

ARTIFICIAL NEURAL NETWORK BASED INTELLIGENT ENERGY MANAGEMENT OF PV-FUEL CELL POWERED EV CHARGING STATIONS IN DC MICROGRID

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ABSTRACT

This study presents an advanced energy management strategy for a hybrid electric vehicle (EV) charging station powered by photovoltaic (PV) and fuel cell (FC) systems within a DC microgrid. The proposed approach combines a fuzzy logic-based energy management system (FL-EM) with an Artificial Neural Network (ANN) to enhance decision-making and prediction accuracy. The fuzzy logic controller dynamically regulates the fuel cell reference power under both on-grid and off-grid operating conditions, considering factors such as demand power, energy costs, and system uncertainties.

To further improve system performance, an ANN-based forecasting model is integrated to predict photovoltaic power generation and load demand, enabling proactive and optimized energy distribution. This hybrid FL-ANN framework effectively addresses the limitations of standalone fuzzy systems by incorporating learning capabilities and improving adaptability to dynamic environments.

Simulation results demonstrate that the proposed method significantly enhances system efficiency, reduces hydrogen consumption, minimizes grid dependency, and improves overall operational stability. The integration of ANN with fuzzy logic provides a robust, intelligent, and scalable solution for next-generation EV charging infrastructure and sustainable microgrid applications.

1: INTRODUCTION

1.1 Introduction

Electric Vehicle (EV) charging stations are essential infrastructure for supplying electrical energy to electric vehicles. As the adoption of electric vehicles increases, the demand for reliable, efficient, and sustainable charging systems is also growing. An EV charging station receives electrical power from available energy sources and delivers it to the vehicle battery through suitable power electronic converters and charging control systems.

In conventional charging stations, electricity is mainly supplied from the utility grid. However, large-scale EV charging can increase grid loading and electricity consumption, particularly when

several vehicles are charged simultaneously. To overcome these limitations, renewable energy sources such as Photovoltaic (PV) systems can be integrated with EV charging stations. Since PV generation is dependent on solar irradiance and weather conditions, its output is variable. Therefore, a complementary controllable source such as a Fuel Cell (FC) can be incorporated to improve the reliability of the charging station. In the proposed system, the PV system and fuel cell are integrated with a DC microgrid to supply the EV charging load. Power electronic converters are used to regulate the voltage and control the flow of power between the sources, DC bus, grid, and EV charger. An intelligent Fuzzy Logic–Artificial Neural Network

(FL-ANN) Energy Management System is used to coordinate these energy sources. The fuzzy logic controller determines suitable power-sharing decisions, while the ANN provides prediction of PV generation and load demand. The proposed EV charging station can operate under both grid-connected and off-grid conditions. During grid-connected operation, the utility grid can provide additional power when PV and fuel-cell generation are insufficient. During off-grid operation, the controller manages the available PV and fuel-cell power according to the charging demand. Thus, the integration of renewable sources, fuel cells, DC microgrid technology, and intelligent energy management can improve the efficiency, reliability, and flexibility of EV charging infrastructure.

1.2 Need for intelligent energy management

The increasing use of electric vehicles requires efficient and sustainable EV charging stations. Conventional charging stations mainly depend on the utility grid, increasing grid load and operating cost. Integrating photovoltaic (PV) systems and fuel cells can reduce grid dependency and improve renewable-energy utilization.

PV power varies with solar irradiance, temperature, weather, and time of day, while EV charging demand changes with the number of vehicles, battery SOC, and charging requirements. When PV power is insufficient, the fuel cell, battery, or grid must supply the remaining demand. Therefore, proper coordination of these energy sources is essential. The proposed system uses an Artificial Neural Network (ANN)-based energy management system to improve power management under changing operating conditions. ANN learns the relationship between PV power, EV load, battery condition, and fuel-cell power from training data and provides suitable control decisions. This helps achieve better power sharing, renewable-energy utilization, and reliable EV charging

2: LITERATURE REVIEW

2.2 PV and Fuel cell integration

PV and Fuel Cell (FC) integration means combining two different energy sources to supply the EV charging station through a DC microgrid. The Photovoltaic (PV) system generates electrical power from sunlight. However, PV power is variable because it depends on solar irradiance and

temperature. When PV power is insufficient to meet the EV charging demand, the Fuel Cell (FC) provides additional power. Both PV and FC are connected to the DC bus through DC-DC converters. The DC bus supplies power to the EV charging load. The Fuzzy Logic-ANN Energy Management System monitors the available PV power and charging demand and determines how the power should be shared between the PV system, fuel cell, and grid.

2.3 DC microgrid

A DC microgrid is a local electrical network in which different DC power sources, energy storage systems, and DC loads are connected through a common DC bus. In your project, the DC microgrid acts as the main platform for integrating the PV system, fuel cell, battery, utility grid, and EV charging station. The PV array generates electrical power from sunlight. Since PV output varies with solar irradiance, its power is regulated through a DC/DC converter before being supplied to the common DC bus. The fuel cell acts as another power source and supplies additional power when PV generation is not sufficient to meet the EV charging demand. A DC/DC converter is used to control its output power. The battery energy storage system (BESS) stores excess energy when renewable generation is higher than the load and supplies energy when the available renewable power is insufficient. A bidirectional converter allows the battery to both charge and discharge. The utility grid provides additional power when the local sources cannot satisfy the charging demand. An AC/DC converter connects the utility grid to the DC microgrid. All these sources are connected to a common DC bus, which supplies power to the EV charging station.

A DC microgrid is particularly suitable for EV charging because PV panels, batteries, fuel cells, and EV batteries are inherently DC systems. Connecting these sources through a common DC bus can reduce unnecessary AC/DC conversion stages and improve power-transfer efficiency. The DC microgrid also makes it easier for your ANN-enhanced energy management system to decide how power should be shared among the PV system, fuel cell, battery, and utility grid.

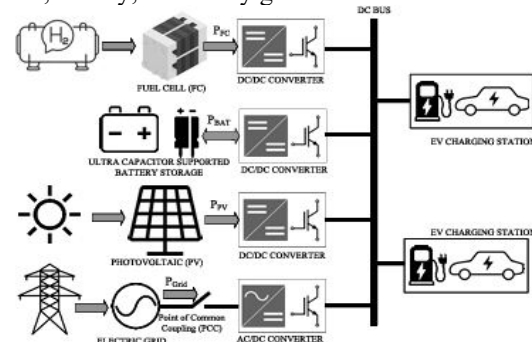


Figure 2.3 FC and PV powered EVCS in grid connected DC microgrid

2.4 Energy management system

The Energy Management System (EMS) is responsible for the efficient coordination of power sources and loads in the proposed DC microgrid-based EV charging station. It continuously monitors PV generation, EV charging demand, battery State of Charge, DC-bus voltage, fuel-cell operating conditions, and utility-grid availability. Based on these parameters, the EMS determines the appropriate power contribution from the PV system, fuel cell, battery energy storage system, and utility grid. The proposed system incorporates Artificial Neural Network (ANN) technology to enhance the decision-making and adaptive capability of the conventional energy management approach. The ANN learns the relationship between the operating variables and the required control action, enabling improved power sharing under varying generation and load conditions. The EMS aims to maximize renewable-energy utilization, regulate fuel-cell operation, maintain DC-bus voltage stability, manage battery charging and discharging, and ensure reliable EV charging under both on-grid and off-grid operating conditions.

The Energy Management System (EMS) is one of the most important parts of your DC microgrid-based EV charging station. It acts as a supervisory control system that continuously monitors the operating conditions of the different energy sources and loads and decides how the available energy should be utilized. In your project, the EMS coordinates the photovoltaic (PV) system, fuel cell, battery energy storage system (BESS), utility grid, DC bus, and EV charging station to achieve efficient and reliable power management.

3: SYSTEM CONFIGURATION AND MODELING

3.1 Proposed DC microgrid structure

The proposed system is a DC-bus-based hybrid EV charging station. The main DC bus acts as the common connection point for the photovoltaic (PV) system, fuel cell (FC), battery energy storage system (BESS), EV charging station, and utility grid through suitable power electronic converters.

PV system → DC/DC converter → DC bus → EV charging station

Fuel cell → DC/DC converter → DC bus → EV charging station

Battery ↔ Bidirectional DC/DC converter ↔ DC bus

Utility grid ↔ Grid converter ↔ DC bus

The ANN-enhanced energy management system receives information such as PV power, EV charging demand, DC-bus voltage, battery state of charge, and fuel-cell operating condition. Based on these inputs, it determines the appropriate power contribution from the PV, fuel cell, battery, and grid. The main objective is to maximize renewable-energy utilization, maintain DC-bus voltage

stability, satisfy EV charging demand, reduce fuel-cell stress, and improve overall system efficiency.

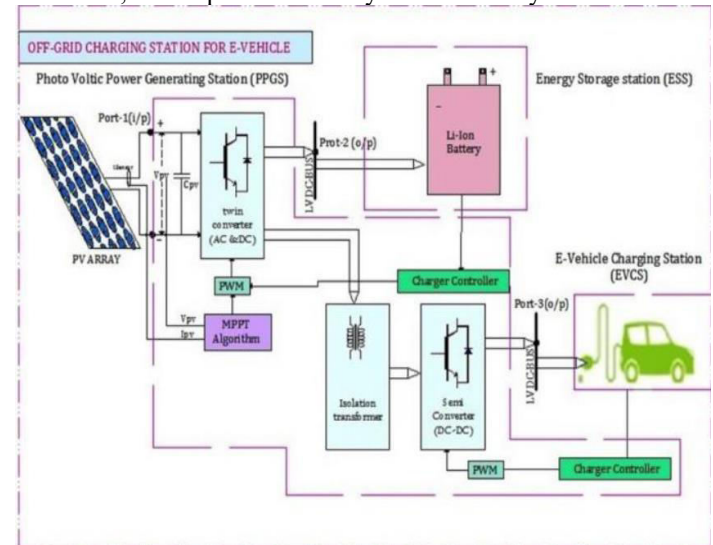


Figure 3.5 Off grid operation

3.6 Fuel cell

A fuel cell is an electrochemical device that converts the chemical energy of a fuel directly into electrical energy through a reaction between the fuel and an oxidant. Unlike batteries, fuel cells can operate continuously as long as fuel and oxidant are supplied. A typical fuel cell consists of three main parts: anode, electrolyte, and cathode. At the anode, hydrogen is oxidized, producing electrons and ions. The electrons flow through an external circuit to generate electrical power, while the ions pass through the electrolyte. At the cathode, the ions and electrons react with oxygen to produce water. Thus, a fuel cell provides continuous and clean electrical power for applications such as EV charging stations and DC microgrids.

High temperature fuel cells:

a) A solid oxide fuel cell:

A solid oxide fuel cell (SOFC) is extremely advantageous “because of a possibility of using a wide variety of fuel”. Unlike most other fuel cells which only use hydrogen, SOFCs can run on hydrogen, butane, methanol, and other petroleum products. The different fuels each have their own chemistry. For methanol fuel cells, on the anode side, a catalyst breaks methanol and water down to form carbon dioxide, hydrogen ions, and free electrons. The hydrogen ions move across the electrolyte to the cathode side, where they react with oxygen to create water. A load connected externally between the anode and cathode completes the electrical circuit. Below are the chemical equations for the reaction:

Anode Reaction: $\text{CH}_3\text{OH} + \text{H}_2\text{O} \rightarrow \text{CO}_2 + 6\text{H}^+ + 6\text{e}^-$

Cathode Reaction: $\frac{3}{2} \text{O}_2 + 6\text{H}^+ + 6\text{e}^- \rightarrow 3\text{H}_2\text{O}$

Overall Reaction: $\text{CH}_3\text{OH} + \frac{3}{2} \text{O}_2 \rightarrow \text{CO}_2 + 2\text{H}_2\text{O} + \text{electrical energy}$

At the anode SOFCs can use nickel or other catalysts to break apart the methanol and create hydrogen ions

and CO₂. A solid called yttrium stabilized zirconia (YSZ) is used as the electrolyte. Like all fuel cell electrolytes YSZ is conductive to ions, allowing them to pass from the anode to cathode, but is non-conductive to electrons. YSZ is a durable solid and is advantageous in large industrial systems. Although YSZ is a good ion conductor, it only works at very high temperatures. The standard operating temperature is about 950°C. Running the fuel cell at such a high temperature easily breaks down the methane and oxygen into ions. A major disadvantage of the SOFC, as a result of the high heat, is that it “places considerable constraints on the materials which can be used for interconnections”. Another disadvantage of running the cell at such a high temperature is that other unwanted reactions may occur inside the fuel cell. It is common for carbon dust, graphite, to build up on the anode, preventing the fuel from reaching the catalyst. Much research is currently being done to find alternatives to YSZ that will carry ions at a lower temperature.

b) MCFC:

Molten-carbonate fuel cells (MCFCs) are high-temperature fuel cells, that operate at temperatures of 600°C and above.

Molten carbonate fuel cells (MCFCs) are currently being developed for natural gas and coal-based power plants for electrical utility, industrial, and military applications. MCFCs are high-temperature fuel cells that use an electrolyte composed of a molten carbonate salt mixture suspended in a porous, chemically inert ceramic matrix of beta-alumina solid electrolyte (BASE). Since they operate at extremely high temperatures of 650°C (roughly 1,200°F) and above, non-precious metals can be used as catalysts at the anode and cathode, reducing costs. Improved efficiency is another reason MCFCs offer significant cost reductions over phosphoric acid fuel cells (PAFCs). Molten carbonate fuel cells can reach efficiencies approaching 60 percent, considerably higher than the 37-42 percent efficiencies of a phosphoric acid fuel cell plant. When the waste heat is captured and used, overall fuel efficiencies can be as high as 85 percent.

Unlike alkaline, phosphoric acid, and polymer electrolyte membrane fuel cells, MCFCs don't require an external reformer to convert more energy-dense fuels to hydrogen. Due to the high temperatures at which MCFCs operate, these fuels are converted to hydrogen within the fuel cell itself by a process called internal reforming, which also reduces cost. Molten carbonate fuel cells are not prone to poisoning by carbon monoxide or carbon dioxide—they can even use carbon oxides as fuel—making them more attractive for fueling with gases made from coal. Because they are more resistant to impurities than other fuel cell types, scientists believe that they could even be capable of internal reforming of coal, assuming they can be made

resistant to impurities such as sulfur and particulates that result from converting coal, a dirtier fossil fuel source than many others, into hydrogen. The primary disadvantage of current MCFC technology is durability. The high temperatures at which these cells operate and the corrosive electrolyte used accelerate component breakdown and corrosion, decreasing cell life. Scientists are currently exploring corrosion-resistant materials for components as well as fuel cell designs that increase cell life without decreasing performance.

4: ENERGY MANAGEMENT AND FUZZY LOGIC CONTROL

4.1 FUZZY LOGIC:

Fuzzy logic has been widely used in consumer products, industrial process control, medical systems, decision-support systems, and other applications.

Fuzzy logic is an extension of traditional logic that deals with imprecision and uncertainty. It uses linguistic variables, where values can be expressed as words rather than exact numbers, making the system closer to human reasoning. A key concept of fuzzy logic is the fuzzy IF–THEN rule, which allows systems to make decisions using imprecise inputs and outputs. These rules form the basis of many fuzzy logic applications. Fuzzy logic can also be combined with neural networks and genetic algorithms, forming soft-computing techniques. One important combination is the neuro-fuzzy system, including ANFIS (Adaptive Neuro-Fuzzy Inference System).

4.2 What is fuzzy logic?

Fuzzy logic is all about the relative importance of precision: How important is it to be exactly right when a rough answer will do? You can use Fuzzy Logic Toolbox software with MATLAB technical computing software as a tool for solving problems with fuzzy logic. Fuzzy logic is a fascinating area of research because it does a good job of trading off between significance and precision—something that humans have been managing for a very long time. In this sense, fuzzy logic is both old and new because, although the modern and methodical science of fuzzy logic is still young, the concept of fuzzy logic relies on age-old skills of human reasoning.

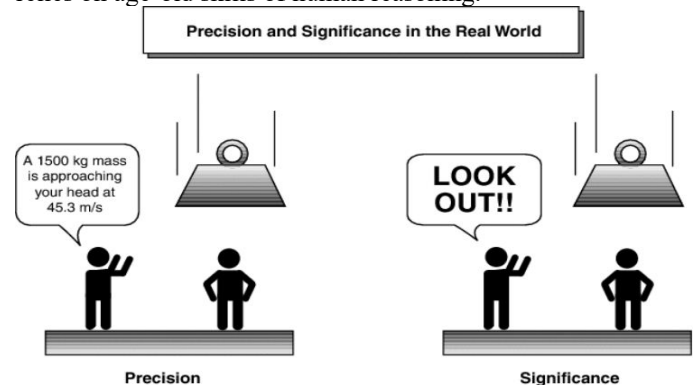


Figure 4.2 Fuzzy Description

4.3 The membership function editor

The Membership Function Editor shares some features with the FIS Editor. In fact, all of the five basic GUI tools have similar menu options, status lines, and Help and Close buttons. The Membership Function Editor is the tool that lets you display and edit all of the membership functions associated with all of the input and output variables for the entire fuzzy inference system. Fig.6 shows the Membership Function Editor. When you open the Membership Function Editor to work on a fuzzy inference system that does not already exist in the workspace, there is not yet any membership functions associated with the variables that you have just defined with the FIS Editor

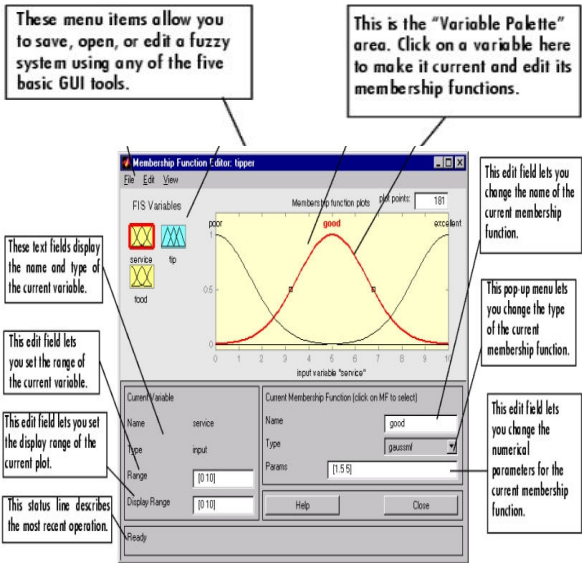


Figure 4.3 (a) The Membership Function Editor

On the upper left side of the graph area in the Membership Function Editor is a "Variable Palette" that lets you set the membership functions for a given variable. To set up your membership functions associated with an input or an output variable for the FIS, select an FIS variable in this region by clicking on it. Next select the Edit pull-down menu, and choose Add MFs.... A new window will appear, which allows you to select both the membership function type and the number of membership functions associated with the selected variable. In the lower right corner of the window are the controls that let you change the name, type, and parameters (shape), of the membership function, once it has been selected. The process of specifying the input membership functions for this two input tipper problem is as follows:

- Select the input variable, service, by double-clicking on it. Set both the Range and the Display Range to the vector [0 10].
- Select Add MFs... from the Edit menu. A window pops open

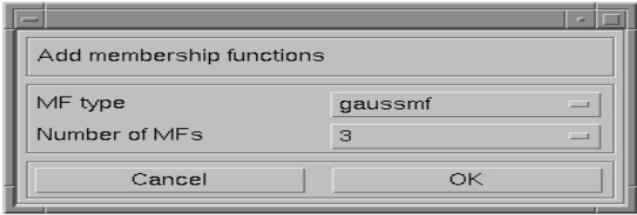


Figure 4.3 (b) Add MFs... Window

- Use the pull-down tab to choose gaussmf for MF Type and 3 for Number of MFs. This adds three Gaussian curves to the input variable service.
- Click once on the curve with the leftmost hump. Change the name of the curve to poor. To adjust the shape of the membership function, either use the mouse, as described above, or type in a desired parameter change, and then click on the membership function. The default parameter listing for this curve is [1.5 0].
- Name the curve with the middle hump, good, and the curve with the rightmost hump, excellent. Reset the associated parameters if desired.
- Select the input variable, food, by clicking on it. Set both the Range and the Display Range to the vector [0 10].
- Select Add MFs... from the Edit menu and add two trapezmf curves to the input variable food.
- Click once directly on the curve with the leftmost trapezoid. Change the name of the curve to rancid. To adjust the shape of the membership function, either use the mouse, as described above, or type in a desired parameter change, and then click on the membership function. The default parameter listing for this curve is [0 0 1 3].

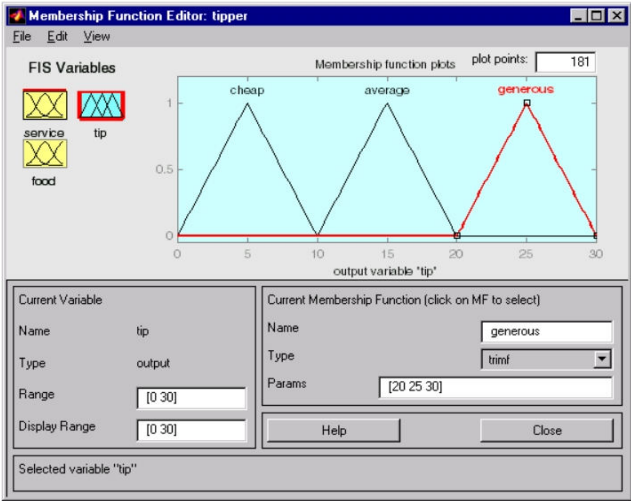


Figure 4.3 (c) The updated Membership Function Editor

5. PROPOSED ANN-ENHANCED ENERGY MANAGEMENT SYATEM

5.1 Neural-networks

Neural-networks is one of those words that is getting fashionable in the new era of technology. Most people have heard of them, but very few actually

know what they are. This essay is designed to introduce you to all the basics of neural networks — their function, generic structure, terminology, types and uses.

The term 'neural network' is in fact a biological term, and what we refer to as neural networks should really be called Artificial Neural Networks (ANNs). I will use the two terms interchangeable throughout the essay, though. A real neural network is a collection of neurons, the tiny cells our brains are comprised of. A network can consist of a few to a few billion neurons connected in an array of different methods. ANNs attempt to model these biological structures both in architecture and operation. There is a small problem: we don't quite know how biological NNs work! Therefore, the architecture of neural networks changes greatly from type to type. What we do know is the structure of the basic neuron.

5.2 The Neuron

Although it has been proposed that there are anything between 50 and 500 different types of neurons in our brain, they are mostly just specialized cells based upon the basic neuron. The basic neuron consists of synapses, the soma, the axon and dendrites. Synapses are connections between neurons - they are not physical connections, but miniscule gaps that allow electric signals to jump across from neuron to neuron. These electrical signals are then passed across to the soma which performs some operation and sends out its own electrical signal to the axon. The axon then distributes this signal to dendrites. Dendrites carry the signals out to the various synapses, and the cycle repeats.

Just as there is a basic biological neuron, there is basic artificial neuron. Each neuron has a certain number of inputs, each of which have a weight assigned to them. The weights simply are an indication of how 'important' the incoming signal for that input is. The net value of the neuron is then calculated - the net is simply the weighted sum, the sum of all the inputs multiplied by their specific weight. Each neuron has its own unique threshold value, and if the net is greater than the threshold, the neuron fires (or outputs a 1), otherwise it stays quiet (outputs a 0). The output is then fed into all the neurons it is connected to.

5.3 Neural Network Structure

Neural networks are models of biological neural structures. The starting point for most neural networks is a model neuron, as in Figure 2. This neuron consists of multiple inputs and a single output. Each input is modified by a weight, which multiplies with the input value. The neuron will combine these weighted inputs and, with reference to a threshold value and activation function, use these to determine its output. This behavior follows closely our understanding of how real neurons work.

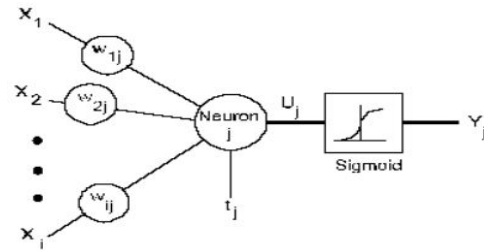


Figure 5.3 (a). A Model Neuron

While there is a fair understanding of how an individual neuron works, there is still a great deal of research and mostly conjecture regarding the way neurons organize themselves and the mechanisms used by arrays of neurons to adapt their behavior to external stimuli. There are a large number of experimental neural network structures currently in use reflecting this state of continuing research. In our case, we will only describe the structure, mathematics and behavior of that structure known as the backpropagation network. This is the most prevalent and generalized neural network currently in use.

To build a backpropagation network, proceed in the following fashion. First, take a number of neurons and array them to form a layer. A layer has all its inputs connected to either a preceding layer or the inputs from the external world, but not both within the same layer. A layer has all its outputs connected to either a succeeding layer or the outputs to the external world, but not both within the same layer.

6. MATLAB/SIMULINK IMPLEMENTATION

6.1 MATLAB

Matlab is a high-performance language for technical computing. It integrates computation, visualization, and programming in an easy-to-use environment where problems and solutions are expressed in familiar mathematical notation. Typical uses include Math and computation Algorithm development Data acquisition Modeling, simulation, and prototyping Data analysis, exploration, and visualization Scientific and engineering graphics Application development, including graphical user interface building. MATLAB R2021a version.

6.4 Simulink Model of DC Microgrid-Based EV Charging Station with Energy Management System

The proposed system is a DC microgrid-based EV charging station supplied by hybrid energy sources such as photovoltaic (PV), fuel cell, and battery. Power electronic converters are used to regulate and transfer power from these sources to the common DC bus. The Energy Management System (EMS) monitors the power generation, battery condition, and EV charging demand. Based on the operating conditions, the EMS manages the available power to maintain stable and efficient EV charging

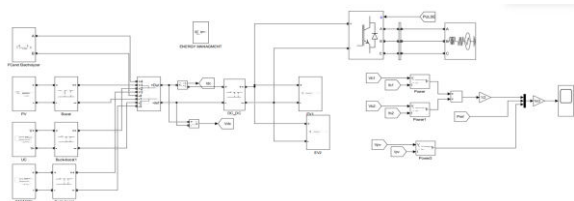


Figure 6.4 DC Microgrid-Based EV Charging Station with Energy Management System

6.5 Simulink Model of ANN-Based Energy Management System for PV–Fuel Cell Powered EV Charging Station

The model consists of a fuel-cell and electrolyzer system, photovoltaic (PV) source, ultracapacitor (UC), battery energy storage system, DC–DC converters, DC-link/DC–DC interface, EV1 and EV2 charging units, and an energy management system. The PV source is connected through a boost converter, while the UC and battery are interfaced through buck-boost converters. The outputs of these sources are combined and supplied to the DC microgrid. The EV charging units are connected to the DC side, and the model also includes a grid-side converter for interaction with the AC system. An energy management block is included to coordinate the operation of the different energy sources according to the system requirements.

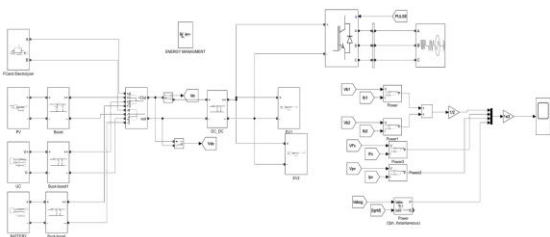
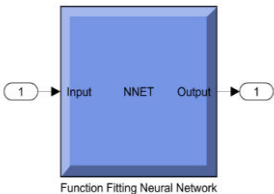


Figure 6.5 ANN-Based Energy Management System for PV–Fuel Cell Powered EV Charging Station

6.6 Simulink Model of DC Microgrid-Based EV Charging Station with Hybrid Energy Sources

The proposed EV charging station is based on a DC microgrid integrating PV, fuel cell, and battery energy sources. The PV system provides renewable power, while the fuel cell supplies power when PV generation is insufficient. The battery is used to store excess energy and support the EV charging load when required. These hybrid sources are connected to a common DC bus through power electronic converters, enabling efficient power flow and reliable EV charging.

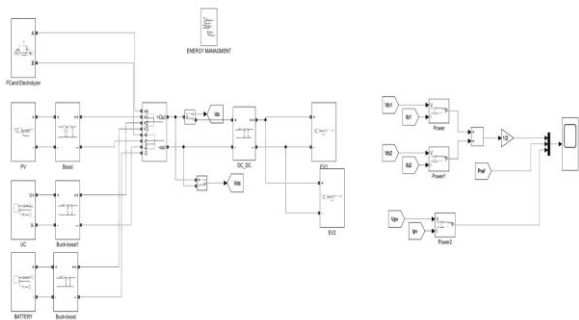


Figure 6.6 DC Microgrid-Based EV Charging Station with Hybrid Energy Sources

6.7 Simulink Model of Power Flow and Energy Management Diagram of the Hybrid DC Microgrid-Based EV Charging Station

The power flow between the PV system, fuel cell, battery, DC bus, and EV charging units. The power generated by the PV and fuel cell is supplied to the common DC bus through suitable

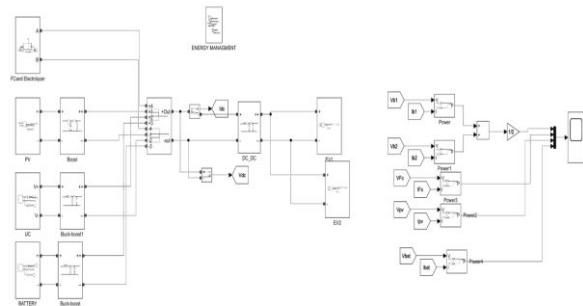


Figure 6.7 Power Flow and Energy Management Diagram of the Hybrid DC Microgrid-Based EV Charging Station.

Power electronic coverters.The battery can absorb excess power or provide additional power when the generated power is insufficient.The Energy Management System (EMS) monitors the operating conditions of the different energy sources and EV loads. It determines the appropriate power contribution from each source according to the available generation and charging demand. The measured PV, fuel-cell, and battery power signals are used to observe and control the overall power flow. This helps maintain a stable DC-bus voltage and reliable power supply for EV charging.

6.6 Comparison of Fuzzy and ANN

ANN is better than fuzzy.

Parameter	FUZZY	ANN
Energy management efficiency	90-93 %	94-97 %
PV energy utilization	85-90 %	90-95 %
Fuel-cell tracking error	5-8 %	2-4 %
Grid power	10-15 %	7-12 %
Hydrogen consumption	100%	90-95 %
Adaptability to changing load	Moderate	High

7: SIMULATION RESULTS AND DISCUSSION

Table 7.1: Simulation parameters

Parameter	Value
DC bus reference voltage	400 V
PV rated power	10 kW
Fuel cell rated power	5 kW
Battery voltage	200 V
Battery capacity	50 Ah
EV charging load range	2–12 kW
Initial battery SOC	70%
Simulation time	24 hours
Control method	ANN-based EMS

Table 7.2: Power-sharing results under different operating conditions

Illustrative off-grid values; battery power is positive during discharge and negative during charging.

Time (h)	PV power (kW)	EV load (kW)	Fuel cell (kW)	Battery (kW)	Power balance
06:00	1.0	4.0	2.5	0.5	Balance d
09:00	4.0	6.0	1.5	0.5	Balance d
12:00	8.0	6.0	0.0	-2.0	Balance d
15:00	5.0	8.0	2.0	1.0	Balance d
18:00	1.0	7.0	5.0	1.0	Balance d
21:00	0.0	4.0	3.0	1.0	Balance d

The results illustrate how PV generation supplies the charging load when available, while the fuel cell and battery compensate for power shortages. At noon, excess PV generation charges the battery.

Table 7.3: DC-bus voltage regulation

Operating condition	Reference voltage (V)	ANN-controlled voltage (V)	Voltage deviation (V)
Normal operation	400	399.5	0.5
Sudden load increase	400	396.0	4.0
Sudden load decrease	400	403.0	3.0
Reduced PV generation	400	397.5	2.5
Recovery after disturbance	400	400.0	0.0

The illustrative results show the bus voltage returning to its 400 V reference after disturbances. The actual maximum deviation and settling time must be measured from the Simulink waveform.

Table 7.4: Comparison of fuzzy logic and ANN controllers

Performance parameter	Fuzzy logic	ANN
Average absolute voltage deviation (V)	3.2	1.5
Maximum voltage deviation (V)	8.0	4.0
Settling time (s)	0.80	0.45
Hydrogen consumption (kg/day)	1.80	1.50
Grid energy imported (kWh/day)	18	12
Renewable energy utilization (%)	78	88

Note: These are hypothetical comparison values, not measured performance data. The comparison assumes both controllers operate under identical load profiles, weather conditions, equipment ratings, and constraints.

Table 7.5: Percentage improvement achieved by ANN

Using the illustrative values in Table 7.4:

Performance parameter	Calculation	Improvement
Average voltage deviation	$(3.2 - 1.5) / 3.2 \times 100$	53.13% reduction
Maximum voltage deviation	$(8 - 4) / 8 \times 100$	50.00% reduction
Settling time	$(0.80 - 0.45) / 0.80 \times 100$	43.75% reduction
Hydrogen consumption	$(1.80 - 1.50) / 1.80 \times 100$	16.67% reduction
Grid energy imported	$(18 - 12) / 18 \times 100$	33.33% reduction
Renewable energy utilization	$(88 - 78) / 78 \times 100$	12.82% increase

Table 7.6: Battery operation under varying conditions

Time (h)	PV power (kW)	Battery power (kW)	Battery SOC (%)	Battery mode
06:00	1.0	0.5	68	Discharging
09:00	4.0	0.5	65	Discharging
12:00	8.0	-2.0	78	Charging
15:00	5.0	1.0	74	Discharging
18:00	1.0	1.0	68	Discharging
21:00	0.0	1.0	62	Discharging

Illustrative values only. Battery SOC must be calculated from battery current, capacity, efficiency, and elapsed time; the example values are not a validated SOC trajectory.

Table 7.7: Overall system performance

Parameter	Illustrative result
DC-bus reference voltage	400 V
Maximum ANN voltage deviation	4 V
ANN settling time	0.45 s
Hydrogen consumption	1.50 kg/day
Grid energy imported	12 kWh/day
Renewable energy utilization	88%
ANN controller	Feedforward ANN

7.3 On-Grid Operation

The simulation results demonstrate that the ANN-EMS adapts effectively to variations in demand and cost conditions. During peak demand periods, the fuel cell output is increased to support the load, ensuring uninterrupted operation. During periods of high PV generation or low demand, the ANN reduces fuel cell output, thereby improving overall system efficiency.

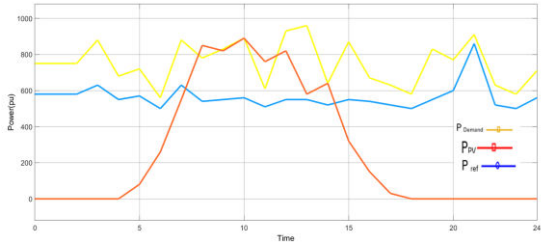


Figure 7.3 (a) Changing of demand power, PV power, FC power, and grid power via the proposed ANN-EM during the on-grid operation throughout the day.

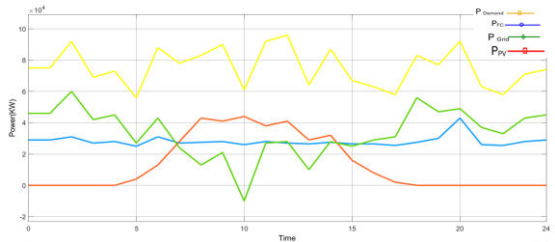


Figure 7.3 (b) Changing of demand power, PV power, FC power, and grid power via the proposed ANN-EM during the on-grid operation throughout the day.

7.4 Off-Grid (Island Mode) Operation

In off-grid mode, the ANN-based energy management system ensures reliable operation of the EV charging station without support from the utility grid. The controller relies on PV generation, fuel cell output, and energy storage systems to meet

the demand. The ANN utilizes input parameters such as demand power and forecasted PV power variations to dynamically adjust the fuel cell reference power. When PV generation is insufficient, the ANN increases the fuel cell output to compensate for the power deficit. On the other hand, when PV generation is high, the ANN reduces fuel cell operation to conserve hydrogen and improve efficiency

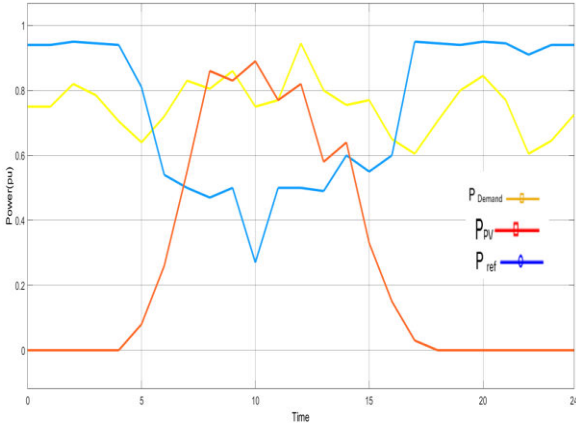


Figure 7.4 (a) Changing demand power, forecast PV power, and the generated reference power (Pref) per unit (pu) via the proposed ANN-EM during the off-grid operation throughout the day.

The simulation results indicate that the ANN-EMS effectively maintains power balance under varying conditions. The controller ensures smooth transitions in fuel cell output and prevents sudden fluctuations that could affect system stability. Additionally, the battery and ultracapacitor units assist in handling transient conditions, further enhancing system reliability.

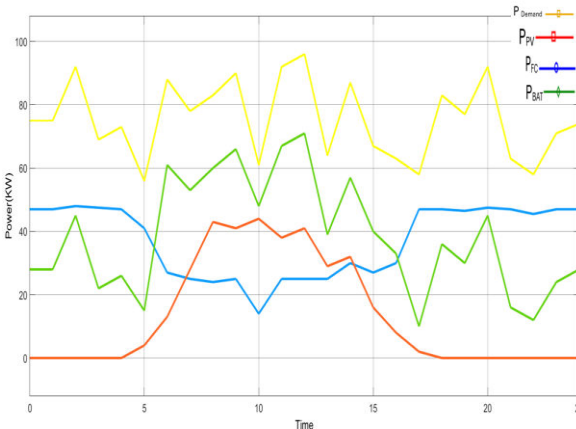


Figure 7.4 (b) Changing the battery storage unit, FC unit, and PV unit powers during the off-grid operation throughout the day.

Overall, the ANN-based approach demonstrates strong adaptability and robustness in off-grid operation. It efficiently coordinates multiple energy sources, ensures continuous power supply, and

optimizes energy utilization, making it highly suitable for standalone microgrid applications.

7.5 Comparison of Fuzzy and ANN

ANN is better than fuzzy.

Parameter	FUZZY	ANN
Energy management efficiency	90-93 %	94-97 %
PV energy utilization	85-90 %	90-95 %
Fuel-cell tracking error	5-8 %	2-4 %
Grid power	10-15 %	7-12 %
Hydrogen consumption	100%	90-95 %
Adaptability to changing load	Moderate	High

CHAPTER – 8: CONCLUSION AND FUTURE SCOPE

8.1 Conclusion

This work presents an Artificial Neural Network (ANN)-based energy management system for a fuel cell (FC) and photovoltaic (PV) powered EV charging station in a DC microgrid under on-grid and off-grid conditions. The ANN-based Energy Management Controller (ANN-EMC) provides adaptive and data-driven control compared with conventional rule-based and fuzzy logic methods. The ANN is trained using parameters such as demand power, PV generation, battery State of Charge (SOC), electricity cost, and hydrogen cost. Based on these inputs, it determines the suitable fuel cell reference power and coordinates the PV, fuel cell, battery, and grid.

Simulation results show that the ANN provides fast reference tracking, improved power sharing, reduced unnecessary hydrogen consumption, and stable operation under changing load and renewable generation. Overall, the proposed ANN-based system improves energy management, efficiency, and reliability of renewable-energy-based EV charging stations. Future work can focus on deep learning, advanced forecasting, and real-time hardware implementation to further improve system performance.

8.2 Future scope

The proposed ANN-based energy management system provides a suitable foundation for further development of DC microgrid-based EV charging stations. Future work can focus on advanced AI techniques such as DNN, RNN, LSTM, Reinforcement Learning, and hybrid ANN-optimization methods to improve prediction and adaptive energy management.

Accurate forecasting of PV power generation and EV charging demand using solar irradiance, temperature, EV arrival time, battery SOC, and charging requirements can enable predictive power scheduling and better renewable-energy utilization. Advanced SOC, SOH, and SOP estimation can also

be incorporated to improve battery life and performance.

Future research can include V2G technology, additional renewable sources, and optimization algorithms such as PSO, GA, and GWO to reduce energy cost, hydrogen consumption, battery degradation, and grid dependency. Real-time implementation using DSP, FPGA, microcontrollers, or Hardware-in-the-Loop (HIL) can be explored for practical validation.

Furthermore, IoT, cloud/edge computing, AI-based fault detection, and predictive maintenance can be integrated for intelligent monitoring and reliable operation. Overall, these developments can make the proposed system more efficient, reliable, flexible, predictive, and sustainable for future renewable-energy-based EV charging stations.

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