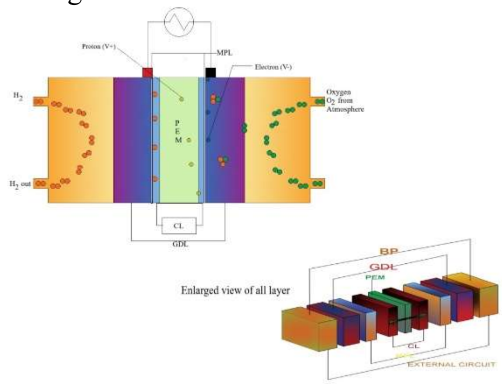

Fig.-1: Cross-section and Enlarged View of PEMFC and Transportation of the Electron, Proton, and Gases

PEM is used to separate the supplied O_2 and H_2. The reaction of Hydrogen oxidation and reaction oxygen reduction is established at the anode and cathode respectively.

$$Anode \rightarrow 2H_2 \rightarrow 4H^+ + \{4e^-\} \quad (1)$$

As a byproduct of the cathode interaction between oxygen and hydrogen ions, water is obtained. The fuel cell releases water. The reduction reaction at the cathode is:

$$Cathode \rightarrow O_2 + \{4e^-\} + \{4H^+\} \rightarrow 2H_2O \quad (2)$$

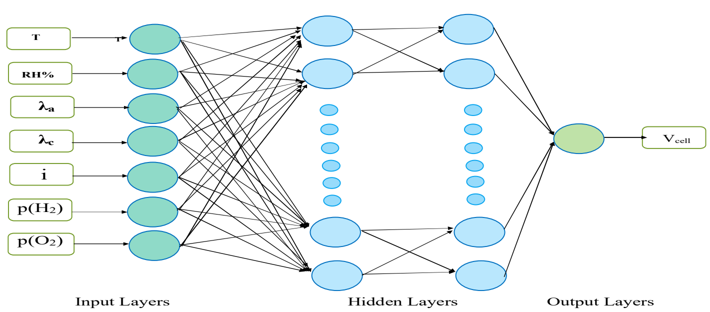

Fig.-2: The Typical PEMFC System and Applications

$$Overall \rightarrow H_2 + \frac{1}{2}O_2 \rightarrow H_2O \quad (3)$$

Operating factors such as stack temperature, hydrogen and oxygen partial pressure, humidity, hydrogen and oxygen mass flow rate, and load change are the key determinants of a PEMFC's output voltage.[11] The polarization curve mostly illustrates a fuel cell's static properties. As the current density rises, the output voltage drops nonlinearly. For the configuration to function at its best, effective and trustworthy operational methods or systems are also required in addition to the PEMFC stack. Cross-section and Enlarged view of PEMFC and transportation of the electron, proton, and gases is displayed in Fig-1. The complicated fuel cell systems were composed of a variety of interconnected subsystems, such as a monitoring system, a controlling system, and another multifunctional system. A fuel cell cannot operate effectively on its own; it requires the collaboration of numerous subsystems. The fuel cell's operating status is monitored by the monitoring system. The reactant system, temperature management systems, and water management systems form the control system, which can set parameters immediately in response to demand.

PEMFC is used in a wide range of applications, including hybrid electric vehicles, portable power sources, home power plants, and automobiles. PEMFCs are required to function effectively in several demanding contexts. Over the past two decades, PEMFC technology has evolved fast. However, several problems are impeding the commercialization of PEMFC. The PEMFC stack's technical issues, including MEA preparation, water and temperature control, flow channel design, etc., must also be handled in addition to the challenges connected with storing and transporting hydrogen. In addition, PEMFC is being designed and implemented using computer intelligence-aided design (CIAD) to reduce costs, increase power density, and improve durability, surpassing existing technologies.[12,13] Precision and effectiveness have increased, and challenging issues that were hard to tackle manually have been resolved. The PEMFC industry is increasingly utilizing AI techniques like deep learning, fuzzy logic, and neural networks, with a significant focus on fuzzy logic in the electric vehicle control[14] system. Heuristic algorithms are the most often used ANN for the multi-objective optimization (MOO) technique.

ANN-MOO FRAMEWORK ALONG WITH METHODS

MOO and Classification

Numerous optimization algorithms have been developed to address optimization issues with multiple competing objectives, primarily based on deterministic or stochastic approaches. To address challenges in optimal design, specific multi-objective stochastic optimizers have been developed. These optimizers can use local or global search techniques. Although this discipline has made great progress, there are still a lot of unresolved problems.

The reality is that both the stochastic and deterministic strategies possess strict boundaries. Under the initial circumstances, the necessary quantity of function evaluations to attain the optimal resolution is typically low, there is a significant risk of becoming ensnared in local minima. In contrast, in the second scenario, the likelihood of reaching the optimal solution is greater, but this advantage is offset by the potential for the computational cost to become prohibitively high. This is true in the context of electromagnetic issues. Modern society is highly reliant on electromagnetic technologies. They are employed in energy conversion and storage, manufacturing processes, magnetic resonance imaging, telecommunications, and other applications. Electromagnetic device design optimization enhances product quality and production effectiveness. Multimodal, non-linear objective functions are produced due to geometric limits and ferromagnetic material behavior, necessitating numerical techniques like Finite Element Method (FEM). Thousands of objectives may need to be examined when several design parameters need to be improved, making it impractical to use a mathematical output throughout the optimization solution. This chapter discusses estimating strategies using artificial neural networks, which can improve optimization problems. It introduces a technique to compete for inverse issues by applying the inverse operation to the neural network approximation model, enabling uniform sampling and load reduction by searching for solutions directly in the space of the goals.[15,16,17,18]

Algorithms

The solutions to multi-objective optimization problems (MOPs), also known as Pareto optimum solutions, are frequently presented. When these solutions are assessed, they provide vectors whose elements indicate Considering alternatives in the objective space. A Decision Model selects vectors x and unique MOPs objective functions k to arrive at acceptable solutions, defining a vector function f(x). $f(x)=[f_1(x), f_2(x), ..., f_k(x)]T$.

The optimization problem can be formalized as follows:

$$\min f(x)$$

s.t $g_j(x) \le 0$ Where, j=1,……….,q

$h_j(x) = 0$ Where, j=q+1,……….,m

The MOP formulation considers two Euclidean spaces, $g_j(x)$ and $h_j(x)$ To determine the acceptable range Ω of the decision attributes.

The n-dimensional space R^n of decision variables refers to vectors x, and y, while the k-dimensional space of objective functions R^k refers to vector $f(x)=f_1,f_2,f_3$ (objective function space).

Understanding the decision space is crucial as it directly relates to a particular point in the objective function space as shown in Fig.-3.

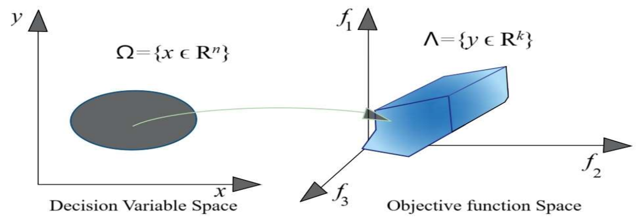

Fig.-3: Mapping the Variable Space into the Objective Spacee

Approximation of Model using Neural Network

Artificial neural networks are a valuable approximation method for optimizing objective values, as they can simulate non-linear interactions between multiple variables, reducing the need for expensive numerical techniques.[17,18] Our method employs a three-layer multi-layer perception (MLP) to comprehend the functional relationship between the optimization problem's objective functions and design parameters, as illustrated in Fig.-4.

$$\underline{W}_2 \cdot \sigma\left(\underline{W}_1.a + \underline{b}_1\right) + \underline{b}_2 = O$$
$$a \in D_{\underline{x}}$$

The network's input and output, 'a' and 'o' respectively, are determined by the design variables, 'y' and 'm' respectively, and the logistic activation function is denoted by σ(.). The output layer in Fig.-4 is characterized by a linear activation function. In the realm of neural networks, we assign the designations b_1 and b_2 to represent biases for the hidden and output layers, respectively. The weights labeled $\mathbf{W_1}$ represent the weights connecting the input and hidden layers, while $\mathbf{W_2}$ represents the weights connecting the hidden and output layers. Constructing such a network entails two independent difficulties: first, determining the ideal quantity of nodes to be included in the discretely hidden layer and calibrating the synaptic weights that connect the layers are important steps. Typically, the latter challenge finds resolution through the application of learning algorithms rooted in error minimization principles, effectively fine-tuning connection weights. Conversely, the former hurdle often necessitates a trial-and-error approach, entailing the training of multiple networks, each of varying sizes, on the same training data.

Recent advancements have ushered in fresh perspectives on neural networks, departing from the conventional error correction methodologies. Many authors have introduced a novel geometric interpretation[19] of neural networks. According to this paradigm, each neuron is a linear separator, where the

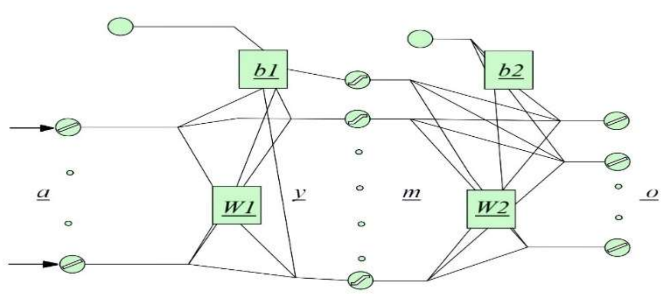

Fig.-4: A Multilayer Perceptron (MLP) Neural Network with a Single Hidden Layer

connection weights come together towards a neuron corresponding to the hyperplane that defines the separation. Work[19] introduces an innovative method for creating Multi-Layer Perceptron (MLP) networks with a hidden layer, capable of accurately classifying any finite real value training dataset. This methodology uses step functions to map the training dataset onto a feature space with a large number of dimensions, as described by.[20] This approach utilizes the linear separability of two training examples within the feature space, allowing for easy selection of a specific output neuron for final separation.

Framework

ANN-MOO solutions offer a quicker, more intelligent, less error-prone, and more efficient decision-making process than traditional modeling approaches. The overall structure for ANN-MOO optimization is shown in Fig.-5. There are four key phases, as demonstrated. The initial data must be gathered in Step 1 from a variety of sources, like experiments, simulations with the model, surveys, etc. The second step is the core of the design and optimization process. Before analysis, it is necessary to preprocess and standardize[20] the raw data during this phase to maintain the impact factor's quantitative scale. After that, the constraints are constructed and fitness functions are specified. Several solutions to the optimization issues are produced by the addition of ANN algorithms, which are presented and used to optimize the parameters. The third stage involves the process of decision-making and suggestion. During this stage, various trade-off techniques are employed to create an optimal solution or to list solutions to balance competing objectives. To get optimized results, move on to step 4.

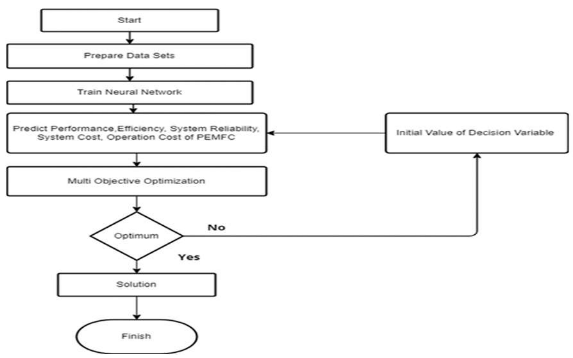

Fig.-5: Multi-Objective Optimization Architecture

Table-1: General ANN-MOO's Multiple Objectives about the PEMFC Field

Types	Goals	Summary	Parameters	Reference
Technical	Material Attribute	The dimensions and efficiency of the elements	The specifications of components and the material traits	[14]
	Effectiveness	Voltage, power, current density, etc. from the system output	Operational Parameters	[15]
	Output Performance	Catalytic performance, chemical reaction performance, hybrid energy system performance, etc.	Components properties, operated fuel conditions,	[16]
	System robustness	The Resiliency of the devices to the energy management strategies	The operation conditions, the current and the voltage, the multi-energy input parameters in a compound system, etc.	[17]
Economical	Cost Function of the system	Component value and hybrid (PEMFC and Batteries) system construction	Environmental variables	[18]
	Consumption of Energy from the system	The expenditure associated with energy consumption.	The expenditure associated with energy consumption	[19]

	Operational expenditure	The cost function is to maintain the regularity of the device.	Analysis of the device's components, expenses, and longevity.	[18,19]
Environmental	Gas Discharge	Emission of carbon dioxide by the hybrid renewable energy system.	The outcome of gas volume	[20]

Table-2: A Summary of Studies that Used Multi-Objective Optimization on Various PEMFC Components

Algorithms Used	Input Features & Parameters	Output Target	Investigated Material	Method	Reference
Neural Network (ANN)	Total Eight Parameters Membrane Thickness Catalyst Layer Thickness Gas Diffusion Layer Thickness Pore Size Distribution Contact Resistance	Activation function over potential	CL	Regression analysis method: Supervised	[21]
Neural Network (ANN)	Material Porosity Membrane Permeability Pore Size Distribution Interfacial Tension	Fluid Interface Pressure Differential	GDL	Regression analysis method: Supervised Learning	[22]
Neural Network (ANN)	Cell temperature Inlet gas temperature Current density	PEMFC stack potential	PEM	Regression analysis method: Supervised Learning	[23]
Neural Network (ANN)	Total Twenty-Six features Catalyst properties Fabrication parameters Operating conditions	Cell Power density and V-I plot	MEA with Nonprecious metal	Regression analysis method: Supervised learning	[24]
Neural Network (ANN)	Flow rate of hydrogen Flow rate of oxygen Operating temperature Voltage	Cell Current density	Wavy serpentine flow channel	Regression analysis method: Supervised learning	[25]
Neural Network (ANN)	Stack current Stack temperature Cathode pressure Anode pressure	PEMFC stack potential	300 cm^2single cell	Regression analysis method: Supervised learning	[26]
Neural Network (ANN)	Stack temperature Air and H_2 Humidification Temperature Air and H_2 flow rate	Cell Current density	5 cm^2 single-cell	Regression analysis method: Supervised Learning	[27]

Neural Network with Taguchi Statistical Toolbox	Stack temp. H_2 and O_2 flow rate Connected Load Current Partial pressure of oxygen and hydrogen	Stack Module Voltage	Single Cell	Regression analysis method: Supervised Learning	[28,29]
ANN (combined with GA)	Relative humidity of cathode and anode Stack Temp.	Cell Current density	Single Cell Three Dimensional PEMFC system	Regression analysis method: Supervised Learning	[30]
ANN, SVR	Input Current, Partial Pressure of H_2 and O_2 Anode and Cathode stoichiometry ratio Anode and cathode relative humidity	Molar concentrations of Gas, H_2O substance, and stack temperature	Three Dimensional PEMFC system	Regression analysis method: Supervised Learning	[31]
DBN, ANN, Bagging neural network	The operational pressure Air flow velocity GDL porosity GDL Permeability	Current density	Three Dimensional PEMFC system	Regression analysis method: Supervised Learning	[32]
ANN	Stack current Stack temperature H_2 and O_2 flow	Stack Module Voltage	500W, 100 cm^2,20 cells	Regression analysis method: Supervised Learning	[33]
PLS, ANN	Input attributes	Module Voltage, Temp.	5 kW-PEMFC stack	Regression analysis method: Supervised Learning	[34]
ANN, SVR	The H_2 and Air inlet pressure Operational temperature Relative humidity of Anode Stack flow current	Stack Module Voltage	1.2 kW fuel cell stack	Regression analysis method: Supervised Learning	[35]
Neural Network (ANN), Support Vector Regression	Current density Stack temperature	Stack Module Voltage	250 W Hybrid bicycle	Regression analysis method: Supervised Learning	[36]
Neural Network (ANN)	H_2 and air flow rate, Stack temperature	PEMFC Stack voltage, Output Power	6 kW PEMFC MATLAB modeling	Regression analysis method: Supervised Learning	[37]
Neural Network (ANN)	Cell Current Stack temperature	Voltage, power, H_2 flow of PEMFC	100W portable Stack	Regression analysis method: Supervised Learning	[38]

Table-3: Optimization Using Different Machine Learning Performance

S. No.	Optimization Method	Speed of Convergence	Difficulty Level	Algorithm Execution Efficiency	Global Optimization Capability	Refs
1	Genetic Algorithm With Neural Network(GA)	Moderate	Maximum	Minimal	Minimal	[39-42]
2	Seagull optimization algorithm(ISOA)	Moderate	Maximum	Minimal	Minimal	[43-45]
3	Particle swam optimization(PSO)	Maximum	Moderate	Maximum	Maximum	[46-48]
4	Artificial Bee Colony Algorithm(ABC)	Maximum	Maximum	Maximum	Maximum	[49-51]
5	Bat Algorithm (BA)	Maximum	Moderate	Moderate	Maximum	[52-53]
6	Sunflower Optimization Algorithm(SOA)	Moderate	Maximum	Moderate	Moderate	[54-55]
7	Harmony search algorithm(HSA)	Moderate	Moderate	Maximum	Maximum	[56-57]
8	The Grey Wolf Optimizer Algorithm(GWO)	Moderate	Moderate	Maximum	Maximum	[58-59]
9	Artificial fish swarm algorithm (AFSA)	Moderate	Moderate	Maximum	Maximum	[60]
10	Shuffled frog leaping algorithm (SFLA)	Maximum	Maximum	Moderate	Moderate	[61]
11	Dragonfly algorithm(DA)	Maximum	Minimal	Moderate	Moderate	[62]
12	Sine Cosine Algorithm(SCA))	Maximum	Minimal	Maximum	Maximum	[63]
13	Krill Herd Algorithm (KHA)	Maximum	Minimal	Moderate	Moderate	[64]

CONCLUSION

Proton Exchange Membrane Fuel Cell (PEMFC) optimization is a challenging process with multiple parameters. Machine learning (ML) techniques provide a more efficient alternative to conventional trial-and-error approaches in the field of Proton Exchange Membrane Fuel Cells (PEMFC). Machine learning utilizes empirical data to develop models that enable the direct correlation of parameters to the intended output. Machine learning (ML) may be trained using numerical simulation models such as Density Functional Theory (DFT) and computing Fluid Dynamics (CFD). This training approach helps to decrease computing expenses and enhance power density. These principles are widespread in a range of materials and components, such as micro electrocatalysts, Catalyst Layers (CL), Gas Diffusion Layers (GDL), Proton Exchange Membranes (PEM), Membrane Electrode Assemblies (MEA), flow fields, single cells, and stacks. Nevertheless, it is essential to acknowledge and tackle current constraints while also pinpointing potential future paths. The third stage involves the process of decision-making and suggestion.[65] Supervised learning currently dominates the landscape of machine learning applications. The acquisition of such data incurs significant costs. To tackle this challenge, several strategies have been proposed. The first approach involves the creation of efficient experimental setups capable of conducting automated experiments. For instance, Cooper *et al.* pioneered the development of robotic chemists endowed with humanoid characteristics, enabling them to autonomously operate within standard laboratories and utilize a variety of experimental instruments, mirroring human capabilities.[66] Machine learning (ML) models, being fundamentally data-driven, remain enigmatic black-box entities. While they demonstrate remarkable predictive prowess when trained on data, researchers grapple with the challenge of comprehending how these models derive output performance from input variables, each laden carrying a distinct physical or chemical meaning. The integration of ML for interpreting the resources emerges as a promising avenue to enhance the trustworthiness of ML models. Simultaneously, these tools empower us to unearth concealed insights buried within intricate systems like Proton Exchange Membrane Fuel Cells (PEMFCs). ML is a powerful tool that researchers can use to enhance their understanding of scientific domains, bridging the gap between empirical predictive capabilities and the interpretive depth of human understanding.

ACKNOWLEDGMENTS

The authors are grateful to acknowledge Jadavpur University, Kolkata, and Heritage Institute of Technology, Kolkata for assisting with the research work.

CONFLICT OF INTERESTS

The authors declare that there is no conflict of interest.

AUTHOR CONTRIBUTIONS

All the authors contributed significantly to this manuscript, participated in reviewing/editing, and approved the final draft for publication. The research profile of the authors can be verified from their ORCID IDs, given below:

Sankhadeep Ghosh http://orcid.org/0009-0008-9498-0252
Avijit Routh http://orcid.org/0009-0005-1102-2058
Saikat Mondal http://orcid.org/009-0003-0072-9926
Mehabub Rahaman http://orcid.org/0000-0001-5581-9142
Avijit Ghosh http://orcid.org/0000-0001-8293-8796

Terminology used

μ = viscosity (Pas^{-1})
ρ = density (kgm^{-3})
P = pressure (atm)
η = overpotential (V) or efficiency
$\vec{u}$ = velocity (ms^{-1})
σ = conductivity (Sm^{-1})
K = permeability (m^2)
γ = concentration exponent

R = universal gas constant ($8.314 Jmol^{-1}K^{-1}$)
c_p = constant − pressure heat capacity ($Jkg^{-1}k^{-1}$)
α = transfer coefficient
k = thermal conductivity ($Wm^{-1}k^{-1}$)
ϕ = phase potential
ζ = stoichiometric ratio
T = temperature (C)
R_{ohm} = ohmic resistance (Ω)
F = Faraday's constant ($96485 Cmol^{-1}$)

REFERENCES

1. M. Rahimnejad, A. Adhami, S. Darvari, A. Zirepour and Oh Sang-Eun, *Alexandria Engineering Journal*, **54(3)**,745(2015), http://doi.org/10.1016/j.aej.2015.03.031
2. A. Parkash, *Journal of Applied and Emerging Sciences*, **6(2)**, 322(2017)
3. X. D. Xue, K. W. E. Cheng, D. Sutanto, *Electrochim Acta* **52(3)**,1135(2006), http://doi.org/10.1016/j.electacta.2006.07.011
4. Qiangu Yan, H. Toghiani, Health Causey, *Journal of Power Sources*, **161(1)**, 492(2006), http://doi.org/10.1016/j.jpowsour.2006.03.077
5. D. Candusso, F. Harel, A. De Bernardinis, X. François, M. C. Péra, D Hissel, *International Journal of Hydrogen Energy*, **31(8)**, 1019(2006), http://doi.org/10.1016/j.ijhydene.2005.11.010
6. P. Mock, S. A. Schmid, *Journal of Power Sources*, **190(1)**, 133(2009), http://doi.org/10.1016/j.jpowsour.2008.10.123

7. P. Kumar, S. K. Kannaiah, S. R. Choudhury, N. Rajasekar, *Electric Power Component and Systems,* **45(10)**, 1152(2017), http://doi.org/10.1080/15325008.2017.1318980
8. R. Ma, T. Yang, E. Breaz, Z. Li, P. Briois, F. Gao, *Applied Energy*, **231(1)**, 102(2018), http://doi.org/10.1016/j.apenergy.2018.09.111
9. L. Xing, W. Shi, H. Su, Q. Xu, P.K. Das, B. Mao, K. Scott, *Energy*, **177(1)**, 445(2019), http://doi.org/10.1016/j.energy.2019.04.084
10. N. Kizilova, M. Sauermoser, S. Kjelstrup, B.G. Pollet, *Entropy*, **22(1)**, 176(2020), http://doi.org/10.3390/e22020176
11. Y. Chen, B. Peng, *Applied Soft Computing,* **43(1)**, 357(2016), http://doi.org/10.1016/j.asoc.2016.02.045
12. S. Mirjalili, P. Jangir, S. Saremi, *Applied Intelligence,* **46(2)**, 79(2016), http://doi.org/10.1007/s10489-016-0825-8
13. M. Zhou and Tingyue Gu*, Journal of Microbial & Biochemical Technology,* **Special issue***,* 1-4 (2013), http://doi.org/10.1080/09593330.2013.813951
14. J. Liu, Y. Feng Liu, C. Feng, A.Wang, T. Tong Jia, L. Gongand and X. Likun, *Energy Science & Engineering,* **5**, 217(2017).
15. A. Junyeong , H. Jeon , J. Lee , I. S. Chang , *Environmental Science & Technolology*, **45(12)**, 5441 (2011), http://doi.org/10.1021/es2000326
16. M. Pandima Dev, *International Journal of Pharma and Bio Sciences*, **7(4)**, 38(2016)
17. M. Ramya, E. Senthilkumar, G. Sivagaami Sundari, K. Thileep Kumar, R. A. Kalaivani1, S. Raghu, and A.M.Shanmugaraj, *Rasayan Journal of Chemistry*, **12(1)**, 91(2019), http://doi.org/10.31788/RJC.2019.1215071
18. J. Singh, A. Jangra, Jai Kumar, Keerti Rani, and Ramesh Kumar*, Rasayan Journal of Chemistry*, **13(1),** 105(2020), http://doi.org/10.31788/RJC.2020.1315382
19. S. Mulijani, G. Syahbirin1, and A.Wulanawati, *Rasayan Journal of Chemistry*, **11(1)**, 151(2018), http://doi.org/10.7324/RJC.2018.111193
20. G Dorffner, H Bischof, K Hornik, *International Conference Vienna,* Austria, August 21-25, 2001 *Proceedings*, **12(9)**, 2013(2001)
21. N. K. H. Dalasm, S. Ahadian, K. Fushinobu, K. Okazaki, Y. Kawazoe, *Journal of Power Sources*, **196(8)**, 3750(2011), http://doi.org/10.1016/j.jpowsour.2010.12.061
22. E.C. Kumbur, K.V. Sharp, M.M. Mench, *Journal of Power Sources*, **176(1)**, 191(2008), http://doi.org/10.1016/j.jpowsour.2007.10.059
23. M. Amirinejad, N Tavajohi-Hasankiadeh, S.S. Madaeni, M.A. Navarra, E. Rafiee, B. Scrosati, *International Journal of Energy Resources*, **37(4)**, 347(2013), http://doi.org/10.1002/er.1929
24. W. Huo, W Li, Z Zhang, C Sun, F Zhou, G Gong, *Energy Conservence Management*, **122(4)**, 243(2021).
25. M. Seyhan, Y.E. Akansu, M. Murat, Y Korkmaz, S.O. Akansu, *International Journal of Hydrogen Energy*, **42(40)**, 25619(2017), http://doi.org/10.1016/j.ijhydene.2017.04.001
26. W Lee, *International Journal of Hydrogen Energy*, **29(9)**, 961(2004), http://doi.org/10.1016/j.ijhydene.2003.01.002
27. Y.S. Bhagavatula, M.T. Bhagavatula, K.S. Dhathathreyan, *International Journal of Energy Research*, **36(13)**, 1215(2012), http://doi.org/10.1002/er.1870
28. K-Y. Chang, *International Journal of Hydrogen Energy*, **36(21)**, 13683(2011), http://doi.org/10.1016/j.ijhydene.2011.07.094
29. F.S. Nanadegani, E.N. Lay, A. Iranzo, J.A. Salva, B Sunden, *Electrochimica Acta,* **389(1)***,* 138793(2021), http://doi.org/10.1016/j.electacta.2021.138793
30. P. Tian, X. Liu, K Luo, H. Li, Y Wang, *Applied Energy*, **288(1)**, 116632(2021), http://doi.org/10.1016/j.apenergy.2021.116632
31. B. Wang, G Zhang, H. Wang, J Xuan, K Jiao, *Energy and AI*, **1(1)**, 100004(2020), http://doi.org/10.1016/j.egyai.2020.100004
32. H.W. Li, B.S. Xu, C.H. Du, Y Yang, *Journal of Power Sources*, **461(1)**, 228154(2020), http://doi.org/10.1016/j.jpowsour.2020.228154

33. S. Jemeı, D Hissel, M.C. P´era, J.M. Kauffmann, *Journal of Power Sources*, **124(2)**, 479(2003), http://doi.org/10.1016/S0378-7753(03)00799-7
34. H.K. Shin, *Korean Chemical Engineering Research*, **53(2)**, 236(2015), http://doi.org/10.9713/kcer.2015.53.2.236
35. I-S Han, C-B Chung, *International Journal of Hydrogen Energy*, **41(24)**, 10202(2016), http://doi.org/10.1016/j.ijhydene.2016.04.247
36. A. Kheirandish, N. Shafiabady, M. Dahari, M.S. Kazemi, D. Isa, *International Journal of Hydrogen Energy*, **41(26)**, 11351(2016), http://doi.org/10.1016/j.ijhydene.2016.04.043
37. Y. Bicer, I. Dincer, M Aydin, *Energy*, **116(1)**, 1205(2016), http://doi.org/10.1016/j.energy.2016.10.050
38. N.S. Sisworahardjo, T Yalcinoz, M.Y. El-Sharkh, M.S. Alam, *International Journal of Hydrogen Energy*, **35(17)**, 9104(2010), http://doi.org/10.1016/j.ijhydene.2010.05.124
39. D.E. Goldberg, J.H. Holland, *Machine Learning* , **3(1)**, 95(1988).
40. A. Mellit, S.A. Kalogirou, *Progress in Energy and Combustion Science*, **34(1)**, 574(2008), http://doi.org/10.1016/j.pecs.2008.01.001
41. A. Sorsa, K. Leiviska, *IEEE International Conference on Intelligent Systems. Varna, Bulgaria*, **4(2)**, 2008, http://doi.org/10.1109/IS.2008.4670495
42. Z. Michalewicz, S. J. Hartley, *Mathematical Intell*, **18(3)**, 71(1996).
43. J. Timmis, M. Neal, J Hunt, *Biosystems*, **55(1)**, 143(2000), http://doi.org/10.1016/S0303-2647(99)00092-1
44. K. Mori, M. Tsukiyama, T. Fukuda, *Trans IEE Jpn*, **113C**, 872(1993), http://doi.org/10.1007/s11771-006-00175
45. A. Askarzadeh, A Rezazadeh, *International Journal of Electrochemical Science,* **6(8),** 3105(2011), http://doi.org/10.1016/S1452-3981(23)18239-3
46. J. Kennedy, *Encyclopedia of Machine Learning, US:Springer*, 760(2011), http://doi.org/10.1007/978-0-387-30164-8_630
47. R. Poli, J. Kennedy, T. Blackwell, *Swarm Intellegence*, **1(1)**, 33(2007), http://doi.org/10.1007/s11721-007-0002-0
48. M. Ye, X. Wang, Y. Xu, *International Journal of Hydrog Energy*, **34(2)**, 981(2009), http://doi.org/10.3390/en15217893
49. A. Askarzadeh, *Communications in Nonlinear Science and Numerical Simulation*, **19(4)**, 1213(2014), http://doi.org/10.1016/j.cnsns.2013.08.027
50. A. Askarzadeh, A. Rezazadeh, *Solar Energy*, **90(1)**, 123(2013), http://doi.org/10.1016/j.solener.2013.01.010
51. A. Askarzadeh, A. Rezazadeh, *International Journal of Energy Research,* **37(10)**, 1196(2013), http://doi.org/10.1002/er.2915
52. J.P. Silva, K.A. Sakallah, *IEEE Computer Society*, **2(1)**, 220(1997).
53. P. Civicioglu, *Applied Mathematics and Computation,* **219(1)**, 8121(2013).
54. C. Dai, Y. Zhu, W. Chen, *Lecture Notes in Artificial Intelligence, Springer-Verlag*, 167(2007), http://doi.org/10.1016/j.neucom.2010.08.025
55. C. Dai, W. Chen, Y. Song, *Journal of Systematic Engineering and Electronics*, **21(2)**, 300(2010), http://doi.org/10.3969/j.issn.1004-4132.2010.02.021
56. https://www.icsi.berkeley.edu/icsi/node/2684
57. R. Storn, K. Price, *Journal of Global Optimization,* **11(4)**, 341(1997), http://doi.org/10.1023/A:1008202821328
58. R. Storn, K. Price, *Journal of Global Optimization*, **23(1)**, 1995.
59. R. Storn, K. Price, *Journal of Global Optimization*, **11(4)**, 341(1997), http://doi.org/10.1023/A:1008202821328
60. C. Jixiang Cheng, Z. Gexiang, *International Journal of Electrical Power and Energy Systems*, **62(1)**, 189(2014), http://doi.org/10.1016/j.ijepes.2014.04.043
61. G. Păun, *Journal of Computer and System Sciences,* **61(1)**, 108(2000), http://doi.org/10.1006/jcss.1999.1693

62. G. Păun, *Springer Berlin, Heidelberg Book Series*, 2002, http://doi.org/10.1007/978-3-642-56196-2
63. Q. Niu, L. Zhang, K. Li, *Energy Conversion and Management*, **86(1)**, 1173(2014), http://doi.org/10.1016/j.enconman.2014.06.026
64. R.V. Rao, V.J. Savsani, D.P. Vakharia, *Information Sciences*, **183(1)**, 1(2012), http://doi.org/10.1016/j.ins.2011.08.006
65. S. Mulijani, G. Syahbirin1, and A.Wulanawati, *Rasayan Journal of Chemistry*, **11(1)**, 151(2018), http://doi.org/10.31788/RJC.2020.1315556
66. K. Jiao, X. Li, *Progress in Energy and Combustion Science*, **37(3)**, 221(2011), http://doi.org/10.1016/j.pecs.2010.06.002

[RJC-8807/2023]