



Research Article

Improving power quality in fuel cell applications and deep learning based analysis

Ünal YILMAZ^{1,*}, Kerim KARADAĞ¹, Süleyman Bayram GÖNÜLLÜ¹

¹Department of Electrical-Electronics Engineering, Harran University, Şanlıurfa, 63000, Türkiye

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ABSTRACT

Power quality issues such as voltage sags, swells, and harmonics that hinder efficient energy transfer in grid-connected systems with sensitive loads lead to grid instability and potential load damage. This study proposes an improved hybrid power architecture that integrates grid and precise load management in a fuel cell system with a maximum power algorithm, performing pulse width modulation (PWM) prediction using an offline-trained deep learning method from dynamic voltage restorer (DVR) data. Grid-injected current and voltage are regulated using proportional–resonant and phase-locked loop (PR-PLL) controllers, while the DVR uses PLL-based synchronization and hysteresis control. Additionally, voltage and switching-signal data are processed with a recurrent neural network (RNN) to enable predictive analysis and estimation of inverter PWM patterns. The proposed data-driven control method aims to reduce the instantaneous processing load and dynamic response times of conventional controllers, thereby achieving high power quality and efficiency in renewable energy integration. The system's success has been verified by testing it under temperature variations and sudden voltage fluctuations. The DC-link voltage was regulated at 400 V, current harmonic distortion was limited to approximately 5%, a power factor above 0.98 was achieved, and the sensitive load voltage remained at its nominal value despite voltage sags and swells. The mean squared error (MSE) was 0.0251 in the RNN method applied for inverter PWM estimation and analysis.

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INTRODUCTION

Along with the rapid depletion of fossil fuels, problems such as gas emissions and climate change that have the potential to threaten the sustainability of life are directing the global energy sector towards alternative energy sources that are sustainable, environmentally friendly and clean [1,

2]. In addition, rapidly developing technology creates new needs and it is observed that the demand for energy has increased significantly as a result of these needs [3, 4]. In this context, fuel cells stand out with their superior features such as simple use, modularity, high efficiency and low/zero emissions [5, 6]. Depending on the application area,

*Corresponding author.

*E-mail address: uyilmaz@harran.edu.tr

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the power values of fuel cells vary between 500 W and 1 MW. In addition, these cells can offer better solutions for power balancing and voltage/frequency regulation compared to wind and solar energy-based systems in terms of their dependence on environmental effects.

In recent years, fuel cell-based applications have begun to increase in the grid connection, residential (standalone) and automotive sectors [7]. Power electronic circuit interfaces are needed for system connections fed from fuel cells. In power systems that can feed sensitive loads from renewable energy sources as well as transfer power to the grid; power quality problems such as voltage sags, swells and harmonics can prevent efficient power transfer, cause grid instability and damage sensitive loads [8, 9]. In order to prevent such problems, dynamic voltage restorer (DVR) offers a serious solution. DVR can be defined as a power circuit structure consisting of a single-phase full bridge inverter, harmonic filter and control algorithms that perform continuous system control by connecting between the power source, load and grid [10]. In the event of a possible voltage sags or swells, it determines the voltage required by sensitive loads to perform at nominal levels and ensures that voltage is injected into the power circuit in series. Thus, sensitive loads continue to operate at nominal levels without being affected by power quality problems [9, 11]. Furthermore, deep learning is a computer-based algorithm that attempts to simulate the way the human brain works, with many layers known as deep neural networks, and utilizes large amounts of data to make decisions, predictions, and classifications. A variant of deep learning, recurrent neural networks (RNN), are a class of neural networks specifically designed to work with sequential data, with high accuracy and performance, system adaptability, and real-time prediction capabilities [12, 13].

Literature studies related to improving power quality in grid-connected power systems have been reviewed. In [8], improving power quality of three-phase grid-connected photovoltaic (PV) systems by proposing a DVR-aided system that combines a two-stage control strategy with a multi-level inverter. In nominal operating mode, it provides voltage

correction using sliding mode control (SMC) and proportional resonance (PR) during voltage outages. The multi-level inverter is used to reduce harmonic distortion. In [14], A dual-function and series-connected compensator is proposed for grid-tied and photovoltaic sourced power circuit. The operating logic of this compensator is based on superconducting magnetic energy storage. The proposed power circuit has two different operating modes. These modes are; dynamic voltage restorer (to prevent voltage fluctuation) and fault current limiter (to prevent short circuit faults). In addition, a modified sliding mode controller (SMSVM) is developed to be applied in the proposed study, which is claimed to provide more effective and advantageous voltage control than traditional methods. In [15], An optimum proportional and integral (PI) based method is proposed for inverter control in the power circuit of single-phase grid-connected photovoltaic systems. The proposed model includes a time domain objective function based on the integral square error (ISE) of current and voltage errors. This function is used to formulate the PI control. With the contributions of the developed method, reactive power compensation is provided and active power is injected into the grid, and thus it is stated that it is a simple, low-cost and attractive method for home energy production. In [16], A technique based on dynamic voltage restorer (DVR) is proposed to provide solutions to power quality problems that may occur in photovoltaic fed systems under harsh weather conditions and to increase the stability of microgrids. Additionally, the comparison of the electrical characteristics and control algorithms of the proposed system with the existing studies in the literature is presented in Table 1 [17, 24].

This study presents an improved integrated power interface architecture for fuel cell systems connected to the grid and supplying sensitive loads (Fig. 1). The proposed framework enables maximum power acquisition through the P&O MPPT algorithm, establishes robust DC junction regulation at a 400 V reference using a PI controller, and achieves high-quality grid synchronization with a power factor exceeding 0.98 through the PR-PLL scheme. To protect sensitive loads under adverse conditions such

Table 1. Electrical properties of studies in the literature

Ref.	Fuel Cell	Rated Power	MPPT	Grid-Tied	Control and Analysis	DVR
[17]	PEMFC	50kW	○	√	VPI Control	○
[18]	PEMFC	3-6kW	○	○	Genetic Algorithm	○
[19]	Hydrogen	NA	○	√	Type-3 Fuzzy	N/A
[20]	Fuel Cell	1.2 kW	○	√	PI-Based	○
[21]	Fuel Cell	200 W	OD-PSO	√	Lyapunov-Based	○
[22]	PEMFC	1 kW	○	√	PQ and Voltage-Mode	○
[23]	PEMFC	7 kW	IC-MPPT	√	MFSO-FLC	○
[24]	SOFC	200 W	○	√	Anti-Islanding Control	N/A
This Paper	SOFC	3481 W	P&O-MPPT	√	PLL-PR- RNN (Deep Learning)	√

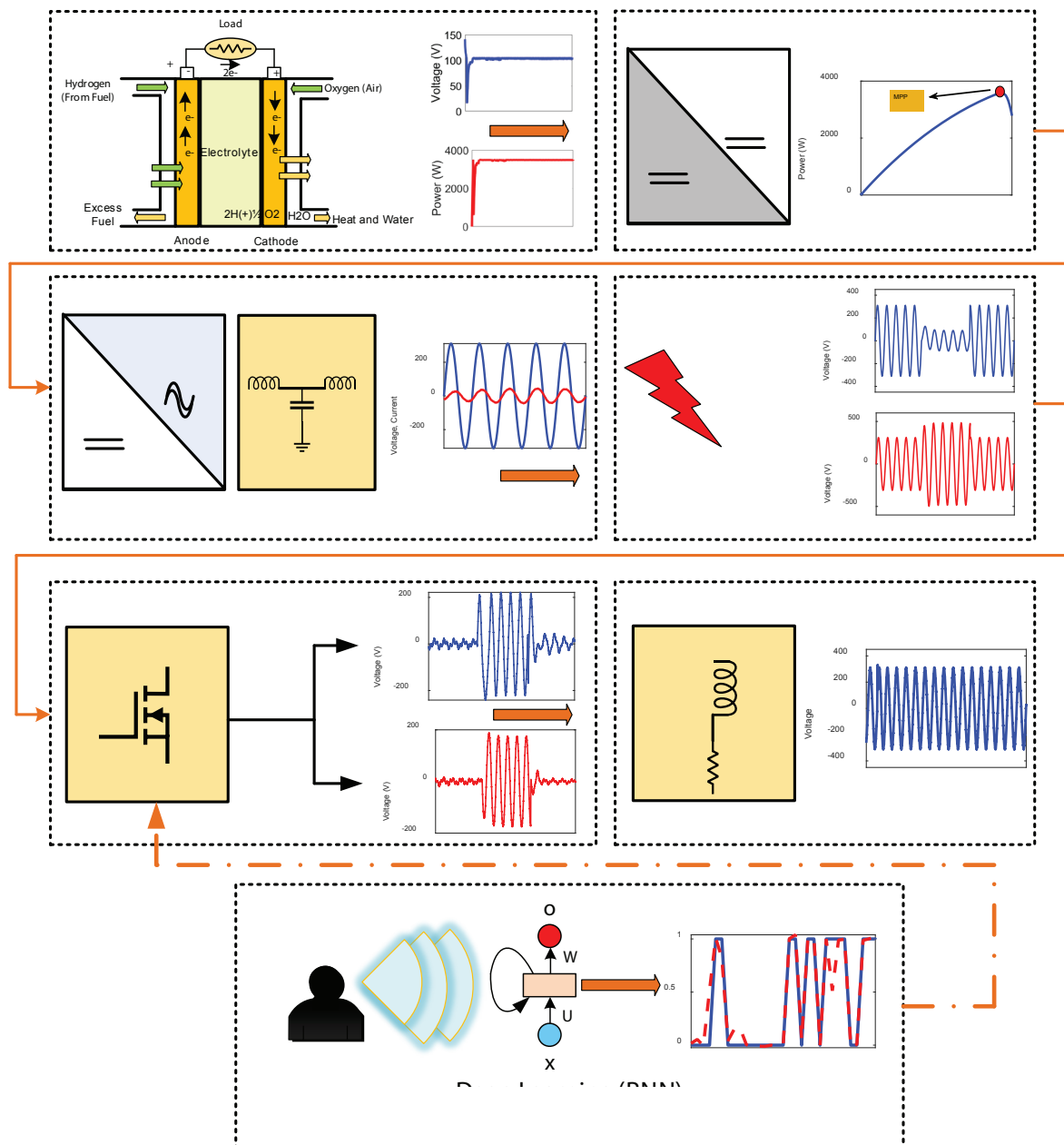


Figure 1. Performance steps and electrical characteristics of the proposed study.

as voltage sags, swells, and temperature fluctuations, a Dynamic Voltage Restorer (DVR) is used, employing a hysteresis control-PLL structure for series voltage injection. Unlike conventional approaches (Table 1), this study presents a data-driven power structure that leverages a Recurrent Neural Network (RNN) algorithm to model the highly nonlinear relationship between instantaneous voltage faults and semiconductor switching profiles. Using datasets collected from switching states, the RNN methodology enables accurate prediction and performance analysis of PWM signals, providing a predictive tool for improved power quality management.

MATERIALS AND METHODS

Materials

In the proposed study, solid oxide fuel cell (SOFC) is used as power source. In addition, MPPT (P&O) algorithm is applied to dc-dc boost converter for maximum power harvesting from fuel cell. Moreover, PLL-PR control method is applied to full bridge inverter for DC-link voltage control and power injection to grid. In addition, PLL-hysteresis control method is applied to full bridge inverter for DVR to provide power flow to sensitive load. Additionally, load voltage and injected voltage data were

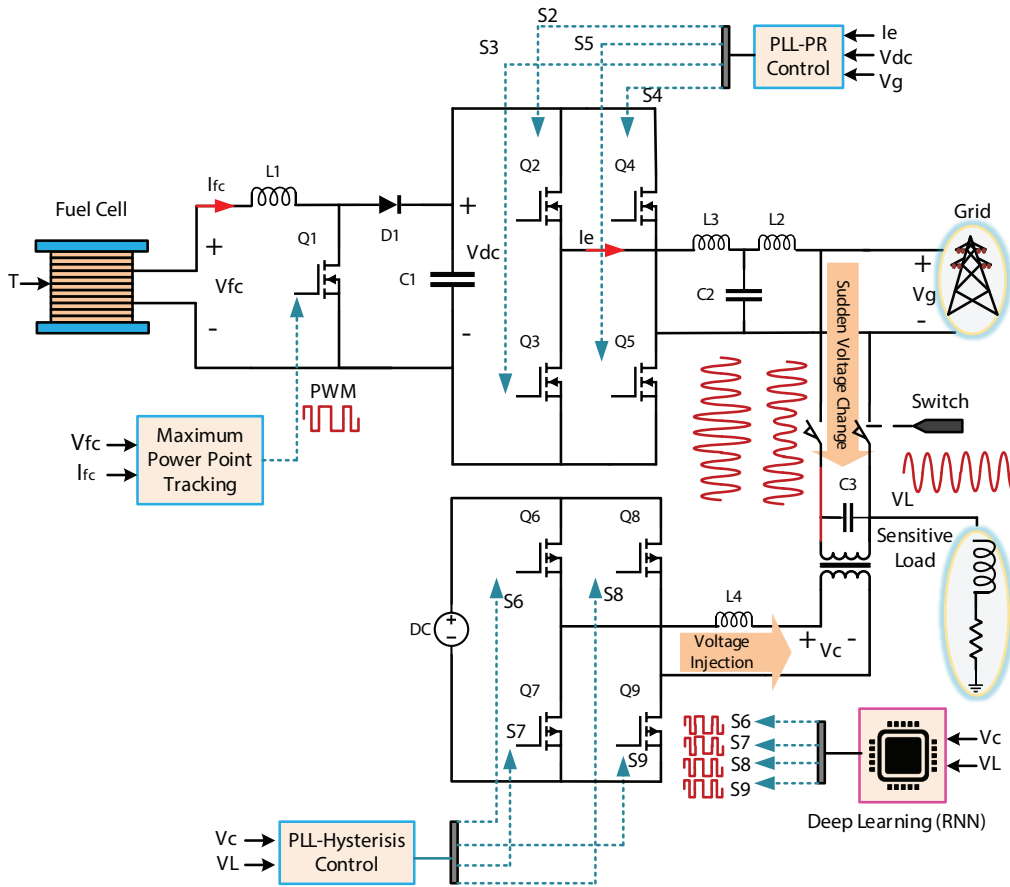


Figure 2. Fuel cell powered and deep learning supported DVR system model.

collected using voltage oscilloscopes, and PWM generation was performed using deep learning (RNN) with offline analysis. Power circuits and control algorithms of the proposed study are presented in detail in Figure 2.

SOFC and MPPT Method

A SOFC is usually defined by its electrolyte material (solid oxide or ceramic electrolyte). While it provides advantages in terms of high heat, cost-effectiveness, stability and efficiency. During the chemical process, oxygen (O_2) ions are transported from the cathode to the anode through the solid oxide electrolyte. This process usually takes place at high temperatures (ranging from 600 to 900 °C). SOFCs can produce power at different rates (100 W to 2 MW). The following equations are used for the steady-state model of a SOFC [25, 26].

$$V_c = E_{rev} - V_{tdrop} = E_{rev} - (V_{con} + V_{act} + V_{om}) \quad (1)$$

Concentration voltage drop is defined as follows.

$$V_{con} = -1 \cdot \ln \left(1 - \frac{I_{den}}{I_{mden}} \right) \quad (2)$$

Activation voltage can be expressed as follows.

$$V_{act} = k \cdot \ln \left(\frac{I_{den}}{2I_{exden}} \right) \quad (3)$$

Ohmic voltage is defined as follows.

$$V_{om} = I_{op} \frac{R}{B_a} \quad (4)$$

Here V_c is the fuel cell output voltage, V_{tdrop} is the total voltage drop, this total voltage drop will be equal to the sum of the concentration drop V_{con} , the activation drop V_{act} and the ohmic drop V_{om} . E_{rev} is the reversible voltage, I_{den} is the current density, I_{op} is the fuel cell output current, R is the total resistance, B_a is the membrane effective area.

The electrical characteristic curves of the SOFC under variable temperatures investigated in this study are presented in Figure 3.

The electrical parameters and values of the SOFC utilized in this study are listed in Table 2.

After using the fuel cell as a source, a power electronic circuit interface is needed for grid connection. DC-DC converter design will be carried out to control the input voltage of the inverter at the reference value, to apply low voltage ripple and maximum power point tracking algorithm. For this purpose, dc-dc boost converter is preferred in this

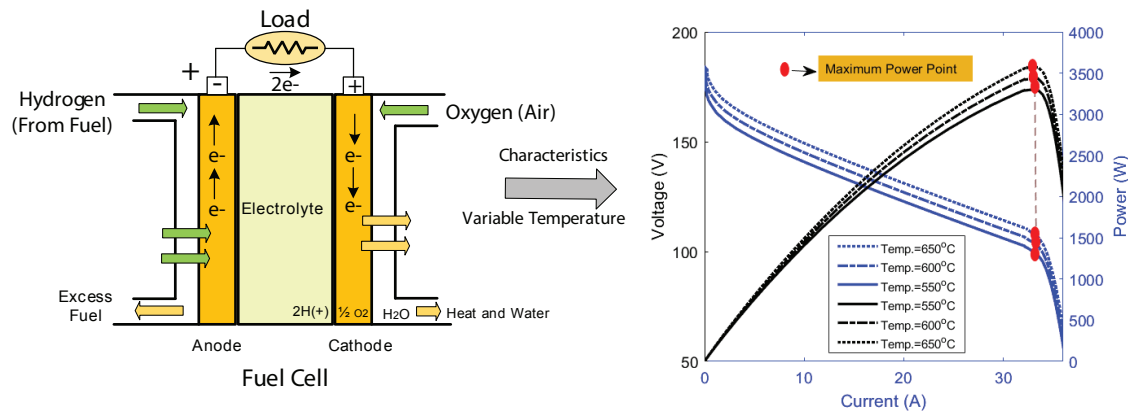


Figure 3. SOFC power-voltage and current characteristics and maximum power points.

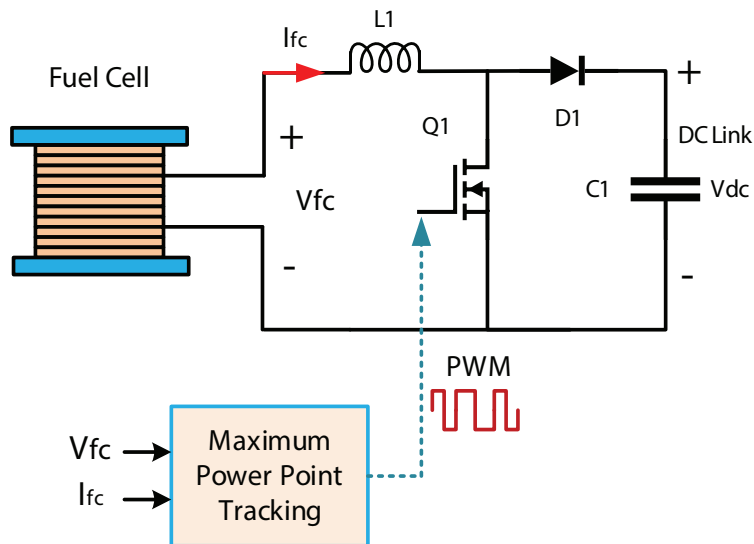


Figure 4. DC-DC converter and maximum power tracking algorithm.

Table 2. Parameters and values of SOFC

Parameters	Values
Nominal Power	3195 W
Maksimum Power	3481 W
Nominal Current, Current at MPP	30 A, 33.2 A
Nominal Voltage, Voltage at MPP	106.5 V, 104.86 V
Fuel Cell Resistance	0.364 Ω
Hydrogen (H2)	%72.82
Oxidant(O2)	%29.82
Fuel	59.21 slpm
Air	49.73 slpm
Cell Number	119
Efficiency	% 52
System Temperature	600°C
Fuel Supply Pressure	1.35 Bar
Air Supply Pressure	1 Bar

study due to its low circuit element count, easy applicability and high efficiency [27]. The implementation circuit of the DC-DC converter and maximum power tracking algorithm is presented in Figure 4.

Duty cycle (D) and passive circuit element (L, C) selection for DC-DC Converter Design are found with the help of the following equations [28].

$$\frac{V_{dc}}{V_{FC}} = \frac{1}{1-D} \quad (5)$$

$$L_1 = \frac{V_{FC} D}{\Delta i_{FC} f_s} \quad (6)$$

$$C_1 = \frac{D}{R \left(\frac{\Delta V_{dc}}{V_{dc}} \right) f_s} \quad (7)$$

Where, V_{dc} represents the dc link voltage, L_1 represents the inductor value in the boost converter design, C_1 represents the capacitor value in the boost converter design, D is the duty cycle. V_{fc} represents the fuel cell voltage, f_s represents the switching frequency, Δi_{fc} represents the inductor current ripple. ΔV_{dc} represents the dc link voltage ripple.

In order to harvest maximum power from the fuel cell, the P&O algorithm, which offers an effective solution in terms of both implementation and cost, is preferred. The characteristic curve based on the working logic of P&O method and step change according to dP/dV slope are shown in Figure 5 [29]. It is obvious that the slope of the

power-voltage characteristic of the fuel cell (dP/dV) is positive on the left side of the MPP and negative on the right side. The duty cycle of the PWM signal applied to the switch of the DC-DC converter (D , in equation 5) increases at points 1, 2 and 4, and decreases at points 3 and 5 [30, 31].

LCL Filter and Control Algorithms

LCL filter carried out to suppress the total harmonic distortion (THD) in the inverter output voltage. As seen in Figure 2, to design the LCL filter, the transfer function and resonance frequency determined by the following equations [32–34].

$$\frac{i_s}{V_{ev}} = \frac{1}{(L_3 L_2 C_2) s^3 + (L_2 + L_3) s} \quad (8)$$

Resonance Frequency is;

$$\begin{cases} w_{res} = \sqrt{\frac{L_2 + L_3}{L_2 L_3 C_2}} \\ f_{res} = \frac{w_{res}}{2\pi} = \frac{1}{2\pi} \sqrt{\frac{L_2 + L_3}{L_2 L_3 C_2}} \end{cases} \quad (9)$$

The designed LCL filter application is expected to have low harmonic current to be injected into the grid and voltage feeding the sensitive load. In this context, the Bode diagram showing the phase-frequency response and magnitude frequency response of the filter applied after the single-phase full bridge inverter is presented in Figure 6.

The DC bus voltage (V_{dc}) is compared with the reference DC bus voltage (V_{ref}) to generate an error signal, the generated error signal is passed through the PI-based control to generate an output signal [35]. The generated signal is then

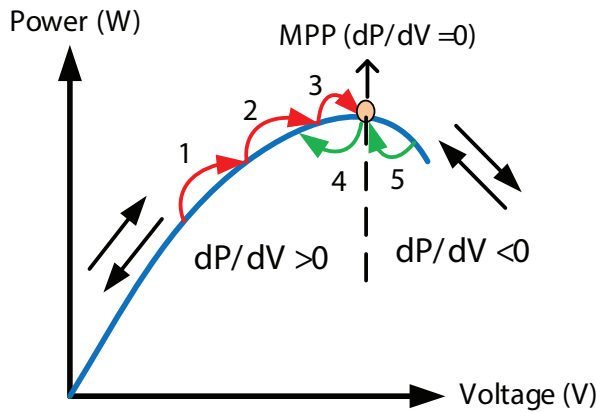


Figure 5. Fuel cell power voltage characteristics and P&O MPPT.

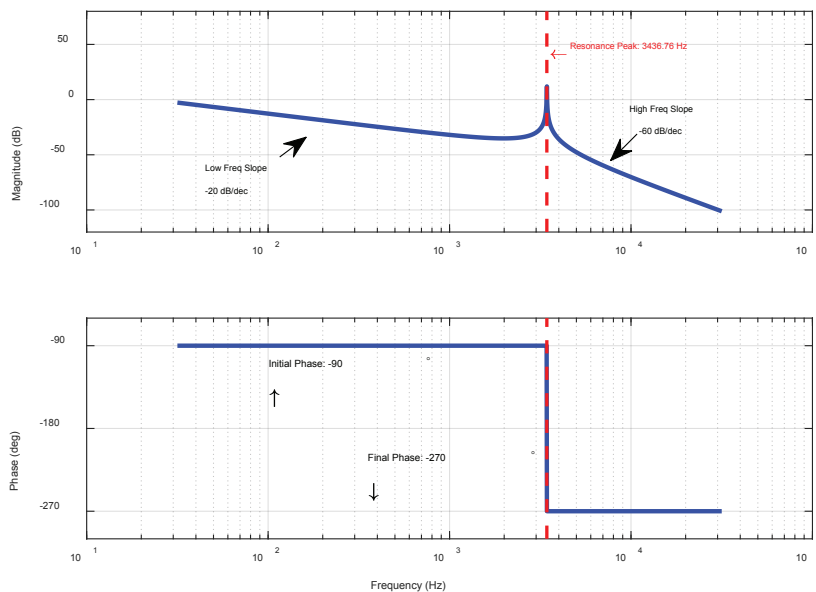


Figure 6. Bode diagram of LCL filter application.

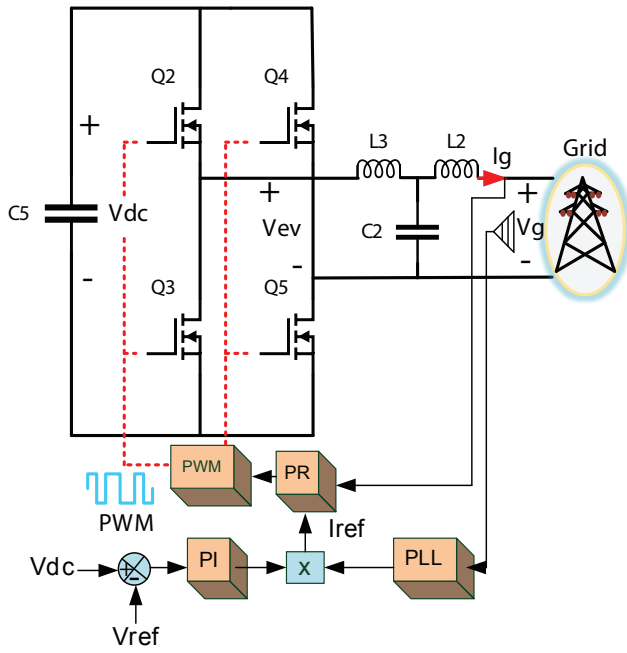


Figure 7. Grid connected single phase inverter and PLL-PR control.

used as an input to the reference current, I_{ref} , Phase Locked Loop (PLL) and the PR controller, which is synchronized with the grid voltage as seen in Figure 7.

The Gain function of the ideal PR control is defined as follows.

$$G_{PR}(s) = K_p + \frac{2K_i s}{s^2 + \omega_0^2} \quad (10)$$

Here K_p and K_i represent the controller gains, ω_0 is the resonant frequency. Although the ideal PR controller provides infinite gain at the AC frequency, its lossless nature limits its practical implementation. Furthermore, this infinite gain can introduce system stability challenges. To

mitigate these issues, a non-ideal PR controller is defined as follows [36, 37],

$$G_{nPR}(s) = K_p + \frac{2K_i \omega_c s}{s^2 + 2\omega_c s + \omega_0^2} \quad (11)$$

PLL and hysteresis control used for DVR control (Fig. 8). While PLL control provides synchronization between load voltage and injection transformer primary voltage (Figure 1), Hysteresis control minimize the error rate between the two voltages and the output signals are used to produce PWM signals for semiconductor switches. In addition, data collected from the inputs and outputs of the hysteresis control method are utilized to train the Deep Learning-based Recurrent Neural Network (RNN) algorithm. The estimation and performance evaluations for PWM generation using this RNN model are analyzed in detail.

The mathematical derivation of the PI loop gains (K_p , K_i) in the PLL structure for the natural frequency (ω_n) and damping ratio (ζ) is presented in the following equations [38].

$$K_p = 2 \cdot \zeta \cdot \omega_n \quad (12)$$

$$K_i = \omega_n^2 \quad (13)$$

To operate the system with minimum overshoot and optimum stability, the damping ratio is $\zeta=1/\sqrt{2}$, where $\omega_n=2\pi f_n$. The resulting value is then divided by the grid peak voltage (V_m) to obtain the physical results.

In hysteresis control, the equation for finding the band-dependent output voltage is as follows [39].

$$V_f = \begin{cases} V_{ref} + HB/2, & \text{Rising Case} \\ V_{ref} - HB/2, & \text{Decreasing Case} \end{cases} \quad (14)$$

The hysteresis band can be found using the following equation [40].

$$HB = \frac{V_{dc}}{8 \cdot f \cdot L_f} - \frac{L_f}{2f \cdot V_{dc}} \left(\frac{v_s(t)}{L_f} + \frac{di_f}{dt} \right)^2 \quad (15)$$

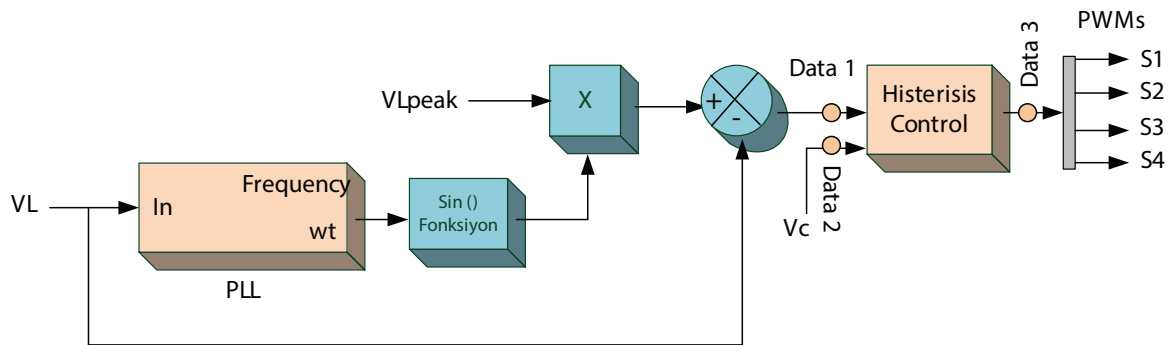


Figure 8. DVR control.

Hysteresis band can be simplified to approximately the following equation.

$$HB \approx \frac{V_{dc}}{8 \cdot f \cdot L_f} \quad (16)$$

Here, V_{ref} represents the reference voltage, V_f the output voltage, V_{dc} the inverter input voltage, and L_f the filter inductance value.

Recurrent Neural Network (RNN)

Recurrent Neural Network is one of the deep learning methods and is specifically designed to work with sequential data. RNNs process each element of sequential data and carry the knowledge gained from previous steps to the next step. While traditional machine learning models treat data as static points, RNN architecture, thanks to its internal memory loops, can capture the temporal characteristics of transient states such as temperature fluctuations and instantaneous voltage surges (sag/swell). This makes RNN superior to other linear and feedforward methods in dynamic PWM signal estimation from instantaneous voltage errors, which can pose a serious threat to sensitive loads [41]. The basic structure of RNN consists of an input layer and an output layer along with a hidden layer. Rather than traditional feedforward neural networks, RNNs have recurrent connections, as shown in Figure 9, which allows data to loop through the networks. The calculation of the hidden state of the RNN model at each time step is provided by the following equation [42, 43].

$$h_t = \sigma_h(W_{xh}x_t + W_{hh}h_{t-1} + b_h) \quad (17)$$

Here h_t represents the hidden state, σ_h is the activation function, W_{xh} is the weight matrix controlling the transition from the input layer to the hidden layer, x_t is the input data at the t -th time step, W_{hh} represents the weight matrix from the hidden layer to the hidden layer, h_{t-1} is the hidden state at the previous time step, and finally b_h represents the bias for the hidden layer. The output at each time step (t) is defined as follows.

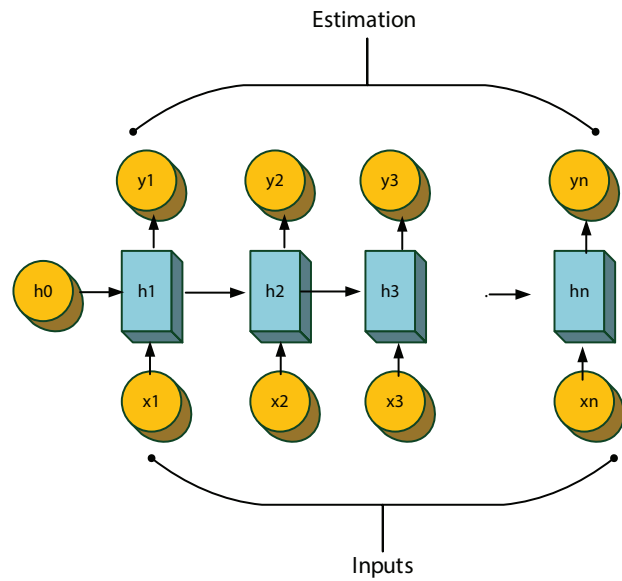


Figure 9. General structure of the RNN method.

$$y_t = \sigma_y(W_{hy}h_t + b_y) \quad (18)$$

As can be seen from the equation, the weight matrix b_h between the hidden and output layers is a bias vector, while σ_y is the activation function of the output layer. The basic representation of the RNN method, which is one of the deep learning methods (Input, output (prediction) and hidden layer) is presented in Figure 7. RNN implementation involves iterative computation of the hidden state, which integrates the current input with the previous hidden state. This enables RNNs to exhibit dynamic and temporal behavior. Additionally, one of the key roles in RNN architecture is the choice of the activation function (σ_h), as it enables the network to learn complex patterns in the data.

The training process of the proposed RNN model for offline estimation of Pulse Width Modulation (PWM) signals in single-phase Dynamic Voltage Regulator (DVR)

Table 3. Structural and algorithmic hyperparameters of the designed Elman RNN Model

Hyperparameter / Parameter Type	Value / Selected Function
Network Model Architecture	Elman Recurrent Neural Network (RNN)
Total Number of Hidden Layers	3 Layers
Neuron Distribution Per Layer	[100, 50, 25, 1]
Layer 1 and 3 Activation	Hyperbolic Tangent (Hyperbolic Tan)
2nd Layer Activation Function	Log-Sigmoid
Output Layer Function	Linear (Pure Linear)
Training Algorithm (Optimizer)	Scaled Conjugate Gradient (SCG)
Performance Metric (Loss)	Mean Squared Error (MSE)
Maximum Epoch Limit	5000
Target Error Threshold (Goal)	1.00e-07
Minimum Gradient Threshold	1.00e-06

technology was carried out to measure the stability of the grid against sudden changes in grid voltage and its generalization ability in generating inverter triggering signals. The network was trained using a 2×994 input matrix containing two defining features of the system and a corresponding 1×994 single output target (PWM reference signal) vector. The structural and algorithmic hyperparameters of the designed RNN model are presented in detail in Table 3.

During the design phase of the proposed study, the power and voltage characteristics of the SOFC are crucial in determining the maximum power that can be transferred to the load and grid. Additionally, the application of the MPPT algorithm to the dc-dc converter design ensures maximum power harvest from the fuel cell under variable

conditions and is cost-effective. Subsequently, the conversion of dc energy at the output of the dc-dc converter to ac requires the use of a single-phase full-bridge inverter and a filter for low-harmonic current and voltage values. DVR control is crucial to prevent sudden voltage dips and spikes from damaging sensitive loads. Finally, the deep learning (RNN) application applied to the single-phase full-bridge inverter's switching signal estimation and generation has ensured that the proposed system has the potential to provide alternative solutions for smart grids and artificial intelligence-based control methods. The flowchart (creation stages) of the proposed system is presented in Figure 10.

Passive circuit elements and parameters in the modeled system are presented with their values in Table 4.

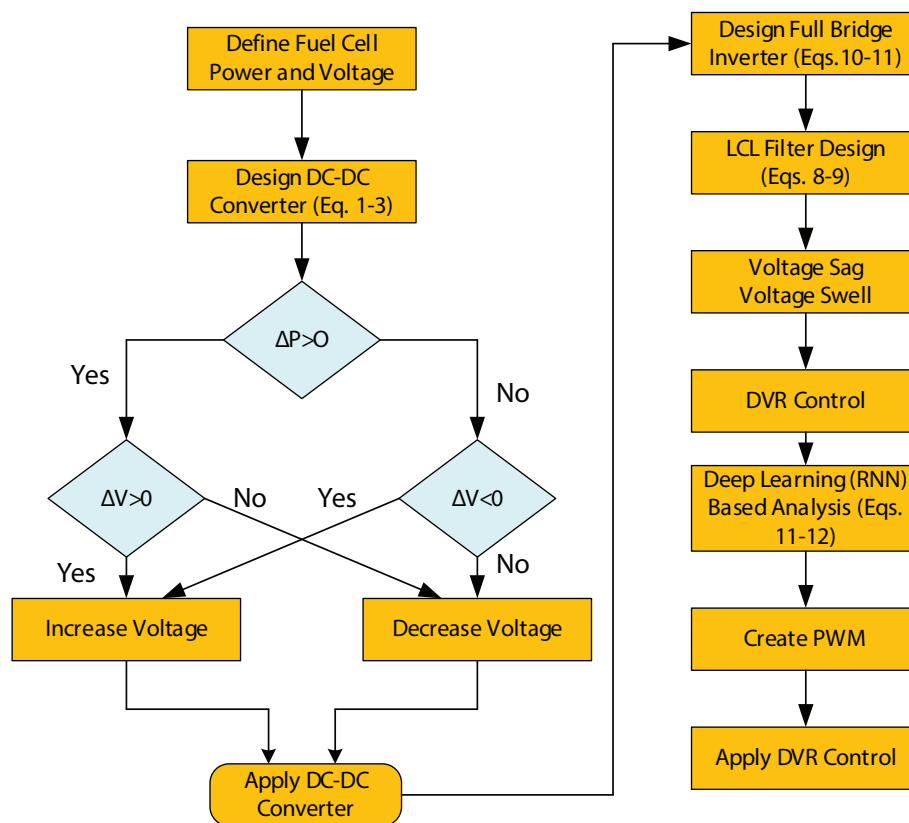


Figure 10. Creation stages of the proposed system.

Table 4. Circuit elements and values

Parameter	Value	Parameter	Value
Lboost	17 mH	L2 (Filter)	3.735 mH
CdcLink	10 mF	L4	0.1μF
L3 (Filter)	3.15 mH	C3	4.7 mF
C2 (Filter)	1.255 μF	Kp(PI)	0.75
Ki (PI)	10	f (Grid)	50 Hz

RESULTS AND DISCUSSION

By applying different temperatures (540°C-600°C) to the fuel cell, the (P&O) MPPT algorithm was ensured to perform at the fuel cell maximum power point for each temperature. In accordance with the power, voltage and current characteristics given in Figure 3 and Table 1. At first case (temp.=600°C), Fuel cell power is 3481 W (Fig. 11), voltage is 104.86 V and current is 33.4 A (Fig. 9). In the second case

(temp.=570°C), the fuel cell power is 3310 W (Fig. 11), the voltage is 98.5 V, and the current is 33.6 A (Fig. 12). In the last case (temp.=540°C), the fuel cell power is 3120 W (Fig. 11), the voltage is 93.5 V, and the current is 33.36 A (Fig. 12).

While the variable temperature changes the voltage and power values of the fuel cell, the DC-link voltage is kept constant at 400 V by applying the Pi-based control method and the DC-link voltage ripple is measured as 2.6 V at the 10 mF capacitor value, which is $\Delta V_{dc} = 0.65\%$ (Fig. 13).

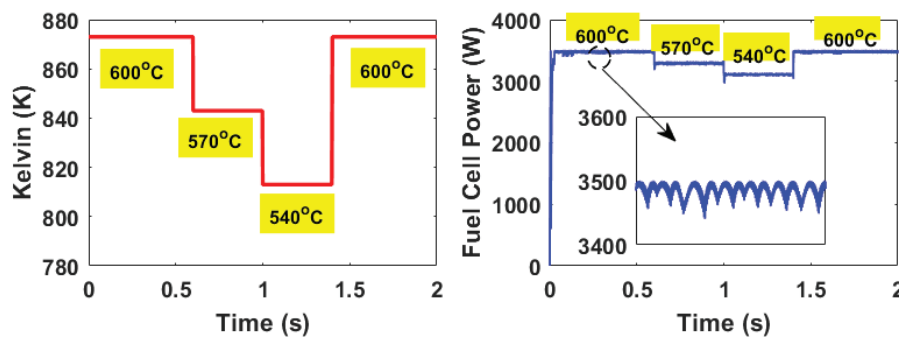


Figure 11. System Temperature and Fuel Cell Power.

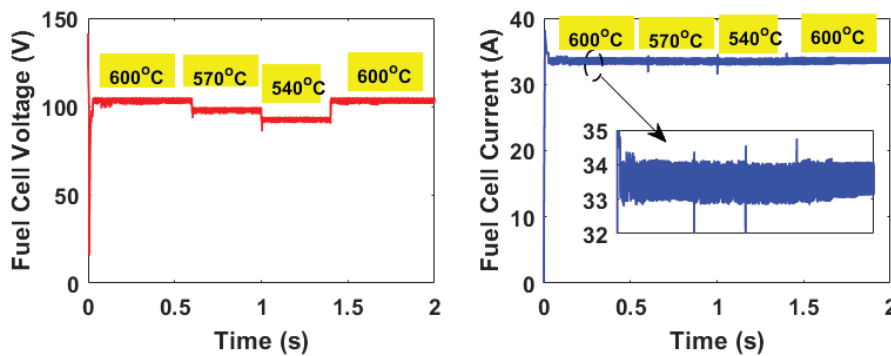


Figure 12. Fuel cell voltage and current.

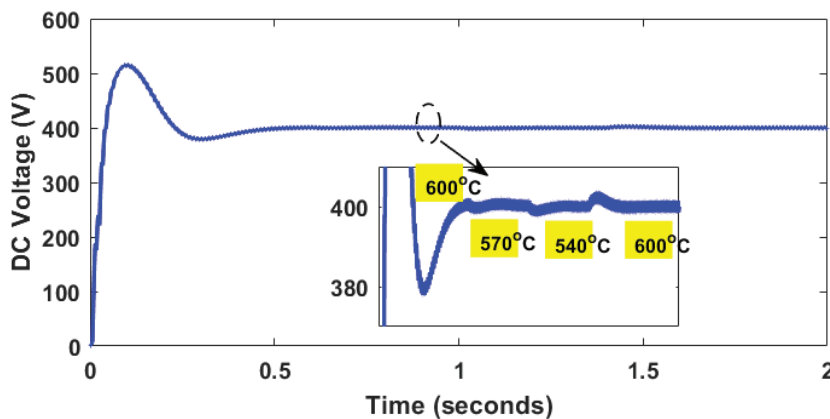


Figure 13. DC link voltage under variable temperature.

The current and voltage injected into the grid are kept in the same phase, thus providing power transfer with high power factor and low harmonic distortion (Fig. 14). For this purpose, the PLL-PR control method is used.

In the first case (temperature=600°C), the grid maximum voltage is 311 (Fig. 14) and the current is 22.5 A (Fig.

15), the power factor $\cos\theta = 0.992$, while total harmonic distortion THD=5.59%, (Fig. 16). In the second case (temperature=570°C), the grid maximum voltage is 311 and the current is 21.5 A (Fig. 12), the power factor $\cos\theta = 0.984$, while total harmonic distortion THD=5.7%, (Fig. 13). In the last case (temperature = 540°C), the maximum voltage

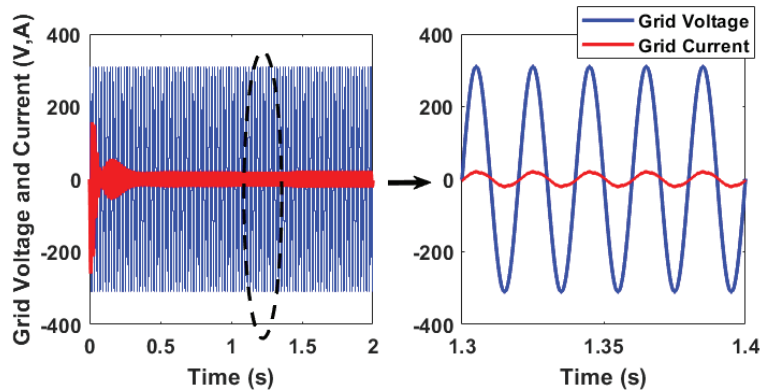


Figure 14. Grid voltage and current.

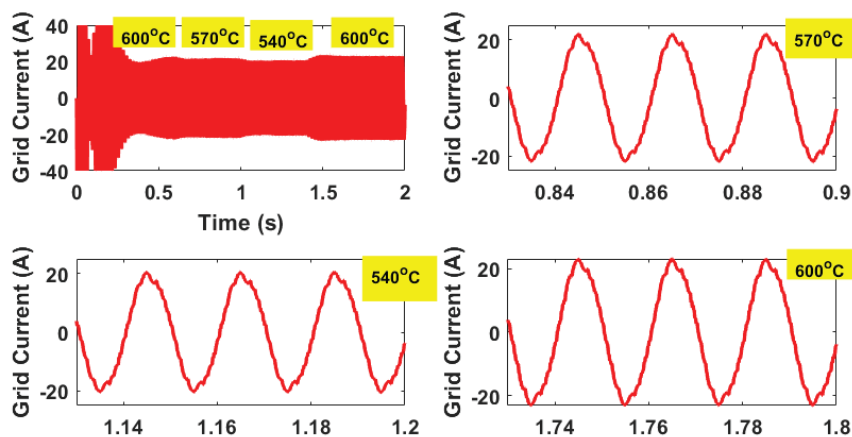


Figure 15. Grid current under variable temperature.

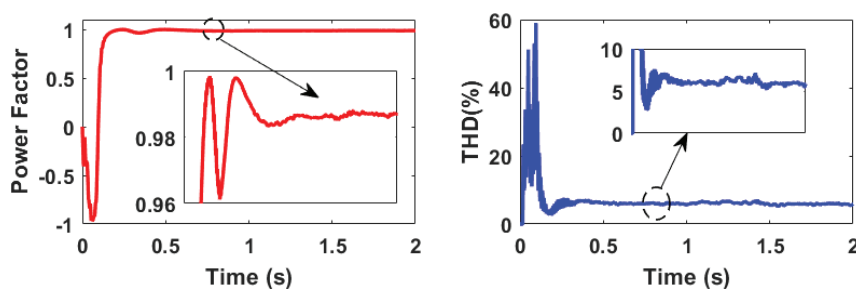


Figure 16. Grid power factor and current THD.

of the network is 311, the current is 20.5 A (Fig. 15), the power factor is $\cos\theta = 0.987$ while the total harmonic distortion THD = 5.1%, (Fig. 13).

As long as there is no voltage fluctuation, the sensitive load is supplied with a maximum of 311 V, which is the mains voltage. When a sudden voltage drop is applied to the load supply voltage, the maximum supply voltage drops to 90 V. Since this value is well below the nominal voltage level of the sensitive load, the load does not operate, so the DVR control method detects this by injecting a series voltage (221 V) into the supply voltage and ensures that the sensitive load continues to operate at the nominal level without being affected by this situation. In the second case, when a sudden voltage

increase is applied to the sensitive load supply voltage, it is seen that the maximum supply voltage increases to 485 V. Applying this voltage for a long time at this value will damage the sensitive load, and the DVR control method detects this by applying a series voltage in the reverse direction of 174 V to the supply voltage and ensures that the sensitive load continues to operate at the nominal level without being affected by this voltage change. Voltage fluctuation conditions and voltage supply voltage, injection voltage, load voltage and current are shown in detail in Figure 17.

Gradient, validation check and mean square error signals in DVR full bridge inverter PWM estimation as a result of RNN application are presented in Figure 18. For this

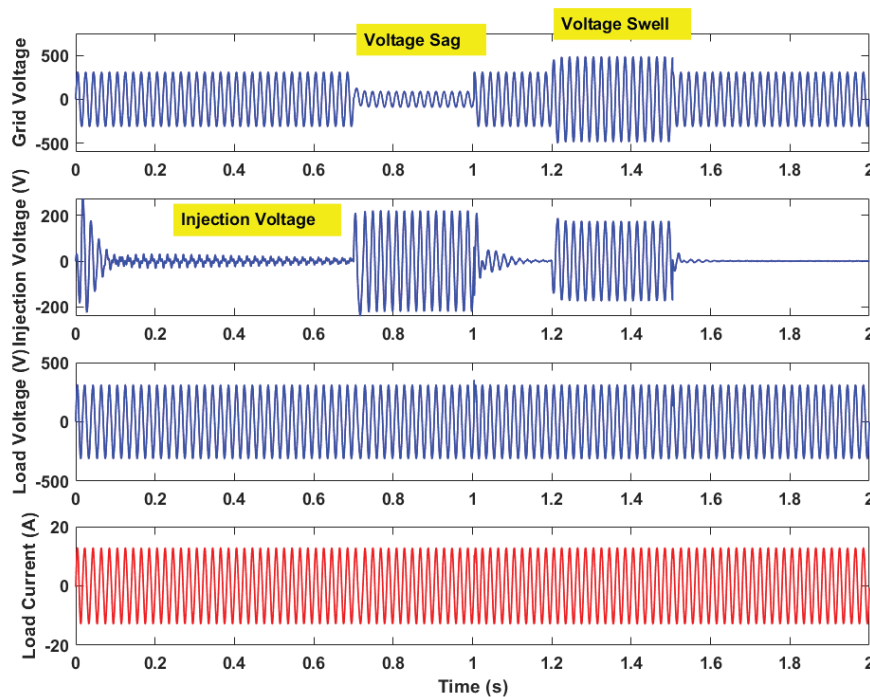


Figure 17. Grid voltage, injection voltage, load voltage and load current.

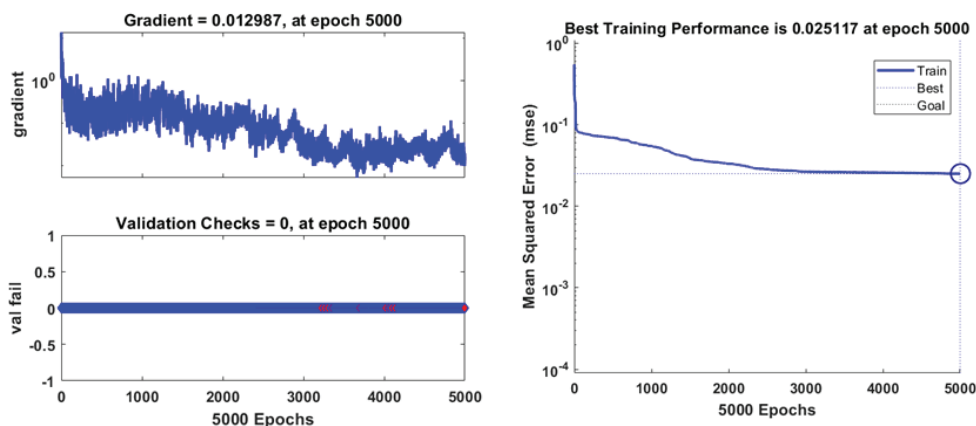


Figure 18. Gradient validation check and training performance.

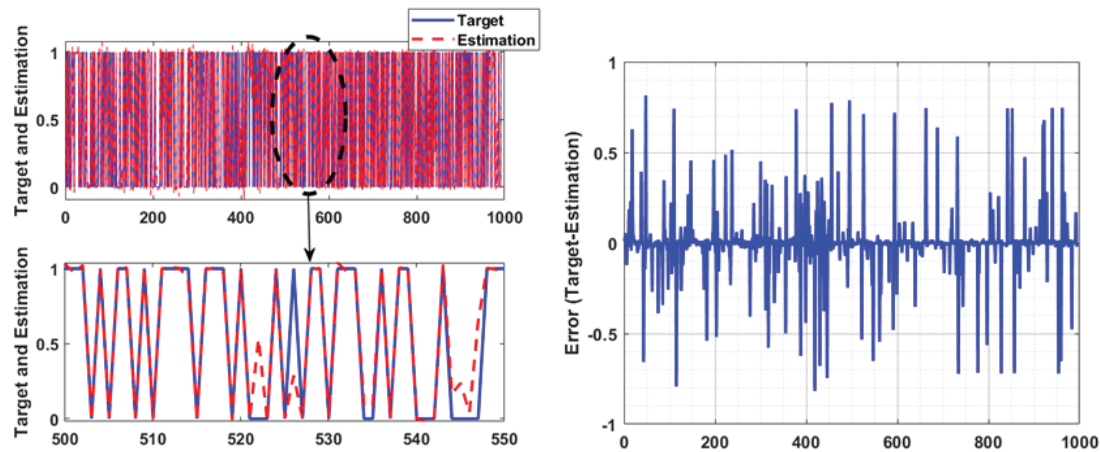


Figure 19. Target and estimation (PWM) and error.

application, the epoch number is 5000, the goal is $1e-7$, and the learning rate is 0.05.

As a result of RNN application, the actual value, estimated value and error rate signals in the DVR full bridge inverter PWM estimation are presented in Figure 19.

As a result of RNN application, error types (Mean Squared Error (MSE), Root Mean Squared Error (RMSE),

Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE)), formulas and calculation results between the real value (y_i) and the estimated ($\hat{y}_i$) value are presented in Table 5.

Electrical characteristics and values of the proposed system in terms of power-voltage and current at variable operating conditions (600°C, 570°C, 540°C) are presented in Table 6.

In this study, an integrated DVR architecture with RNN-based PWM signal estimation was tested in a simulation environment to protect sensitive loads in a fuel cell-based and grid-connected system. The findings show that the proposed deep learning model (RNN) can simulate the nonlinear switching dynamics of a conventional Hysteresis-PLL controller with high accuracy. The current THD values obtained from the system were observed to vary between 5.1% and 5.7%. The IEEE 519 and IEC 61000-2-2 standards, widely accepted in the power quality literature, prescribe a maximum THD limit of 5.0% in steady-state conditions for current waveforms injected into a low-voltage grid. The fact that the proposed model remains slightly above this legal limit is entirely reasonable and acceptable considering the extremely dynamic and multivariate test conditions to which the system is subjected. In the literature, THD values can only be lower in DVR systems

Table 5. RNN application error types and values

Error Type	Formula	Calculated value
MSE	$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2$	0.0251
RMSE	$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2}$	0.0316
MAE	$MAE = \frac{1}{n} \sum_{i=1}^n y_i - \hat{y}_i $	0.0615
MAPE	$MAPE = \frac{1}{n} \sum_{i=1}^n \frac{ y_i - \hat{y}_i }{y_i} \cdot 100\%$	0.0051

Table 6. Power, voltages and current characteristics of the proposed system

States (Temperature) →	600°C	570°C	540°C
Fuel Cell Power (W)	3481	3310	3120
Fuel Cell Voltage (V)	104.86	98.5	93.5
Grid Voltage (V) (max)	311	311	311
Grid Current (A)	22.5	21.5	20.5
THD (%)	5.59	5.7	5.1
Power Factor	0.992	0.984	0.987
DC Link Voltage (V)	400	400	400

operating under ideal grid conditions; However, in this study, the model was simultaneously subjected to both electrical and environmental disturbances such as voltage sags, swells, and variable temperature profiles. Temperature-dependent instantaneous power fluctuations in the fuel cell on the source side created micro-fluctuations in the DC bus (400V), straining the inverter's modulation index. It has been observed in the literature that in traditional methods or in the variable conditions (unstable regimes) of advanced methods produce $>5\%$ THD [16, 44-46]. Accordingly, the proposed system has been proven to exhibit acceptable and competitive harmonic performance against challenging disturbances, in line with the literature. The study was conducted entirely in a simulation environment (Matlab/Simulink) with noise-free ideal datasets. In real-world applications, sensor noise and quantization errors originating from current/voltage transducers can distort the input matrix, affecting RNN prediction accuracy. Furthermore, the deep matrix computational overhead of RNN models can cause hardware latency and consequently microsecond phase shifts in PWM signals when running in real-time in embedded systems (DSP/FPGA). To overcome these limitations and definitively reduce the THD profile below the 5.0% standard limit, future studies plan to test the model in real-time on dSPACE or Hardware-in-the-Loop (HIL) platforms. Additionally, the goal is to completely eliminate high-frequency switching harmonics by integrating an adaptive damping LCL filter into the system.

CONCLUSION

In this study, a single phase efficient power circuit structure where fuel cells feed both the grid and sensitive loads is modeled and inverter PWM estimation and analysis are performed with RNN. In order for sensitive loads not to be affected by voltage changes (sags and swells), DVR application is implemented (the proposed system model is presented in detail in Fig. 2). In addition, in order to provide maximum power performance of the fuel cell at variable temperatures, P&O MPPT algorithm is applied to the dc-dc boost converter (Fig. 4). While PLL-PR and dc-link control methods are used for the grid connection of the study, PLL-Hysteresis control methods are used for the DVR application. As a result of the application, the fuel cell produces 3481 W power at 600°C, 3310W at 570°C and 3120W at 540°C (Table 5 and Fig. 11). In addition, the DC link voltage is kept constant at 400 V (reference value) (Table 5 and Fig. 13). While the grid current harmonics fluctuate between $5.1\% < \text{THD}\% < 5.7$, the power factor fluctuates between $0.984 < \text{pf} < 0.992$ (Fig. 16 and Table 5). In DVR technology used to eliminate voltage irregularities in sensitive loads, offline analysis of the RNN method for PWM estimation has been performed, and the result of process, MSE is determined as 0.0251, while the performances of other error types are presented in detail in Table 4. The sensitive load continued to perform at the nominal level without being affected by the voltage changes (Fig.

17). The contributions of the proposed study and the features of the designed system can be summarized in the light of the findings mentioned below.

1. In order to maximize the power harvested from the Fuel Cell (SOFC) under different operating conditions and to reduce the implementation cost, the PWM generated from the MPPT algorithm was applied to the dc-dc boost converter.
2. Injecting the generated power into the grid and supplying the load with low harmonics and high power factor, achieved using PLL-PR control and DC-link control, ensuring reliable power flow.
3. A single-phase DVR based on Hysteresis control was implemented to protect sensitive loads from sudden voltage sag and swells. Reliability was ensured by testing it under sudden voltage changes.
4. The infrastructure for integrating the proposed system into smart grids was established by estimating the switching signal of the single-phase full-bridge inverter using Deep Learning (RNN) technology.

The modeling, analysis, and implementation of the proposed study are performed within the MATLAB/Simulink environment

NOMENCLATURE

Abbreviations

SOFC	Solid Oxide Fuel Cell
LCL	Inductor-Capacitor-Inductor
PLL	Phase-Locked Loop
PR	Proportional Resonance
MSE	Mean Squared Error
RNN	Recurrent Neural Network
THD	Total Harmonics Distortion
AI	Artificial intelligence
MPPT	Maximum Power Point Tracking
DVR	Dynamic Voltage Restorer
PI	Proportional and Integral
PWM	Phase Width Modulation

Variables

V_C	Fuel Cell Output Voltage
V_{con}	Concentration Voltage
V_{act}	Activation Voltage
B_a	Membrane Effective Area
V_{om}	Ohmic Voltage
V_{tdrop}	Total Voltage Drop
R	Total Resistance
V_{dc}	DC Link Voltage
y_t	Output At Each Time Step
b_h	Bias Vector
σ_y	Activation Function
W_{xh}	Weight Matrix
x_t	Input Data
h_t	Hidden State
f_{grid}	Grid Voltage Frequency
L_b	Boost Converter Inductor
C_b	Boost Converter Capacitor
ΔI_L	Inductor Current Ripple
L_3 (Filter)	Filter Primer Inductor
C_2 (Filter)	Filter Capacitor
L_2 (Filter)	Filter Seconder Inductor

ω_o	Ac Frequency
ω_c	Cut-off Frequency
D	Duty Cycle
K_p	Proportional Gain
K_i	Integral Gain
$W_{res.}$	Resonant Frequency
I_{den}	Current Density
I_{op}	Fuel Cell Output Current
V_{ref}	Reference Voltage
ω_o	Ac Frequency
ω_c	Cut-off Frequency
D	Duty Cycle
K_p	Proportional Gain
K_i	Integral Gain
$W_{res.}$	Resonant Frequency
I_{den}	Current Density
I_{op}	Fuel Cell Output Current
V_{ref}	Reference Voltage

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AUTHORSHIP CONTRIBUTIONS

Ünal YILMAZ: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Data curation, Conceptualization. **Kerim KARADAĞ:** Validation, Software, Resources, Methodology, Investigation, Data curation, Conceptualization. **Süleyman Bayram GÖNÜLLÜ:** Validation, Software, Resources, Methodology, Investigation, Data curation, Conceptualization.

DATA AVAILABILITY STATEMENT

The authors confirm that the data that supports the findings of this study are available within the article. Raw data that support the finding of this study are available from the corresponding author, upon reasonable request.

CONFLICT OF INTEREST

The authors declared no conflict of interest.

ETHICS

There are no ethical issues with the publication of this manuscript.

STATEMENT ON THE USE OF ARTIFICIAL INTELLIGENCE

During the preparation of this study, the author(s) used ChatGPT and Gemini AI for the purposes of proofreading, checking the grammar, improving the readability, and correcting spelling. The authors have reviewed and edited the output and take full responsibility for the content of this publication.

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