Journal of Renewable Energies ICREPS'24 Naama (2024) 151 – 164

DOI: https://doi.org/10.54966/jreen.v1i3.1299

Journal of Renewable Energies

Revue des Energies Renouvelables

journal home page: https://revue.cder.dz/index.php/rer

Conference paper

Proton Exchange Membrane Fuel Cells: An Effective Neural Fuzzy System for Optimal Power Tracking

Assala Bouguerra [a,*], Abd Essalam Badoud [a], Saad Mekheilef [b]

[a] *Department of Electrical Engineering, Automatic Laboratory of Setif, University of Setif 1, Setif, Algeria*

[b] *School of Science, Computing and Engineering Technologies, Swinburne, University of Technology, Hawthorn, VIC 3122, Australia*

ARTICLE INFO

Article history:

Received September 29, 2024

Accepted October 23, 2024

Keywords:

Proton Exchange Membrane (PEM) Fuel Cell,
Neuro-Fuzzy,
Pressure variation,
Temperature variation,
Maximum Power Point Tracking.

ABSTRACT

The revolutionary future of proton-exchanging membrane fuel cells (PEMFC) has recently garnered a great deal of excitement, as has their green energy source. Maximizing the production of electricity from PEMFC is crucial to maintaining effectiveness. This research article thoroughly analyzes a research study using a strategy known as MPPT, or maximum power point tracking that uses the neuro-fuzzy method for PEMFC operating under diverse temperatures, pressures, and joining constraints. The neuro-fuzzy controller cleverly regulates the point of maximal operation of a hydrogen fuel cell system, allowing exact adherence to the highest possible power scale. According to simulation results, the neuro-fuzzy MPPT technique improves PEMFC validity across a wide range of operating scenarios.

1. INTRODUCTION

Researchers have extensively studied the sources of renewable energies in the past few decades, primarily because of the depletion of fossil fuel reserves and their negative ecological effects. These energy sources are additionally recognized for their environmentally sustainable characteristics *(Khelifi et al. 2021)*. While F. T. Bacon's oxygen-hydrogen fuel cell concept from 1932 was the first device to be successfully utilized in industrial uses, NASA has been working on the development of alkaline fuel cells for use in astronaut program instruments since the 1960s. Following that point, fuel cells have found their way into many useful contexts. It is possible to categorize FCs in terms of their electrolytes, electrodes, fuel, and the temperatures at which they operate. There are now only six different FC types. The following are a variety of fuel cell types now in use, a few of which are listed below: Some examples of energy sources made from fuel cells include Methanol (DMFC), Solid Oxide (SOFC), Phosphoric

[*] *Corresponding author, E-mail address: assala.bouguerra@univ-setif.dz*

ISSN: 1112-2242 / EISSN: 2716-8247

Acid (PAFC), Molten Carbonate (MCFC), Alkaline (AFC), and the Proton Exchange Fuel Cell (PEMFC) *(Aboshosha et al. 2023).*

Since its debut, the PEMFC has attracted a lot of attention *(He et al. 2023)*. The PEMFCs that utilize hydrogen as their main source of fuel are of significant importance for current energy infrastructures that prioritize sustainability and the complete absence of carbon dioxide releases. PEM fuel cells are a clean and efficient way to produce electricity, characterized by their eco-friendliness, lightness, and remarkable power output *(Li et al. 2023; Badoud et al. 2021)*.

The voltage produced by a PEMFC varies as a function of several variables; these involve the temperature of the cell, fuel hydrogen and oxygen pressure, air humidity, and the amount of water in the membrane. Fuel cells have nonlinear voltage-current characteristics (V-I), and they have a single performing position where the power output and voltage are both maximized under constant conditions *Karthikeyan et al. 2021; Badoud et al. 2022)*.

The current piece focuses on polymer membrane batteries, specifically PEMFCs. These devices have a straightforward structure, which makes them suitable for many different purposes, including uses in renewable resources and battery-powered cars. This study talks about how a neuro-fuzzy MPPT controlling method with PEMFC can be used in real life, with standard and changing temperatures, pressures, and combination settings. The findings of the study demonstrate the efficacy of the approach operator in enhancing the efficacy of the fuel cell in various environments of operation.

2. SYSTEM DESCRIPTION

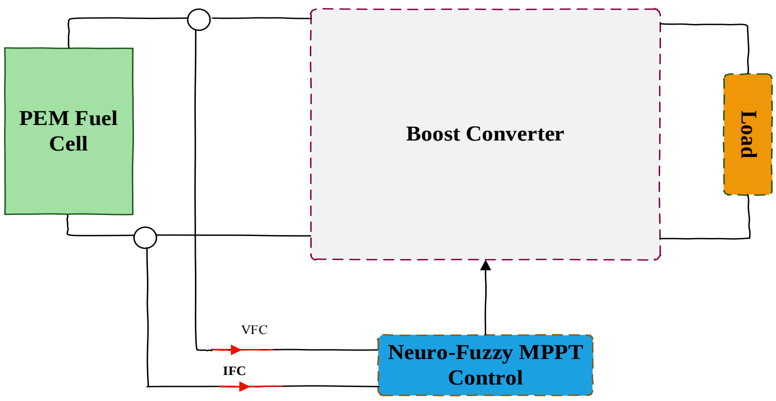


Fig. 1.Configuration of the system

The system architecture shown in Fig. 1 includes a PEMFC, an embedded DC-to-DC booster that changes the voltage of a load within the power system, and a neuro-fuzzy controller that lets the PEMFC system's peak performance be adjusted in a variety of ways. Current and voltage are measured and then utilized in control. Subsequently, the controller generates a signal that the Pulse Width Modulation (PWM) generator employs to activate the converter switching.

2.1 A Schematic of a Fuel Cell Based on a Proton Exchange Membrane

One such kind of fuel cell that's popular is the hydrogen PEMFC with electrodes, which uses the chemical energy present in oxygen and hydrogen to generate electricity. A proton-exchanging membrane, a cathode, and an anode make up its three main parts. The anode receives the gas hydrogen, whereas the cathode receives oxygen (going from the air). At the electrodes, chemical processes take place, producing electricity, liquid water, and heat, as can be seen in Fig. 2.

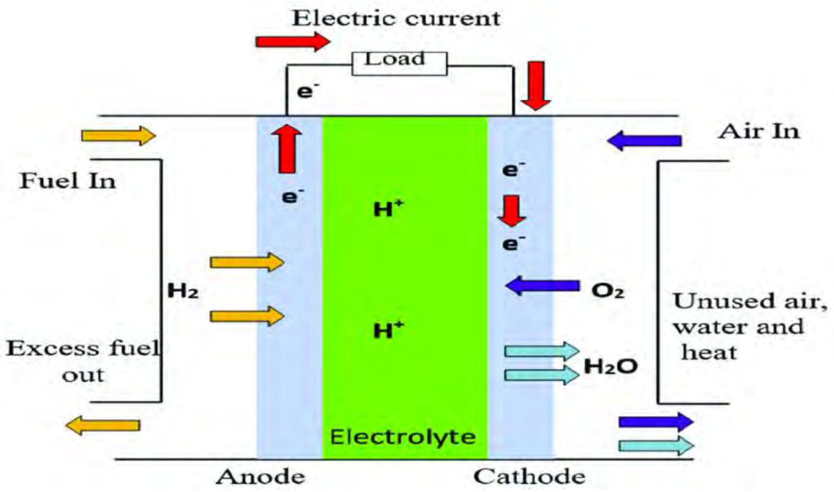


Fig 2. A simplified model of a PEM Fuel Cell

Several factors affect the voltage of PEMFC, including the pressure of hydrogen (P_{H2}) and oxygen (P_{O2}), the temperature of the fuel cell (T), and the Membrane Water Content (MWC) expressed in λ. Additionally, the voltage level of one fuel cell exhibits non-linear features, namely a wilting effect, due to activation, concentration, and Ohmic losses lowering the value of voltage. The losses mentioned in *Gugulothu et al. (2022)* can serve as a basis for the fuel's symbolic representation in voltage distribution mathematics.

In the electrochemical anode:

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

In the electrochemical cathode:

$$\frac{1}{2}O_2(g) + 2H^+ + 2e^- = H_2O \tag{2}$$

Reaction overall:

$$2H_2 + O_2 = 2H_2O + Electricity + Heat \tag{3}$$

$$V_{cell} = E_{Nernst} - V_{act} - V_{ohmic} - V_{con} \tag{4}$$

The variables used are:

V_{cell}, V_{act}, V_{con}, V_{ohmic}.

This four variables stand, respectively for, the output voltage of a fuel cell, the activation drop as a result of chemical reactions, the concentration loss as a result of excessive water flooding in the fuel cell catalyst, and the Ohmic loss as a result of internal fuel cell resistance. Reversible open-circuit voltage, or V_{Nernst} , is a measure of the single-cell thermal-electric current. The simplified expression for the E_{Nernst} equation is represented as:

$$E_{Nernst}=1.229-8.5\times10^{-4}(T-298.15)+4.308\times10^{-5}(\ln(P_{h_2})+0.5\ln(P_{O_2}) \quad (5)$$

Egiziano et al. (2009) conducted a study and provided the voltage drop associated with activation, denoted as V_{act} :

$$V_{act}=\left[\xi_1+\xi_2 T+\xi_3 T\ln\left(Co_2\right)+\xi_4 T\ln\left(I_{FC}\right)\right] \quad (6)$$

Where $\xi_i\,(i=1-4)$ is the characteristic coefficient of Fuel Cell (FC), $CO2\ \ atm$ is the concentration of oxygen in mol/cm3, and IFC is FC current. V_{ohmic} Refers to the Ohmic over-voltage drop, which is determined in the following manner:

$$V_{ohmic}=I_{FC}\left(R_M+R_C\right) \quad (7)$$

An electrolyte membrane and conductive materials reduce FC V_{ohmic} . Lead contact resistance R_C is believed to be constant since FC operating temperature does not affect it. R_M is the resistance of the PEM.

The equation for calculating the voltage loss, V_{con} resulting from excessive water flooding in the fuel cell catalyst is as follows:

$$V_{con}=-B\ln\left(1-\frac{j}{j_{\max}}\right) \quad (8)$$

In the given context, the variable $J_{\max}$ represents the Maximum current density. B represents an Empirical constant that depends on the type of battery and its operation and j is the maximum current.

$$V_{FC}=N_{FC}V_{cell} \quad (9)$$

$$P_{FC}=V_{FC}I_{FC} \quad (10)$$

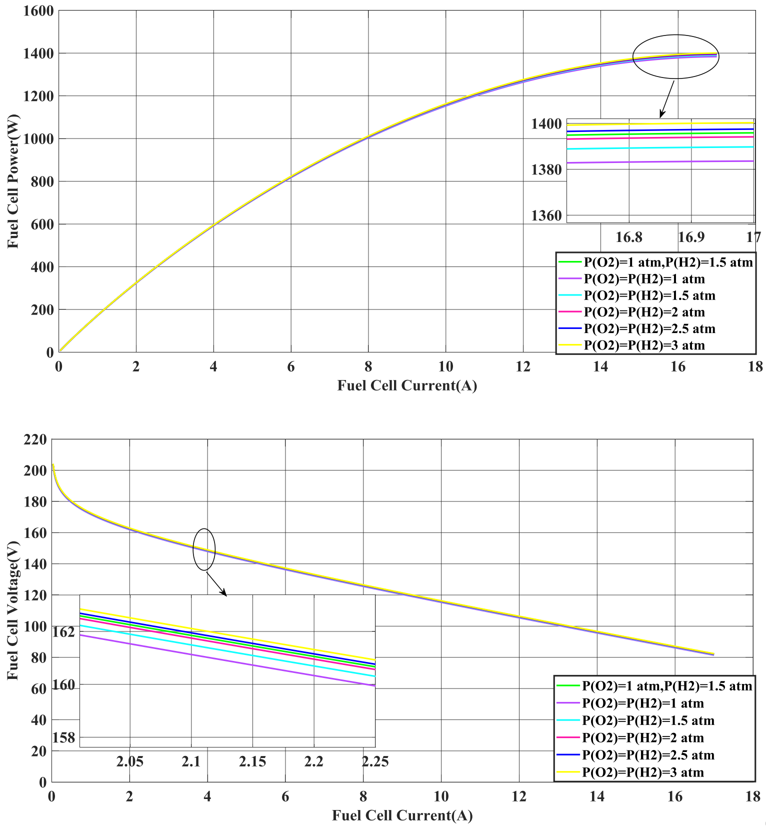
The total number of fuel cells, denoted as $N_{FC}=120$, is the sum of the output voltage (V_{FC}), current (I_{FC}), and power of the fuel cell (P_{FC}).

Fig. 3 (a) and (b) elucidate the power-current and voltage-current characteristics at a temperature of 345 Kalven while considering various levels of oxygen pressure (PO2) and hydrogen pressure (PH2). As seen in Fig. 3, the performance of PEM fuel cells is very susceptible to variations in pressure. Reduced pressure leads to decreased reaction time and output power.

Fig. 4 (a) and (b) elucidate the (P-I) and (V-I) characteristics for (PH2) = 1.5 and (PO2) =1, while considering various temperatures. As seen in Fig. 4, temperature variations have an impact on the reaction kinetics and material conductivity in PEM fuel cells. Higher temperatures may lead to material degradation, whereas lower temperatures can slow down response rates.

Table 1. The PEMFC cell's defining characteristics

Physical Parameters	Values	Description
λ	27.7	Water content in the membrane
B	$0.0165V$	An Empirical constant that depends on the type of battery and its operation
R_C	$15e^{-4}\Omega$	Equivalent contact resistance to conduction of electrons
$J_{\max}$	$2A/cm^2$	Maximum current density
ξ_1	-0.944	Coefficients of parameters for every cell model
ξ_2	0.00354	Coefficients of parameters for every cell model
ξ_3	$7.8e^{-8}$	Coefficients of parameters for every cell model
ξ_4	$-1.96e^{-4}$	Coefficients of parameters for every cell model
n	$120cells$	Number of cells
P_{O2}	$1atm$	Pressure of oxygen
P_{H2}	$1.5atm$	Pressure of hydrogen
A	$70cm^2$	An Active area of the Fuel Cell
T	$345(Kalven)$	Absolute Fuel Cell operating temperature



(a)

(b)

Fig 3. (a) The power-voltage curve, and (b) the current-voltage curve, at constant temperature and different pressures

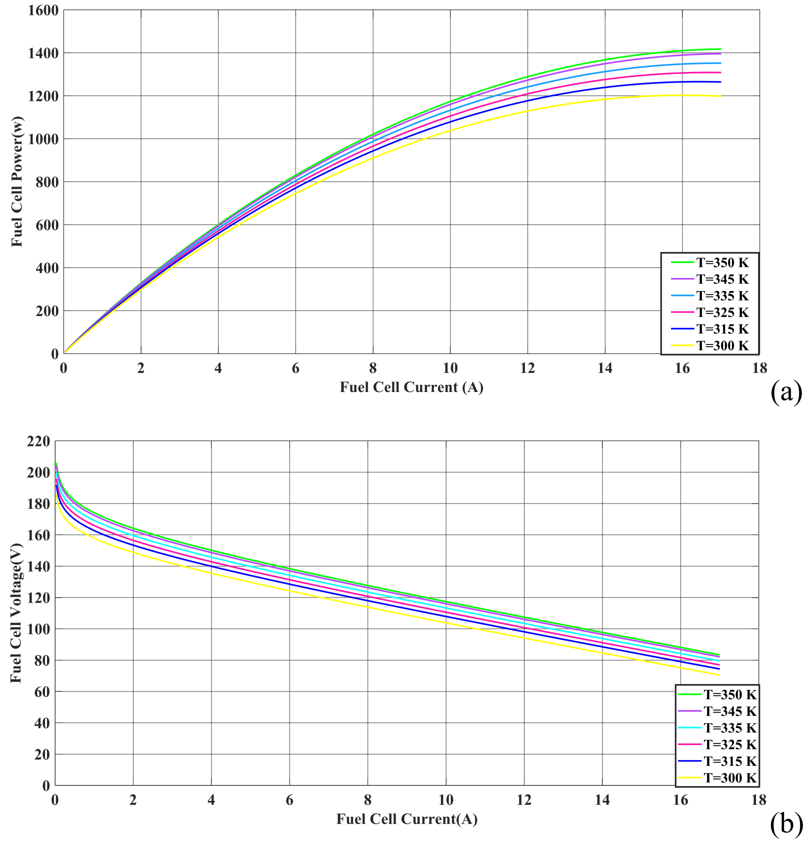


Fig 4. (a) The power-voltage curve, and (b) the current-voltage curve for various temperature and a steady pressure

2.2 Boost Converter DC to DC

PEMFC uses the boosting converted as an intermediate between the PEMFC and the load to generate power. The converter increases the voltage and electrical current of the PEMFC. Adjusting the converter's duty cycle effectively tracks the MPPT of PEMFC. Several essential components comprise a comprehensive DC-to-DC boost converter, including a capacitor denoted as C, a conductor represented by L, a diode labeled as D, a load resistor denoted as R, and a switch transistor represented by S. To provide a consistent output, it is crucial to acquire the correct value, as elevated levels of current rippling and voltage rippling may result from insufficient capacitance and inductance *(Kanouni et al. 2021a)*.

2.3 The Neuro-Fuzzy MPPT Control: Architecture and Explanation

A neuron framework and an algorithm that uses fuzzy logic are the two components that make up the complete neuro-fuzzy combo. While the fuzzy controller contributes to the process of identification, the major purpose of the neural network model is to seek the precise position of the MPP within that area. This solution incorporates the utilization of the MPPT fuzzy logic controller, but with a reduction in the rate at which the duty cycle is adjusted. This adjustment is necessary in order to achieve a higher level of accuracy and precision. Conversely, the purpose of an artificially intelligent neural network is for it to guide its processor in the direction of the precise location where its highest power point is *Kanouni et al. 2021b)*.

The architectural structure of the fuzzy perceptron closely resembles that of the conventional multilayer perceptron. However, the key distinction lies in representing pounds, which characterize sets of fuzzy numbers. Consequently, modifications are introduced to the activations, outputs, and propagation functions. The primary objective of this system is to ensure its interpretability through linguistic rules and its ability to utilize pre-existing databases of rules. In this subsection, we talk about MPPT systems that use a fuzzy neural network to operate. An organizational diagram of the core operations of a neuro-fuzzy system is shown in Fig. 5 using a combination of fuzzy logic and artificial neural networks.

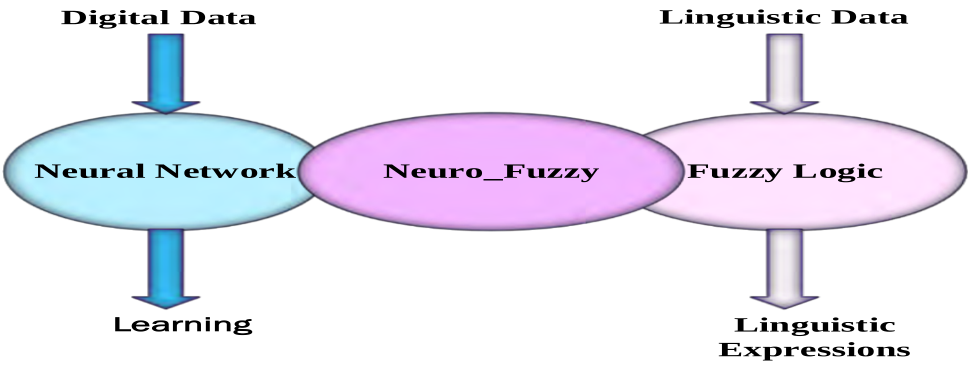


Fig 5. Structure of Neuro-Fuzzy combination

3. SIMULATION AND RESULTS

3.1 Simulation Procedure

A simulated configuration is devised to test the efficacy of the system. Integration additionally involves communication between a hydrogen fuel cell, a boost converter, and a neuro-fuzzy controller. The system is subjected to testing via various pressure and temperature settings, employing the MATLAB-Simulink tool, according to what is seen in Fig. 6.

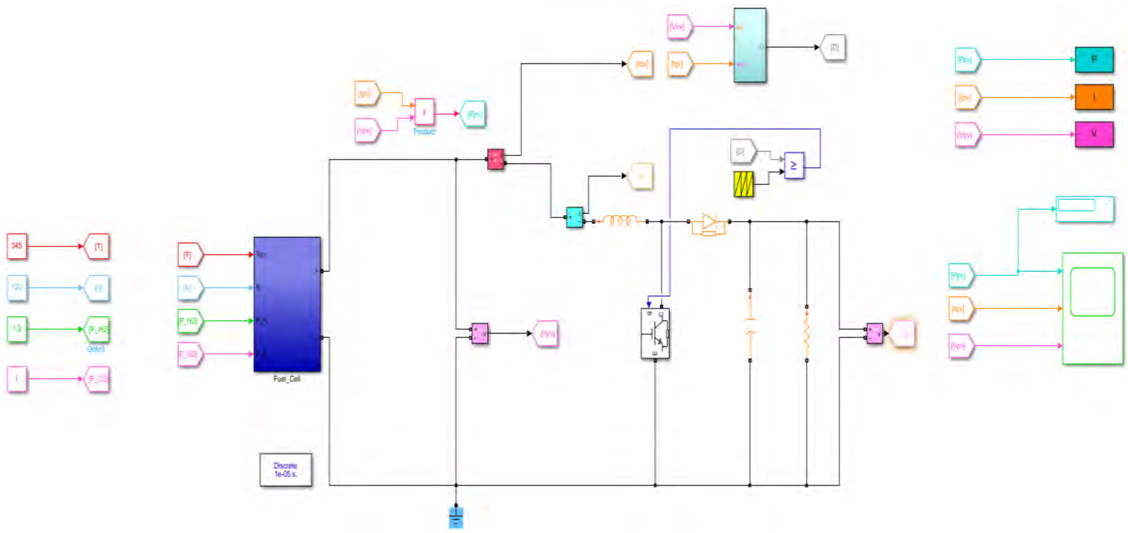


Fig 6. The MATLAB-Simulink model of the system

The model in Fig. 7 represents a two-block, integrator structure. Initial block calculations for $x = \frac{dp}{dv}$ and $y = dx$ are based on the PEMFC's current and voltage. The neuro-fuzzy controller's internal framework constitutes an additional building block. The integrator calculates the duty cycle amount D by calculating the ratio of the duty cycle variance, dD using variables x and y.

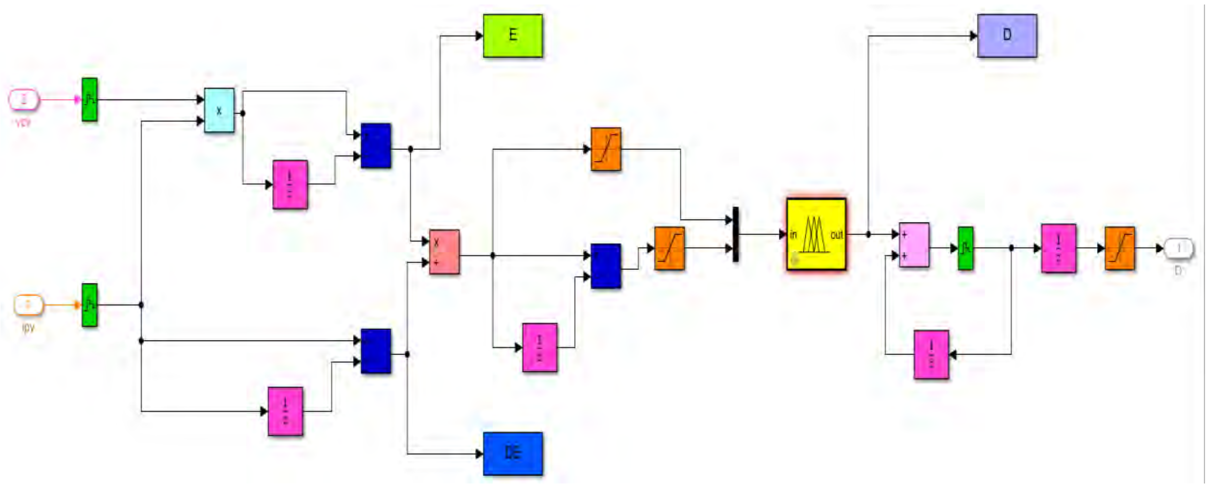


Fig 7. Neuro- Fuzzy model in MATLAB-Simulink

3.2 Results and Analysis

3.2.1 Standard Conditions

In the present investigation, the operating temperature of PEMFC (T = 345 K), the oxygen partial pressure (PO2 = 1 atm), and the hydrogen gas pressure (PH2 = 1.5 atm) were established and maintained at constant levels. The neuro-fuzzy approach exhibits superior results in terms of steady-state outcomes.

According to the set parameters, Fig. 8 shows how the neuro-fuzzy technique can be used for MPPT, focusing on finding power, current, and voltage in normal operation situations. The boost converter carefully controls the duty cycle in order to optimize power transmission.

3.2.2 Change Temperature

In order to assess the effectiveness of the neuro-fuzzy approach, an analysis of a specific situation was conducted. This analysis involved determining oxygen's partial pressure (1 atm) and hydrogen gas's (1.5 atm) under varied temperature conditions, as seen in Fig. 9.

Fluctuations in temperature influence the conductive properties of PEMFC and the rate of change of electrochemical processes. Whereas lower temperatures lead to diminished reaction dynamics, while rising temperatures expedite the speed of chemical reactions, they may additionally give rise to stress due to heat. The control technique is designed to continually modify its parameters in response to variations in temperature, thereby optimizing the power-generated efficiency. Figure 10 demonstrates the usage of the neuro-fuzzy approach for a particular use case that focuses on the tracking of power, current, and voltage under fluctuating temperatures during functioning in line with predetermined criteria. The Neuro-Fuzzy MPPT algorithm enhances power extraction efficiency by dynamically adapting the duty cycle to compensate for performance loss caused by fluctuating temperature conditions.

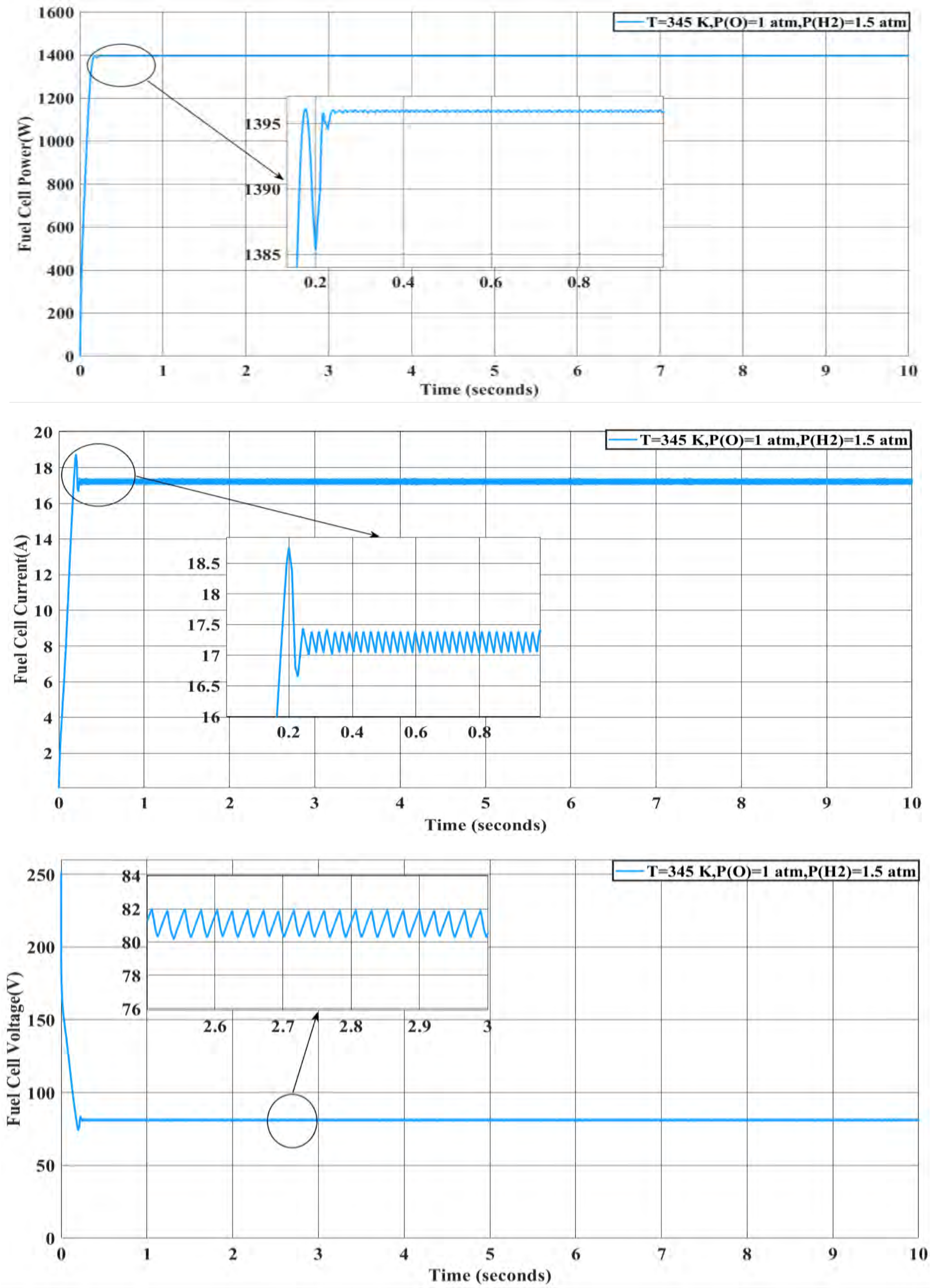


Fig 8. Neuro-Fuzzy MPPT recording power, current and voltage under a typical operational environment

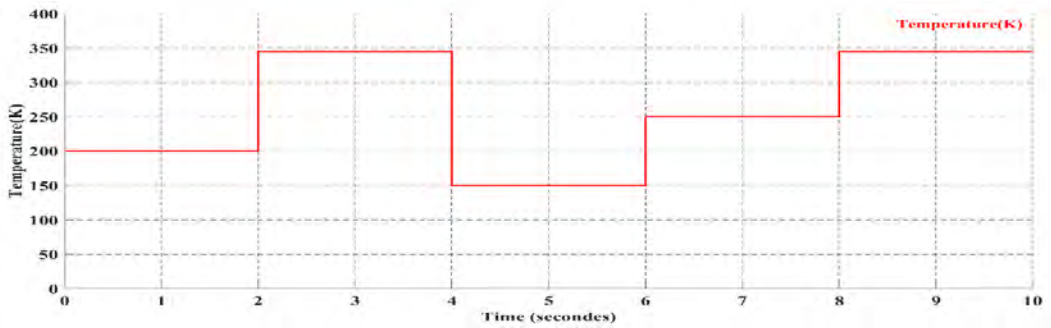


Fig 9. Varying levels of temperatures

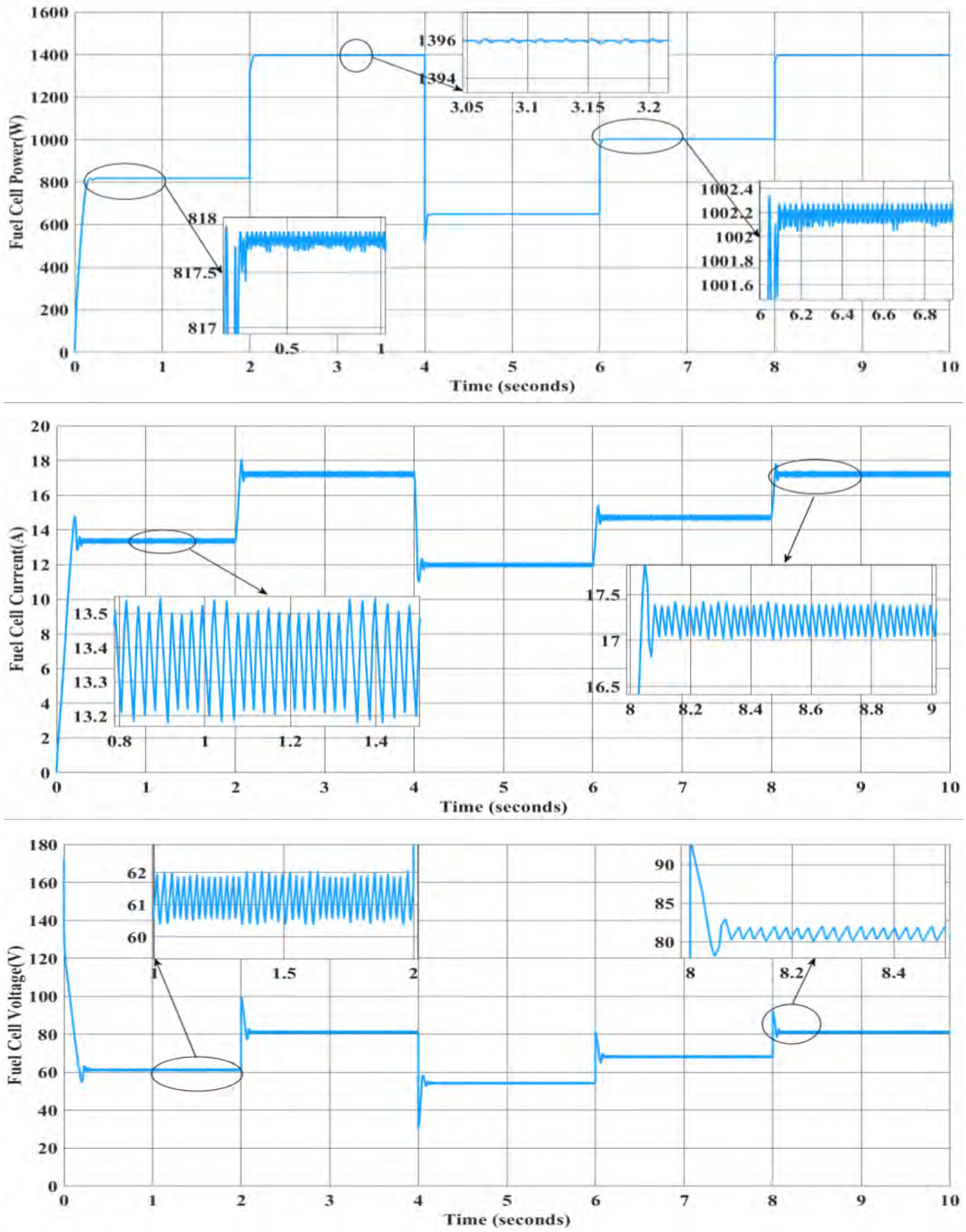


Fig 10. Neuro-Fuzzy MPPT recording power, current and voltage under varying levels of temperatures

3.2.3 Change Pressure

A comprehensive study was undertaken on a particular scenario. The present study encompassed the assessment of temperature (T = 345 K) within various scenarios of oxygen and hydrogen gas pressures, as demonstrated in Figure 11.

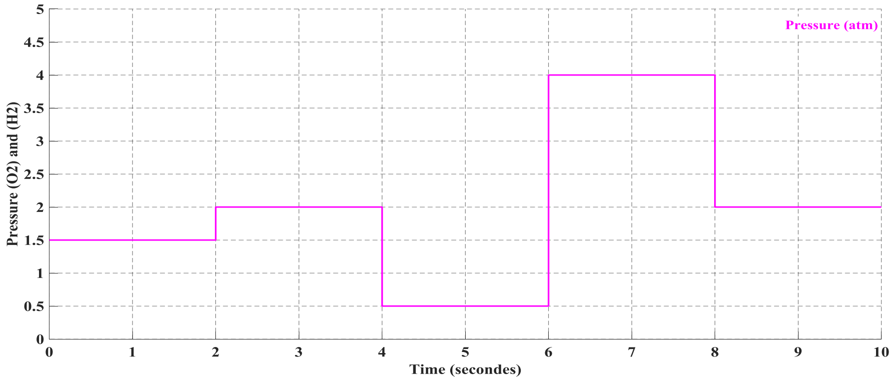


Fig 11. Varying levels of pressures

Variations in pressurization noticeably influence the movement of reactants as well as products inside the PEMFC. A decrease in pressure causes reaction rates to decrease and power output to decrease subsequently. However, greater pressure has the potential to augment the availability of reactants and thus elevate the speed of reaction, resulting in enhanced power production. The Neuro-Fuzzy algorithm employs constant monitoring of pressure fluctuations and dynamically modifies aspects of operation to ensure the best possible energy harvesting. The NF MPPT algorithm adjusts duty cycles to follow Maximum Power Point, while the boost converter ensures output stability by addressing pressure-induced voltage fluctuations. Figure 12 demonstrates the practical use of the neuro-fuzzy approach in monitoring power, current, and voltage under varying pressures while adhering to predefined parameters.

3.2.4 Change Temperature and Pressure

The finished analysis was conducted under a specific circumstance. The current investigation involved evaluating various temperatures; as seen in Figs. 9 and 11, different situations are depicted, illustrating the variations in the partial pressure of oxygen and hydrogen.

The system of control takes temperature and pressure variables and uses them together to make the best possible predictions. By preserving optimum efficiency regardless of external factors like temperatures and pressures, proton exchange membrane fuel cells can keep on serving their intended purpose consistently and effectively, as seen in Fig. 13. The neuro-fuzzy MPPT improves the performance of hydrogen PEMFC by intelligently adjusting the period of duty to maintain the MPP, thereby lowering efficiency losses.

4. CONCLUSION

This research presents a detailed examination of the performance of a PEMFC across a wide range of temperature, pressure, and combined situations. The MPPT control proves its flexibility in responding to and optimizing PEMFC performance, which guarantees efficient electrical energy production in a wide range of operational contexts. The widespread use of membrane fuel cells and proton exchange currently remain as they are. However, they might greatly benefit from the addition of advanced control methods like Neuro-Fuzzy, which tracks the maximum power point.

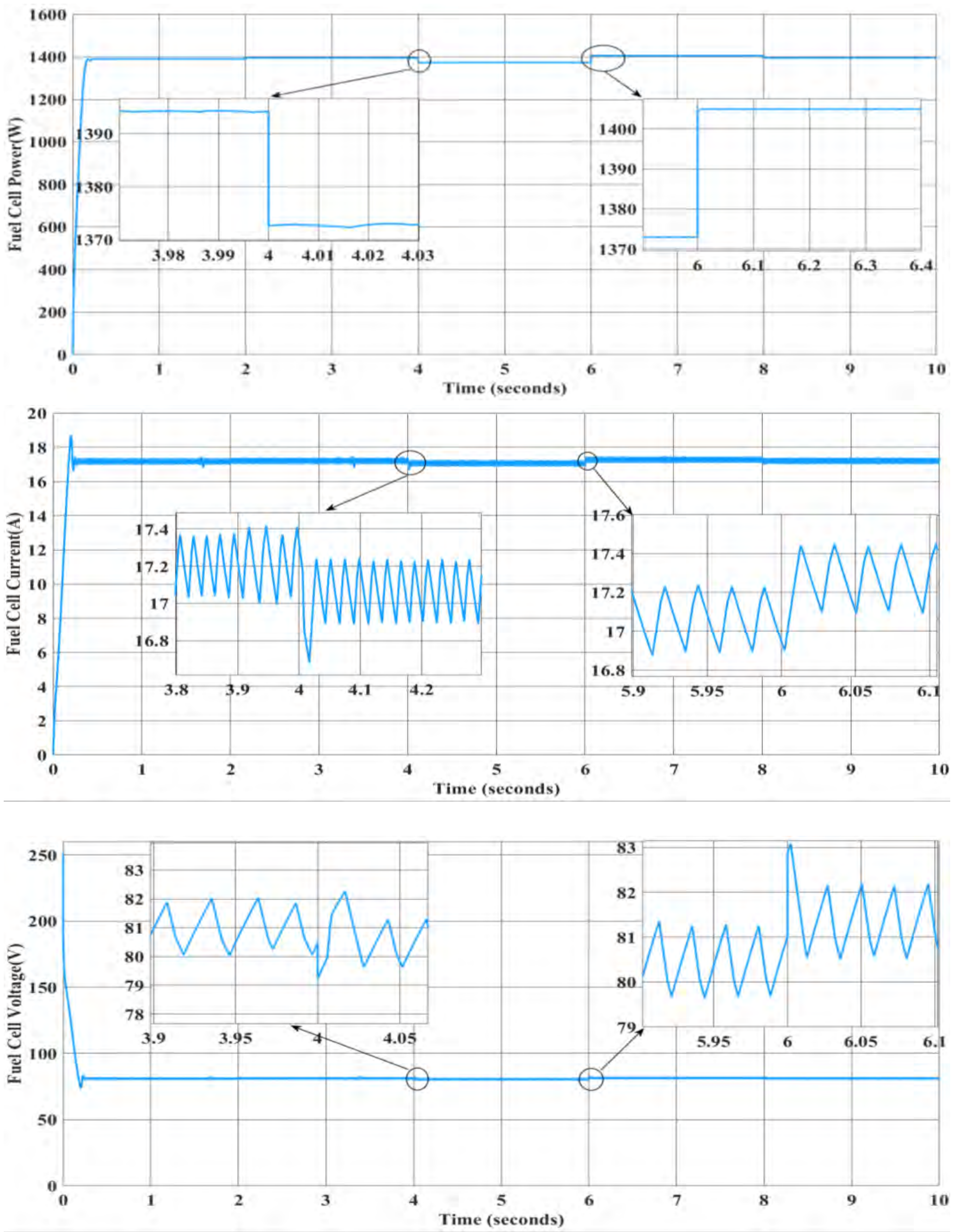


Fig 12. The Neuro-Fuzzy MPPT recording power, current and voltage under varying levels of pressures

Table 2. Neuro-Fuzzy MPPT performance at different temperatures and pressures

Period(s)	[0-2]	[2-4]	[4-6]	[6-8]	[8-10]
oxygen partial pressure and the hydrogen gas pressure(atm)	1.5	2	0.5	4	2
Temperature(K)	200	345	150	250	345
Power generated(W)	815	1394.25	642.58	1007.798	1394.26
Time for response (s)	0.17	0.08	0.04	0.054	0.033

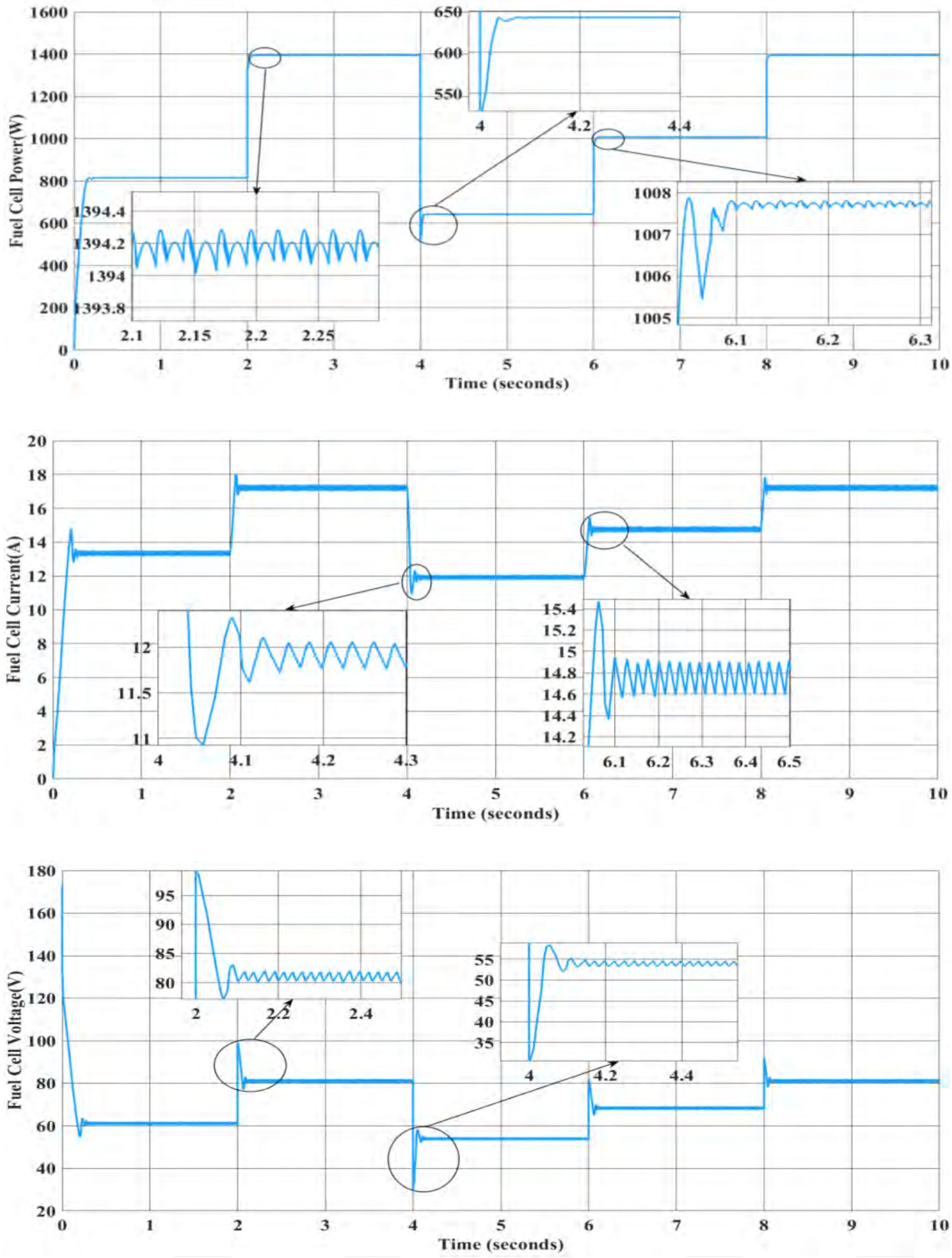


Fig 13. The Neuro-Fuzzy MPPT recording power, current and voltage under varying levels of temperatures and pressures

NOMENCLATURE

PO2	pressure of oxygen [atm]
T	Temperature [kalven]
PH2	pressure of hydrogen [atm]
PEMFC	Proton exchange membrane fuel cell

REFERENCES

Aboshosha, A., Gouda, M.M., Awad, H. and Hamad, H.A. (2023). AI based Metaheuristic Optimization of PEMFC Control System for Robust and EEcient Operation. doi: 10.21203/rs.3.rs-3159560/v1.

Badoud, A.E., Merahi, F., Ould Bouamama, B. and Mekhilef, S. (2021). Bond graph modeling, design and experimental validation of a photovoltaic/fuel cell/ electrolyzer/battery hybrid power system," Int J Hydrogen Energy, 46(47), 24011–24027. doi: 10.1016/j.ijhydene.2021.05.016.

Badoud, A.E., Mekhilef, S. and Ould Bouamama, B. (2022). A Novel Hybrid MPPT Controller Based on Bond Graph and Fuzzy Logic in Proton Exchange Membrane Fuel Cell System: Experimental Validation. Arab J Sci Eng, 47(3), 3201–3220. doi: 10.1007/s13369-021-06096-3.

Egiziano, L. et al. (2009). Optimization of perturb and observe control of grid connected PEM fuel cells. International Conference on Clean Electrical Power, 176, 775–781. doi:10.1109/iccep.2009.5211962

Gugulothu, R., Nagu, B. and Pullaguram, D. (2022). A computationally efficient jaya optimization for fuel cell maximum power tracking. Energy Sources, Part A: Recovery, Utilization and Environmental Effects, 44(1), 1541–1565. doi: 10.1080/15567036.2022.2055229.

He, C., Wen, Q., Ning, F., Shen, M., He, L., Li, Y., Tian, B., Pan, S., Dan, X., Li, W., Xu, P., Liu, Y., Chai, Z., Zhang, Y., Liu, W., and Zhou, X. (2023). A New Integrated GDL with Wavy Channel and Tunneled Rib for High Power Density PEMFC at Low Back Pressure and Wide Humidity. Advanced Science, 10(28). doi: 10.1002/advs.202302928.

Kanouni, B., Badoud, A.E. and Mekhilef, S. (2021). Fuzzy logic MPPT control algorithm for a Proton Exchange Membrane Fuel Cells System. Algerian Journal of Renewable Energy and Sustainable Development, 3(1), 13–22. doi: 10.46657/ajresd.2021.3.1.2.

Kanouni, B., Badoud, A.E. and Mekhilef, S. (2022). A multi-objective model predictive current control with two-step horizon for double-stage grid-connected inverter PEMFC system. Int J Hydrogen Energy, 47(4), 2685–2707. doi: 10.1016/j.ijhydene.2021.10.182.

Karthikeyan, B., Sundararaju, K. and Palanisamy, R. (2021). ANN-Based MPPT Controller for PEM Fuel Cell Energized Interleaved Resonant PWM High Step Up DC-DC Converter with SVPWM Inverter Fed Induction Motor Drive. Iranian Journal of Science and Technology - Transactions of Electrical Engineering, 45(3), 861–877. doi: 10.1007/s40998-021-00413-0.

Khelifi, B., Ben Salem, F., Zdiri, M.A., Salem, B. and Abdallah, H.H. (2021). A Stand-Alone PV-PEMFC System Based SMANN-MPPT Controller: Solar Pumping Application Using PMSM. International Journal of Renewable Energy Research. 11(2), 662-672. Available at https://www.researchgate.net/publication/352538989

Li, C., Lin, W., Wu, H., Li, Y., Zhu, W., Xie, C., Gooi, H. B., Zhao, B., and Zhang, L.. (2023). Performance degradation decomposition-ensemble prediction of PEMFC using CEEMDAN and dual data-driven model. Renew Energy, 215. doi: 10.1016/j.renene.2023.118913.