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DESIGN AND IMPLEMENTATION OF A ZERO EMISSION VEHICLE INTEGRATED WITH MULTIPLE ENERGY SOURCES

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ABSTRACT
Due to the rising fuel prices, there is a global shift towards the adoption of hybrid electric vehicles (HEVs) because of their environmental benefits, lower maintenance needs, and alignment with green technology. In HEVs, the energy management system (EMS) is crucial for ensuring efficient energy storage and managing the power flow between the different energy sources, such as the internal combustion engine, battery, and electric motor. The EMS optimizes energy usage, enhances overall vehicle efficiency, and contributes to reducing fuel consumption and emissions, playing a pivotal role in the performance and sustainability of HEVs. This research work proposes an electric vehicle concept powered by multiple energy sources. The design will integrate solar photovoltaic (PV) energy, wind turbine and a fuel cell (FC), (PV + FC) to generate electrical energy. The vehicle will incorporate onboard solar panels, wind energy systems, proton exchange membrane (PEM) fuel cell and supercapacitor units to ensure uninterrupted energy supply during operation which can be achieved with fuzzy-based EMS. Poor design of the EMS will have effect on the performance limitations of the battery state of charge (SOC), and not fully optimizing energy recovery during braking will result in lower overall energy efficiency. This work addresses the above challenges by using fuzzy-EMS. The Simulation results showcase the system's ability to achieve zero emissions, reduce operational costs, and promote environmental sustainability.

Keywords: Energy management system, Zero-emission, Hybrid Electric Vehicle, State of charge, Multiple energy sources

INTRODUCTION
The electric vehicle is not a recent invention of the 21st century. In the early 1900s, at the dawn of the automotive industry, three main types of vehicles dominated the market: 40% were steam-powered, 38% were electric, and only 22% used gasoline. Electric vehicles were favored for their convenience as they were quiet, free from vibrations and fumes, and easy to start without the need for cranking (Albatayneh et al., 2020). However, they had limitations such as a limited range of 50-65 km, a top speed of about 30 km/h, and long recharge times. These challenges are similar to those faced by modern EVs. Consequently, despite their initial success, particularly in urban areas, electric vehicles were eventually replaced almost entirely by internal combustion engine (ICE) vehicles, like Benz's models and Ford's ubiquitous Model T. For many decades, the electric vehicle market was virtually nonexistent, except for specific applications and a few rare instances (de Carvalho Pinheiro, 2023). Despite advancements in EV energy management, existing EMS implementations struggle with real-time decision-making under uncertainty and fail to integrate multiple renewable sources in a scalable framework
Additionally, according to a report by the European Union, the transport sector is responsible for nearly 28% of total carbon dioxide (CO_2) emissions, with road transport accounting for over 70% of these emissions. As a result, authorities in most developed countries are advocating for the use of Electric Vehicles (EVs) to reduce the concentration of air pollutants, CO_2, and other greenhouse gases (Sanguesa et al., 2021). They are promoting sustainable and efficient mobility through various initiatives, including tax incentives, purchase aids, and special measures like free public parking and free use of motorways. EVs offer several advantages over traditional vehicles (Gultom et al., 2023):

Table 1: Advantages of EV

Category	Benefit
Environment	Zero emissions, lower pollution
Efficiency	Higher energy conversion, regenerative braking
Cost	Lower fuel and maintenance costs
Performance	Instant torque, smooth ride
Sustainability	Supports renewable energy and energy independence
Grid Integration	Smart charging and vehicle-to-grid (V2G) capabilities
Social Impact	Improved air quality, innovation, and job creation

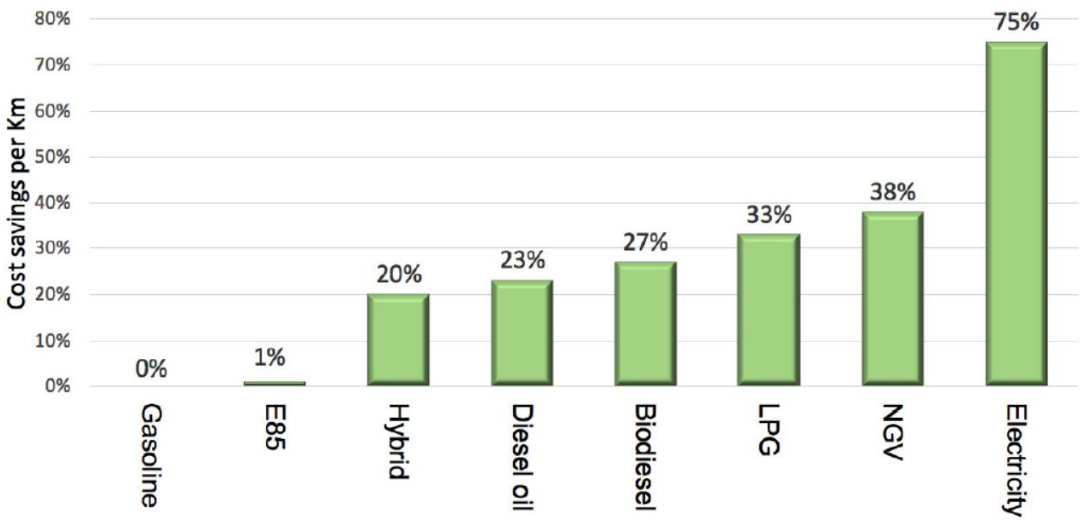

Figure 1: Comparison of savings in cost per kilometer offered by vehicles powered by different sources (Sanguesa et al., 2021)

Various researchers have attempted to address the energy management problem of hybrid electric vehicle but are faced with some of the following challenges like, the actual energy efficiency been impacted by factors like power losses in the converters or the performance limitations of the battery and supercapacitor, not fully optimizing energy recovery during braking resulting in lower overall energy efficiency, and suboptimal performance in energy distribution. In this research work, the integration of multiple energy sources into Zero EVs represents a transformative step in the evolution of sustainable transport systems, combining environmental benefits, enhanced energy flexibility, cost-efficiency, and technological innovation. It lays the foundation for future smart mobility solutions aligned with green energy transitions and zero-carbon targets.

The main contributions of this work are as follows:

i. Development an integrated architecture that combines various renewable energy sources (e.g., photovoltaic panels, wind turbine and fuel cell) with energy storage systems, enabling continuous zero-emission operation regardless of environmental variability.
ii. Implementation of a fuzzy logic controller (FLC) for the dynamic allocation and switching between energy sources based on real-time inputs such as battery state of charge (SOC), power demand, and environmental conditions (solar irradiance) and wind speed.
iii. The fuzzy logic EMS is designed to be scalable and adaptable, allowing integration into various types of electric vehicles (two-wheelers, passenger cars, or delivery vans), thus contributing toward future smart mobility solutions.

Review of Similar Works

(Chen et al., 2015), introduces an energy management strategy utilizing a particle swarm optimization (PSO) algorithm. The primary objective is to minimize the total energy cost, encompassing both fuel and electricity, during vehicle operation. To address the common challenge of optimal strategies being impractical for real-time control, the authors propose a rule-based strategy with three distinct operation modes. The PSO algorithm is then applied to optimize four threshold values within this rule-based framework, enhancing its efficiency and applicability. However, the approach assumes specific energy cost structures and may not adapt well to fluctuating electricity and fuel prices or renewable energy contributions. The integration of PSO for threshold optimization could require significant computational resources during initial setup or recalibration, which might not be feasible for all vehicles. (Rafael & Carri, 2015), focuses on examining the operational impacts of integrating a significant number of plug-in electric vehicles into a power system primarily supported by renewable energy. It explores various approaches to coordinate the interaction between the power system operator and the charging process of plug-in electric vehicles within a smart grid framework. The system's operation is represented through a network-constrained stochastic economic dispatch model. The problem is formulated using a two-stage stochastic programming model, accounting for uncertainties related to the charging behavior of plug-in electric vehicles and the availability of renewable energy sources, both of which are modeled as stochastic processes. However, the two-stage stochastic programming model used in the study may become computationally intensive as the number of variables and scenarios increases, which could limit its practicality for real-time or large-scale applications. The effectiveness of the proposed model might be restricted to certain types of power systems or grid configurations. Applying the same approach to different grid setups or varying levels of renewable penetration might require adjustments or additional considerations. (Yin et al., 2015), presents an Adaptive Fuzzy Logic-Based Energy Management Strategy (AFEMS) designed to optimize the power split between a battery pack and an ultracapacitor (UC) pack in hybrid energy storage systems. The strategy leverages fuzzy logic to dynamically adapt to varying operating conditions, ensuring efficient energy distribution and enhanced system performance. However, if the AFEMS is not designed to interact seamlessly with other vehicle control systems (e.g., engine control, regenerative braking), it may lead to conflicts or suboptimal performance in energy distribution. (Hu et al., 2016), discusses a multi-objective optimization approach for the powertrain system of a passenger car, focusing on fuel economy and system durability. Based on an analysis of the optimal results obtained through dynamic programming, a soft-run strategy is proposed for designing a real-time, multi-objective control algorithm. The soft-run strategy is further optimized by considering the size of the lithium battery and implemented using two real-time algorithms. Compared to the dynamic programming results, the power demand-based control method is found to be more suitable for powertrain systems with larger capacity batteries, while the state of charge-based control method performs better in other scenarios. However, while two real-time algorithms are proposed, their performance under varying real-world conditions, such as temperature changes or unpredictable driving patterns, may not match the idealized simulations. (Ravichandran et al., 2016), presents an online optimal control strategy aimed at managing power flow in microgrids equipped with on-site batteries, renewable energy sources, and integrated electric vehicles (EVs). It formulates an optimization problem as a mixed-integer linear program, executed over a rolling time horizon. The optimization process utilizes predicted values for microgrid electricity demand, renewable energy generation, EV connection and disconnection times, and the state of charge of EVs at the time of their connection. The solution to this optimization problem determines the charge and discharge powers for both the on-site battery and the electric vehicles. The strategy considers both bidirectional and unidirectional charging scenarios for EVs. The proposed optimal controller aims to maximize economic benefits while ensuring that user-specified charge levels are achieved by the time EVs disconnect from the microgrid. However, the effectiveness of the control strategy hinges on the accuracy of the predicted values for electricity demand, renewable generation, and EV connection times. Inaccurate predictions could lead to suboptimal energy management and reduced economic benefits. Frequent charge and discharge cycles, particularly in bidirectional scenarios, can accelerate battery degradation. The strategy may not account for the long-term impacts of battery cycling on performance and lifespan. (Horrein et al., 2016), examine how the heating system affects fuel consumption in a Hybrid Electric Vehicle (HEV). Since the internal combustion engine (ICE) is used less frequently in an HEV compared to a traditional vehicle, cabin heating is partially provided by electric resistances. However, because the battery's state of charge (SoC) is primarily maintained through the ICE's charging function, the use of electrical heating influences the vehicle's overall fuel consumption. (Rahbari et al., 2017), presents a practical approach to address the challenges of integrating renewable energy sources and electric vehicles into the electric grid. It focuses on handling the intermittency of power generation and inconsistencies in energy consumption through a new adaptive intelligent controller. The research outlines a smart grid composed of power plants and distributed generation units, powered by photovoltaic panels and wind turbines, and enhanced with electric vehicles functioning as power storage systems. The use of parking lots to manage challenges like the limited penetration of electric vehicles equipped with Vehicle-to-Grid (V2G) capabilities presents two main difficulties: determining optimal installation locations and effectively modeling bi-directional power flow among electric vehicles, the grid, and the distributed generation system. However, the smart grid described relies heavily on photovoltaic panels and wind turbines. However, fluctuations in weather and environmental conditions can impact the consistency of power supply, introducing reliability issues that the intelligent controller may not be fully equipped to handle. (Li et al., 2017), examines challenges related to vehicle battery technology, focusing on energy consumption and environmental impact, while also emphasizing the role of nanotechnologies and system design. It outlines the current state and future development trends of batteries, highlighting that graphene batteries offer advantages such as higher specific energy, greater capacity, and lower costs compared to traditional batteries. If nanographene technology can further enhance battery performance and lifespan, it holds promising potential for advancing electric vehicle applications. Despite improvements in lifespan, maintaining the stability of graphene-based batteries over prolonged use can be challenging. Additional graphene batteries are more eco-friendly than conventional options, the processes for extracting and synthesizing graphene might still have environmental implications. However, the two-stage stochastic programming model can be computationally intensive, particularly for large-scale systems with numerous plug-in electric vehicles and renewable sources, potentially limiting its practical implementation. (Zheng et al., 2018), introduces an optimal energy management strategy based on Pontryagin's Minimum Principle (PMP). The strategy dynamically allocates the required propulsion power between two energy storage systems (ESSs) during vehicle propulsion and distributes regenerative braking energy between the ESSs during braking. The primary goals of the strategy are to minimize the electricity consumption of the electric vehicle (EV) and to extend the battery's lifespan. A simulation study compares the proposed strategy with a rule-based energy management approach. Results demonstrate that the proposed strategy achieves greater electricity savings than the rule-based method and single ESS systems across three typical driving cycles analyzed in the study. However, Pontryagin's Minimum Principle requires precise system modeling and can be computationally intensive, which may pose challenges for real-time implementation. (Wu et al., 2018), introduces a novel real-time energy management strategy (R-EMS) designed to enhance the fuel economy performance of power-split hybrid electric vehicles (HEVs). The proposed strategy focuses on optimizing energy allocation between the internal combustion engine and the electric motor in real-time, ensuring efficient operation and improved fuel efficiency under varying driving conditions. However, the R-EMS may not fully optimize energy recovery during braking, resulting in lower overall energy efficiency. (Eseye et al., 2019), explores the benefits of demand resources in buildings for optimal energy trading in day-ahead and real-time energy markets. The building flexible demand resources considered are electric vehicles and batteries. The research work examines the combined optimization of EVs and batteries in the day-ahead and regulation electricity markets with the objective of maximizing the total profit of the building microgrid. It takes EVs driving pattern into consideration. The major contribution of the paper is the exploitation of the energy flexibility of buildings using EVs as dynamic energy storage device and batteries as manageable demand facility. The devised optimization problem is formulated as a double-stage mixed-integer linear programming (MILP) problem, and solved using the CPLEX solver. However, the double-stage MILP formulation may involve a significant number of decision variables and constraints, making the optimization process computationally intensive, particularly for large-scale microgrids. Integrating the optimization strategy into existing building energy management systems and scaling it for larger networks or multiple buildings may require additional efforts and technical adaptations. (Marzougui et al., 2019), presents an analysis of energy management for a hybrid power system composed of a fuel cell, ultra-capacitor, and battery, specifically designed for electric vehicles. An energy management strategy is applied to efficiently distribute the energy flow among the three power sources. However, efficiently managing the energy flow between three different power sources (fuel cell, ultra-capacitor, and battery) can be complex, requiring advanced algorithms and precise control to ensure optimal performance under varying conditions. (Kandidayeni et al., 2020), introduces a framework for online parameter identification of a proton exchange membrane fuel cell (PEMFC) model during vehicle operation. The proposed method integrates seamlessly with energy management systems (EMS) of any type. A Kalman filter (KF) is used to extract the PEMFC model parameters online, with special emphasis placed on the initialization process, distinguishing this work from similar studies. To initialize the KF effectively, the shuffled frog-leaping algorithm (SFLA) is employed. Initially, the SFLA operates offline to determine optimal initial values for the PEMFC model parameters using the polarization curve. These values are then utilized to tune the covariance matrices of the KF. Once tuned, the KF is applied online for real-time parameter updates. The results demonstrate high accuracy and improved convergence in estimating PEMFC characteristics, validating the efficacy of the proposed framework. However, the integration of the shuffled frog-leaping algorithm (SFLA) and Kalman filter (KF) may introduce computational overhead, potentially challenging real-time implementation, especially in resource-constrained systems. (Mou et al., 2020), introduces a novel adaptive dynamic wireless charging approach that allows mobile electric vehicles (EVs) to be powered by renewable wind energy. This system leverages a traffic flow-based charging demand prediction program to anticipate charging needs efficiently. However, wireless charging technology inherently faces energy transfer losses due to distance and alignment issues between transmitters and receivers. These losses may reduce the overall efficiency of the system and could require additional energy input to achieve desired charging outcomes. While the system aims for dynamic wireless charging, there could be limitations in the range or coverage of wireless charging stations. This may restrict its applicability to specific routes or densely populated areas with sufficient infrastructure. (Gupta et al., 2020), presents a probabilistic approach for optimal reactive power planning, considering uncertainties in renewable energy generation (specifically wind and photovoltaic systems), fluctuating loads, and electric vehicle (EV) charging demand. The proposed methodology uses a probabilistic AC/DC load flow analysis to address the uncertainties and connections between offshore wind farms and the grid. However, the analysis of AC/DC load flow includes offshore wind farm connections, which may present challenges related to grid integration, transmission losses, and stability, particularly in regions with significant offshore wind penetration. (Chandrasekar et al., 2020), design and analyze a proposed triple-port DC-DC buck-boost converter for high step-up/step-down applications. The converter features two unidirectional ports (port-1 and port-3) and one bi-directional port (port-2) for harnessing photovoltaic (PV) energy and charging a battery. At port-1, a combined buck and buck-boost converter structure is used, featuring a specific arrangement of switches and inductors. This configuration offers a higher step-up/step-down voltage conversion ratio compared to traditional buck-boost converters, while maintaining a positive output voltage polarity. The bi-directional port (port-2) facilitates energy storage by integrating a bi-directional boost converter to charge or discharge the battery. The switches operate synchronously in most modes, simplifying the control strategy and enhancing the overall system efficiency. However, the high step-up/step-down voltage conversion ratio and bi-directional energy flow can place significant stress on the switches, inductors, and capacitors, potentially reducing efficiency and reliability, especially under high load or fluctuating input conditions. (Binkowski, 2020), introduces a novel maximum power point tracking (MPPT) method for photovoltaic (PV) inverters connected to a single-phase 400Hz vehicle or aircraft grid, supplying drives operating in critical mode. The method addresses the issue of power fluctuations that cause voltage ripples at the terminals of photovoltaic panels, which are connected to the DC-link capacitor. The proposed solution utilizes a conductance-based MPPT approach to mitigate the impact of varying voltage. This technique ensures a stable reference current for grid current calculation, effectively solving problems identified in previous studies related to voltage fluctuations. However, the conductance-based MPPT method may not perform optimally in rapidly changing environmental conditions, such as varying light intensity or temperature, potentially leading to slower adaptation to changing maximum power points. (Ishaque et al., 2021), focuses on the design, modeling, and results-driven approach for creating an Energy Management System (EMS) for Hybrid Electric Vehicles (HEVs) using a fuzzy logic controller (FLC). The system utilizes batteries as the primary energy storage and supercapacitors (SCs) as the secondary energy storage. The EMS integrates the Ultra-Power Transfer Algorithm (UPTA) and FLC methods to regulate power flow. The UPTA method is employed to charge the battery during regenerative braking mode with the assistance of a single-ended primary inductor converter (SEPIC). However, the combination of fuzzy logic controllers and the Ultra-Power Transfer Algorithm (UPTA) could increase the complexity of the system, making it more challenging to implement and optimize in real-world applications. While the system aims to manage energy flow effectively, the actual energy efficiency may be impacted by factors like power losses in the converters or the performance limitations of the battery and supercapacitor. (Chakir et al., 2022), propose a management system for a future household equipped with controllable electric loads and an electric vehicle equipped with a PV–Wind–Battery hybrid renewable system connected to the national grid. The proposed management system is based on a linear programming model with non-linear constraints solved with MATLAB toolboxes. The simulation is based on a database of meteorological conditions resulting from TRNSYS and processed to achieve a frequency of one hour. The system decisions provide switch control states of the connection architecture as well as the variation according to the V2H (vehicle to home), H2V (home to vehicle) and involved G2V (grid to vehicle) scenarios when grid comes into play during H2V mode. However, despite integrating PV panels and wind turbines, the system remains exposed to the inherent variability of renewable energy sources. During extended periods of low sunlight or wind, the reliance on battery storage and grid support may increase, reducing the system's autonomy. (Mamun et al., 2022), presents a hybrid electric vehicle (HEV) concept powered by renewable energy resources (RERs), including solar photovoltaic (PV) energy, wind energy, a fuel cell (FC), and a supercapacitor (SC). The proposed design integrates these components (PV + WE + FC + SC) to generate electrical energy via a proton exchange membrane (PEM) fuel cell and SC, addressing high torque requirements. A battery pack and SC cater to power demands, while the FC serves as a backup energy source. Additionally, a wind-driven alternator generates electricity to charge the battery when the vehicle is in motion. The design aims to achieve zero carbon emissions, enhance energy efficiency, and reduce vehicle weight by incorporating in-wheel motors to eliminate mechanical transmissions. Subsystem modeling and simulation were performed using MATLAB and

Simulink, while ANSYS Fluent was employed for wind energy analysis, including standard parameters like pressure, velocity, and vector contours. A rule-based supervisory controller manages the energy flow, prioritizing sources logically: the SC for stop-and-go situations, the battery as the primary source, the FC as backup, and wind and solar energy for recharging the battery. Solar charging is activated automatically when the vehicle is parked, with the alternator contributing to energy flow under the controller's regulation during movement. However, the supervisory controller follows a predefined logic, which might not adapt optimally to varying real-world conditions or unforeseen circumstances. The concept is validated through simulations, which may not account for practical challenges such as wear and tear, safety, or component integration in real-world conditions. (Pirpoor et al., 2022), proposes a high-gain, single-switch, and efficient DC-DC boost converter that integrates switched-capacitor and switched-inductor cells. These components enhance voltage levels while minimizing input current ripple. The design achieves this by repositioning the input inductors and employing a switched-inductor block, where inductors magnetize in parallel and demagnetize in series, reducing input current stress. The converter uses a single switch, simplifying the control circuitry and enabling stable DC output voltage for variable input voltages or load conditions. Voltage levels are further boosted using the switched-capacitor cell, which can be expanded by adding diodes and capacitors, providing a modular and scalable design. This approach offers high efficiency, reduced complexity, and adaptability for diverse applications. However, while efficient at certain operating points, the converter's efficiency may decrease under heavy load conditions due to increased conduction and switching losses. (Xiaodong et al., 2023) presents an adaptive energy management strategy (EMS) based on the equivalent consumption minimization strategy (ECMS), leveraging real-time traffic data characterized by average speed, average acceleration, and speed variability across road segments. The proposed system integrates offline and online components to enhance adaptability and efficiency. In the offline phase, velocity characteristic parameters are derived using vehicle data, and road segments are classified using the K-means clustering algorithm. Markov transition matrices are then constructed for different road types based on these parameters, enabling the prediction of future vehicle speeds for subsequent time intervals. In the online phase, the EMS utilizes the predicted vehicle speeds and road segment classifications to dynamically adjust the equivalent factors in the ECMS. By incorporating real-time traffic and road information, the strategy ensures adaptive and optimized power distribution between energy sources, aiming to improve fuel efficiency and overall system performance in hybrid electric vehicles. However, the EMS heavily depends on accurate speed and traffic predictions. Errors in the Markov-based speed prediction model could negatively impact the performance of the energy management strategy. (Ibrahim et al., 2023), introduces a hybrid maximum power point tracking (MPPT) algorithm that combines Particle Swarm Optimization (PSO) with two conventional methods: Perturb and Observe (PO) and Incremental Conductance (IC). The proposed PSO-based method optimizes the maximum power output of photovoltaic (PV) systems by dynamically adjusting the step size, which is traditionally fixed in the PO and IC methods. In this approach, the step size varies based on solar irradiance, improving tracking efficiency. To evaluate the hybrid MPPT algorithm, a single-stage grid-connected PV system is designed and tested under various weather scenarios. The performance of the hybrid algorithm is compared to that of the conventional PO and IC methods. The results show that the PSO+IC hybrid method outperforms the conventional methods, achieving a tracking time of only 43.4ms and an efficiency of 99.07% under standard test conditions. This demonstrates the enhanced performance of the hybrid MPPT algorithm in real-world conditions. However, the PSO algorithm requires careful tuning of parameters (such as swarm size and inertia weight) for optimal performance. Incorrect parameter settings could reduce the efficiency and effectiveness of the algorithm, potentially leading to suboptimal power tracking. (Yilmaz et al., 2023), proposes an Artificial Neural Network (ANN)-based Maximum Power Point Tracking (MPPT) method, called the ANN-based Adaptive Reference Voltage (ARV) method, to determine the optimal operating point of the photovoltaic (PV) panel. The ARV method is a voltage-controlled approach that adapts to changing atmospheric conditions, offering an advantage in dynamic environments. The method's performance is evaluated using both a standard Proportional-Integral (PI) controller and an anti-windup PI controller. A comparative analysis is conducted against widely used methods like Perturb and Observe (P&O) and Incremental Conductance (INC) in a MATLAB/Simulink environment, considering three different atmospheric scenarios with varying radiation levels, in accordance with EN50530 standards. The results show that the proposed method achieves efficiencies of 99.4%, 95.9%, and 96% in scenarios 1, 2, and 3, respectively. Notably, the ANN-based ARV method demonstrates superior performance in rapidly changing atmospheric conditions, making it an efficient solution for real-world PV systems. However, the performance of the ANN-based ARV method is highly dependent on the quality and quantity of training data. If the training data does not adequately represent all possible atmospheric conditions, the network may not generalize well to real-world scenarios, leading to suboptimal performance. (Adedeji, 2024), explores the use of supervised machine learning techniques, including Random Forest (RF), K-Nearest Neighbor (KNN), Multiple Linear Regression (MLR), and Artificial Neural Networks (ANNs), to predict energy parameters in plug-in hybrid electric vehicles (PHEVs). The primary goal is to develop a machine learning model capable of accurately estimating combined energy consumption for both city and highway driving. For predicting combined, city, and highway fuel consumption, the mean square error (MSE) ranges are as follows: KNN: 3.40–6.13, MLR: 0.029–0.0625, RF: 0.030–0.091, ANN: 0.022–0.038. The ANN model demonstrated the highest prediction accuracy among the techniques. Specifically: For combined fuel consumption, ANN was 183.51, 42.53, and 1.85 times more accurate than KNN, RF, and MLR, respectively. For city fuel consumption, ANN was 113.33, 19.75, and 2.06 times more accurate than KNN, RF, and MLR, respectively. For highway fuel consumption, ANN was 34.58, 16.62, and 1.17 times more accurate than KNN, RF, and MLR, respectively. However, the study focuses on combined, city, and highway fuel consumption but does not address other energy-related factors such as emissions, battery degradation, or energy recovery during braking and integration of other energy sources.Top of Form

MATERIALS AND METHODS

The aim and objectives of this research work was actualized by taking the following steps

Mathematical Model

Electric Motor

The electric motor in electric vehicles plays an important role. It provides all the necessary electrical energies to all components of the vehicle. The electric power of the motor is at a maximum if the motor obtains sufficient power energy from the battery (Khan & Samuilik, 2024). A mathematical equation of the electric motor power is represented by equation (1)

$$P_{EM} = \eta_{EM}.P_{bat} \quad (1)$$

Where P_{EM} is the power output of an electric motor, η_{EM} represents motor efficiency, and P_{bat} stands for battery power.

Regenerative braking

Regenerative braking tool captures the moving energy decrease of the vehicle and then converts it as an electrical energy in order to feed it back into the battery source.

$$W_c = \frac{1}{\eta_c}\left(\frac{mv^2}{2} + mgh\right) \quad (2)$$

Where W_c is Energy stored in the vehicle's power source, m is Total vehicle mass, V is Vehicle speed, h is Maximum height difference of the BEV, and η_c is Energy efficiency of the power source (Kasoju, 2021).

Energy Storage System

A battery that stores and provides electrical energy to the electric motor makes up the energy storage of a dynamic EV system. The battery state charge equation is defined as (Abulifa, 2017),

$$SOC(t) = \frac{E_{bat}(t)}{E_{max}} \quad (3)$$

Where $E_{bat}(t)$ is the energy stored in the battery at time t, $SOC(t)$ is the battery state of charge at time t, and E_{max} is the battery's maximum energy storage capacity (Jadhav & Nair, 2019). The battery energy is shown in equation (2.4)

$$E_{bat}(t) = \int_{t_0}^{t} P_{bat}(t)dt + E_{bat}(t_0) \quad (4)$$

Where $E_{bat}(t)$ is the initial energy stored in the battery, $P_{bat}(t)$ is the battery power output at time t, and t_0 is the initial time.

Driver Model

Aiming to develop an appropriate throttle and brake commands by PI controller, driver model considers the objective speed and the present real speed. Simulating the role of the driver and the vehicle is explained by this model. To guarantee having the exact reference speed tracking by the vehicle, a feedback control loop of a vehicle speed is utilized. Provided by the electric motor the throttle command from the driver model is transferred into torque and became an input to the transmission model.

Vehicle Dynamic Model

The movement and acceleration of the vehicle are described by the vehicle dynamics model. The following mathematical formulas provide the equations for the vehicle dynamics model (Khan & Samuilik, 2024). The vehicle acceleration equation is represented by equation (5):

$$a = \frac{P_{total}}{m.g} - \frac{1}{C_r.g} - \frac{1}{C_d}.\frac{1}{2}.\rho.A.v^2 \quad (5)$$

Where a is the vehicle acceleration, m is the mass, g is the acceleration caused by gravity, C_r is the rolling resistance coefficient, C_d is the aerodynamic drag coefficient, ρ is the air density, A is the frontal area, and v is the speed.

The vehicle speed v(t) at time t can be calculated as

$$v(t) = \int_{t_0}^{t} a(t)dt + v(t_0) \quad (6)$$

Where t_0 is the initial time and $v(t_0)$ is the vehicle initial speed.

Electric Vehicle Simulink Model

The mechanical transmission part of the electric vehicle is modelled as shown in Figure 2. The wind speed and the road inclination are set to zero. The motion speed sensor is incorporated to determine the speed of the motor. Table 2 shows the parameter for the Electric vehicle.

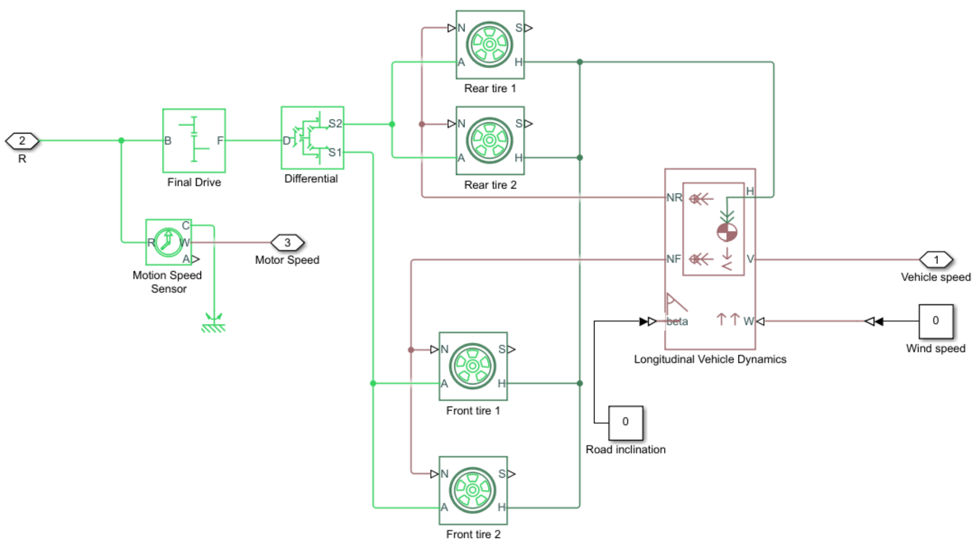

Figure 2: Electric vehicle dynamic model

Table 2: Parameter of Electric vehicle model

Parameters	Symbol	Values	Units
Vehicle total mass	m	1300	kg
Rolling resistance force constant	fr	0.015	
Air density	ρ_{air}	1.18	kg/m3
Frontal surface area of the vehicle	Af	2	m2
Tire radius	R	0.3	m
Aerodynamic drag coefficient	Cd	0.25	

PV Power Model

A solar cell is an electronics device use for conversion of photon energy into pollution-free electricity. The connection of the device in series and parallel pattern forms a PV module. Furthermore, to build PV arrays these modules are coupled in series and parallel arrangement to generate clean and green electricity. Figure 4 shows a 7kW PV model with an inverter control incorporated with an MPPT. Maximum power point tracking (MPPT) is a control algorithm implanted in a DC–DC power system converter with the function to extract maximum power from a PV array system. The main purpose of MPPT technique is to ensure that the maximum power to be extracted from a PV system always matches the peak value of the power and voltage characteristic curve under solar irradiation (G) and temperature (T) variations.

The solar PV device can be represented as an ideal solar cell with a current source (I_{ph}) parallel to the diode as shown in Figure 3 excluding the series and parallel resistors. Applying Kirchhoff's first law, the output current of an ideal solar cell is described in equation (6).

$$I = I_{ph} - I_d \quad (6)$$

From semiconductor theory, the fundamental mathematical equation that describes the I-V characteristics of the PV solar cell is known as Shockey's diode current equation as illustrated in equation (6) (Vinod et al., 2018).

$$I_d = I_s \left[exp\left(\frac{qV_{oc}}{N_s KAT_o}\right) - 1\right] \quad (7)$$

Substituting equation (7) into equation (6), the output current I of an ideal solar cell can be described by equation (8)

$$I = I_{ph} - I_s \left[exp\left(\frac{qV_{oc}}{N_s KAT_o}\right) - 1\right] \quad (8)$$

Figure3.1 shows a more realistic circuit model of solar PV cell with series resistance (R_s) and parallel resistance(R_p). Ideally R_s and R_p are ignored but in reality it is not possible to overlook these resistances, because efficiency of the PV solar cell is affected by these parameters (Vinod et al., 2018). So, R_s is taken into consideration and R_p is considered to be finite, then the diode current I_d in equation (6) can be modified as shown in equation (9)

$$I_d = I_s \left[exp\left(\frac{q(V+IR_s)}{N_s KAT_o}\right) - 1\right] \quad (9)$$

Equation (9) can also be modified taken R_s into account

$$I = I_{ph} - I_s \left[exp\left(\frac{q(V+IR_s)}{N_s KAT_o}\right) - 1\right] \quad (10)$$

If the PV cell is coupled in a series-parallel pattern, the output current I in equation (6) can be modified as illustrated in equation (11)

$$I = N_p * I_{ph} - N_p * I_s \left[exp\left(\frac{q(V+IR_s)}{N_s KAT_o}\right) - 1\right] \quad (11)$$

$$I_{ph} = [I_{sc} + K_i(T_o - T_r)] * \frac{G}{G_{ref}} \quad (12)$$

Equation (12) describes the photocurrent (I_{ph}) which is proportion to the incident flux and independent of V or R_s but it linearly dependent on the solar radiation and also influence by the

A single-diode PV model is mathematically modeled in this work. This is because of its accuracy and simplicity.

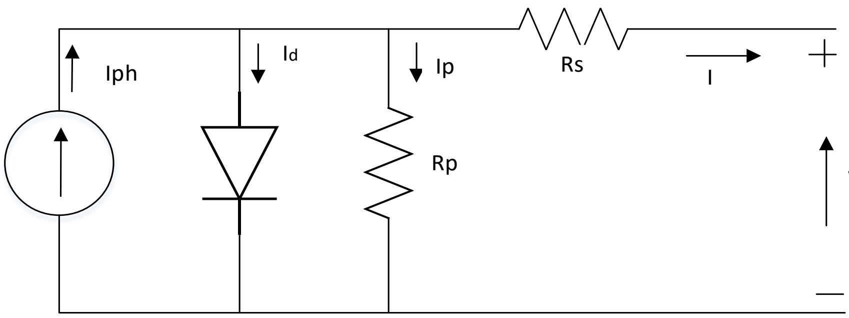

Figure 3: Ideal one-diode PV cell model (Abbassi et al., 2019)

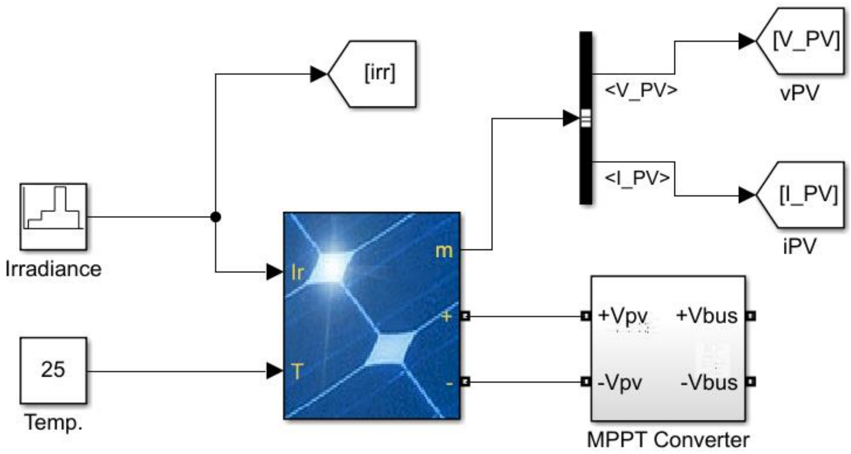

Figure 4: Simulink model of a Photovoltaic Module

The non-linear I-V characteristic of the PV module is written in equation 13.
Where I_{PV} is the photovoltaic current, I_o, α are the reverse bias current and ideality factor of the diode, R_s and R_p are the series and parallel resistances, and V_t is the thermal voltage. The series-parallel connection scheme is applied to create a large-scale PV system. In general, PV modules are connected to the network through a combination of a boost converter and an inverter (Hasanien & El-Fergany, 2019).

$$I = I_{PV} - I_O\left[exp\left(\frac{V+R_sI}{aV_t}\right) - 1\right] - \frac{V+R_sI}{R_p} \qquad (13)$$

3.4 Wind Power Model
A 7kW wind power is model using MATLAB/Simulink environment. The power captured from wind P_m can be express mathematically as follows

$$P_m = 0.5\rho\pi r^2 {V_w}^3 C_p(\lambda,\beta) \qquad (14)$$

Where ρ equals air density, r represents blade radius, V_w represents wind speed, λ equal tip speed ratio, β is blade pitch angle, R is radius of WT rotor, ω_B equals blade speed and the power coefficient $C_p$is given by the following equation

$$\lambda = \frac{\omega_B R}{V_w}, \lambda_i = \frac{3600R}{1609\lambda} \qquad (15)$$

$$C_p = 0.5(\lambda_i - 0.022\beta^2 - 5.6)e^{-0.17\lambda_i} \qquad (16)$$

3.5 Proton Exchange Membrane Fuel cell (PEMFC)
The model of the PEMFC stack as shown in Figure 5 is based on the FC stack detailed model included in Simulink. The mathematical model of PEMFC is shown in Equations (17 – 24) (Huang & Zhang, 2019). The voltage of the FC stack VFC is:

$$V_{FC} = E_{OC} - NAIn\left(\frac{i_{FC}}{i_0}\right)\frac{1}{\frac{sT_d}{3}+1} - R_{iFC} \qquad (17)$$

where EOC is open circuit voltage, iFC is the current of FC stack, A is the Tafel slope, i0 is the exchange current, N is the number of cells, Td is the reaction time, and R is the internal resistance. The open circuit voltage EOC is:

$$E_{OC} = K_C E_n \qquad (18)$$

where KC is the voltage constant at the nominal condition of operation and En is Nernst voltage. The exchange current i0 is calculated as:

$$i_0 = \frac{zFk(P_{H_2}+P_{O_2})}{Rh} e^{\frac{-\Delta G}{RT}} \qquad (19)$$

where z is the number of moving electrons, F is Faraday's constant, k is Boltzmann's constant, R is ideal gas constant, h is Planck's constant, T is the cell temperature (K), ΔG is the size of the activation barrier, PH2 is the partial pressure of hydrogen, and PO2 is the partial pressure of oxygen inside the stack (atm). The Tafel slope A is shown as:

$$A = \frac{RT}{z\alpha F} \qquad (20)$$

where α is the charge transfer coefficient. The partial pressure of hydrogen and oxygen are expressed as:

$$P_{H_2} = (1 - U_{fH_2})x\%P_{fuel} \qquad (21)$$

$$P_{fO_2} = (1 - U_{fO_2})y\%P_{air} \qquad (22)$$

where Pfuel is the fuel pressure, U_{fH_2} (%) is the nominal utilization rate of hydrogen, x% is the percentage of hydrogen in the fuel, Pair is the air pressure, U_{fO_2}(%) is the nominal utilization rate of oxygen, and y% is the percentage of oxygen. The utilization rates of hydrogen and oxygen are calculated as follows:

$$U_{fH_2} = \frac{6000RTNi_{FC}}{zFP_{fuel}V_{fuel}x\%} \qquad (23)$$

$$U_{fH_2} = \frac{6000RTNi_{FC}}{2zFP_{air}V_{air}y\%} \qquad (24)$$

where Vfuel(L/min) is the flow rate of hydrogen fuel and Vair is the airflow rate.

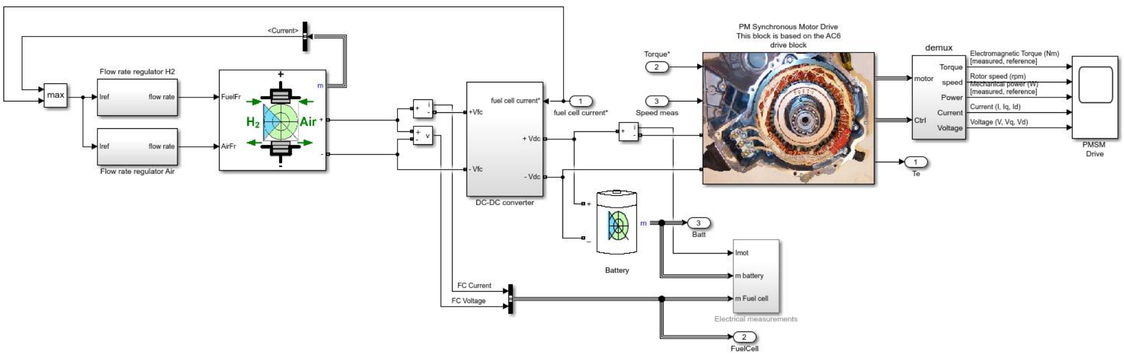

Figure 5: Block diagram of a PEMFC

Induction Machine

A permanent magnet synchronous machine (PMSM) is selected as the electric motor because of its high operation efficiency and reliability. Table 3 depict the induction motor parameters.

Table 3: Induction Motor Parameter

Parameters	Symbol	Values	Units
Shaft Power	pu	6	kW
Number of poles	p	2	
Stator resistance	Rs	7.14	Ω
Rotor resistance	Rr	4.12	Ω
Mutual inductance	M	0.1772	H
Stator (rotor) self-inductance	Ls=Lr	0.1891	H
Inertia moment	J	0.0146	kg.m2
Viscous friction	f	0.00001	N.ms2

Battery Model

Comparing different battery technologies, Lithium–ion batteries is a suitable option for hybrid energy storage systems due to their high energy density and efficiency, light weight, good life cycle, and longer life (Jadhav & Nair, 2019). The generic Li–ion battery model is used. The battery state of charge (SOC) is an indication of the energy reserve and is expressed by equation (25), (Jadhav & Nair, 2019).

$$SOC = 100\left(1 - \frac{\int_0^t idt}{Q}\right) \tag{25}$$

where, i is the battery current (A) and Q is the battery capacity (Ah).

The discharge and charge equation of the lithium-ion battery is given in equation (26) and (27).

$$f_1(iti^*i) = E_o - \left(k + \left(\frac{Q}{Q-it}\right) + it\right) + it + A + \exp(-B + it) \tag{26}$$

$$f_2(iti^*i) = E_o - \left(k + \left(\frac{Q}{Q-0.iQ}\right) + it\right) + it + A + \exp(-B + it) \tag{27}$$

where E_0 is initial voltage (V), K is polarization resistance (W), i^* is low-frequency dynamic (A), it is the battery extraction capacity (Ah), A is exponential voltage (V), B is exponential capacity $(Ah)^{-1}$. A lithium-Ion battery is used in this work for energy storage. It has two modes of operation, charging and discharging modes. When the current to the battery is positive, the battery is in the charging mode. When the current to the battery is negative, the battery is in the discharging mode. To obtain the desired SOC, the fuzzy controller is designed to be in charging or discharging mode.

3.8 Energy Management System (EMS)

EV using batteries storage must be recharged regularly. Those using fuel cells for feeding electrical energy, a supply for hydrogen is necessary. And those equipped with PV panels, solar energy provides them energy only during sunshine period. Generally, EV uses batteries for storage, but due to the less autonomy, hydrogen or fuel cell vehicle, solar vehicle or a combination of solar, FC and battery bank can be a competitive solution. Power management control is necessary to make coordination between the different energy sources. In our work, we choose to use the battery bank system to starts producing energy. Then Hydrogen is used by the fuel cell to produce energy and at least photovoltaic system works to convert irradiation to electrical energy provided to a DC bus. The total power is calculated as in equation (28). The Energy management system (EMS) is developed based on a Fuzzy logic control (FLC) strategy. Since the PVWFCHEV is a highly nonlinear system, a fuzzy logic method is suitable for use because it is flexible and can work well without precise mathematical models. Moreover, fuzzy logic can incorporate the expert experience into the control strategy, which helps to deal with the complex environmental conditions such as the intermittent and stochastic characteristics of solar energy and wind energy.

$$P_{load} = P_{batt} + P_{FC} + P_{PV} + P_{wind} \tag{28}$$

Fuzzy Logic Controller Design

A FLC consists of five functional blocks. The rule base, the database, the fuzzifier, the inference engine and the defuzzifier. There are many different inference algorithms that can be used to produce the fuzzy set values for the output fuzzy variable. In the present work, Mamdani inference system is used. The demand power of the electric motor, the output power of the PV array, SOC of the battery and the wind power are considered as four input parameters to the fuzzy logic controller as shown in Figure 6 to 9 respectively, and the output parameter is the reference power of the FC as shown in Figure 10.

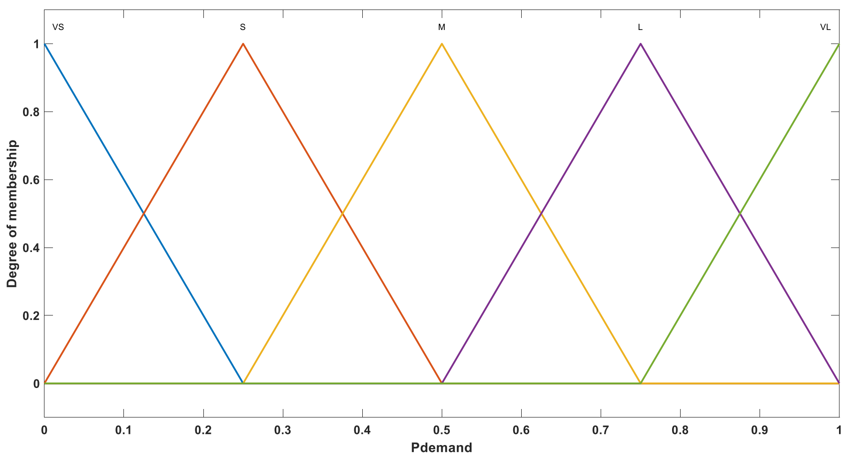

Figure 6: Electric motor input demand power

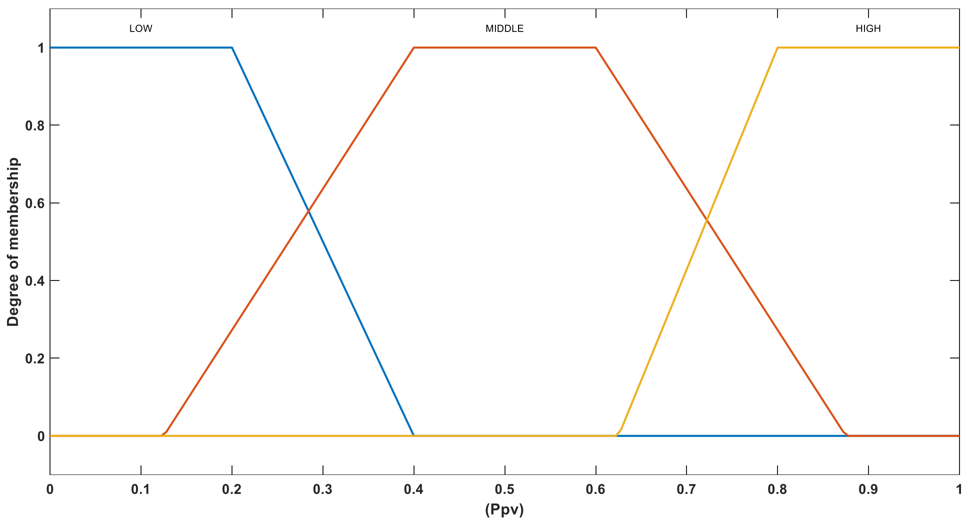

Figure 7: PV input demand power

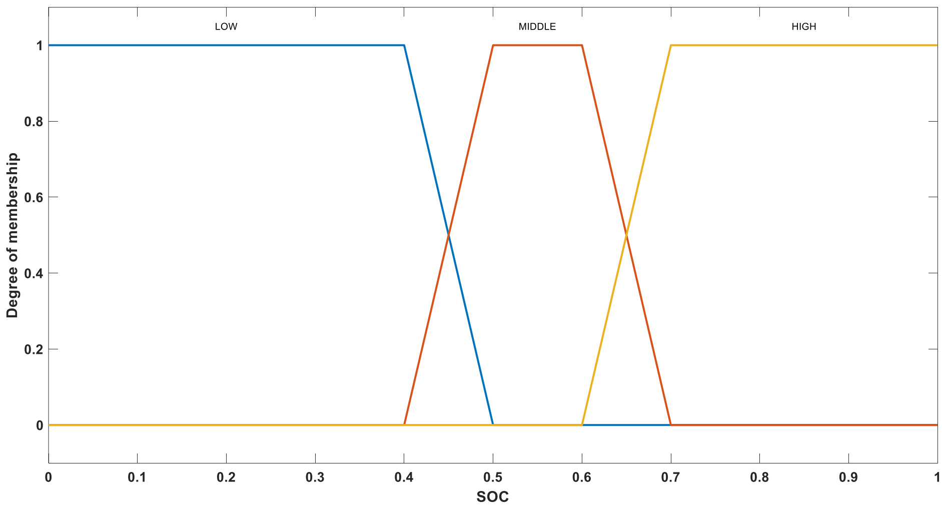

Figure 8: SOC of Battery

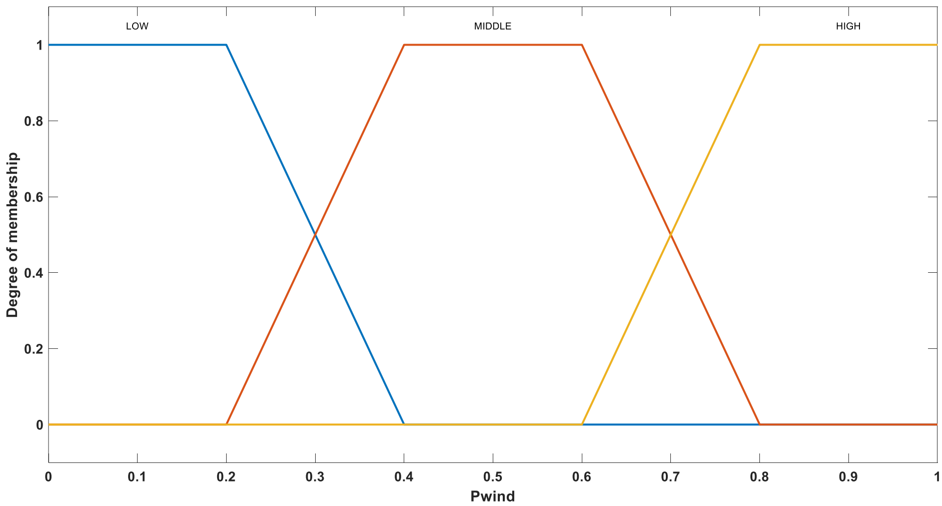

Figure 9: Wind input demand power

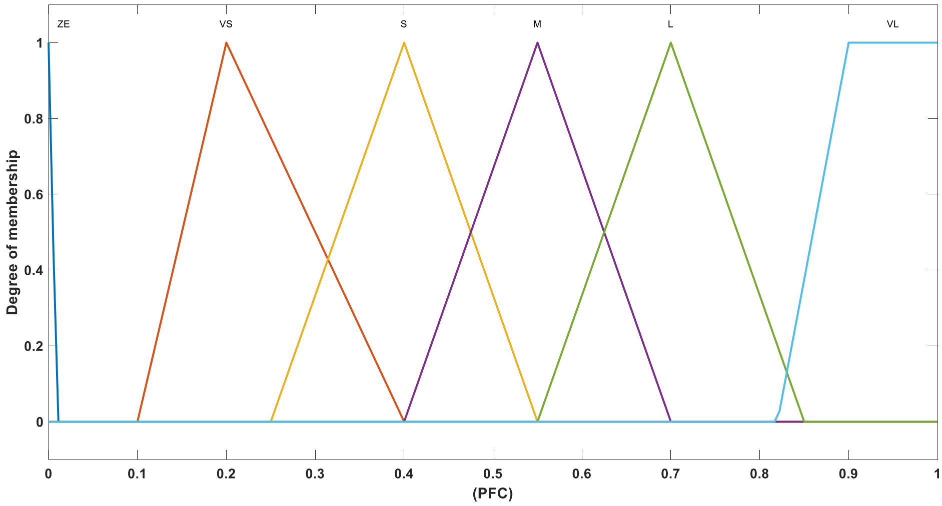

Figure 10: Output demand power

Multiple Energy Sources Model

This multi-source HEV system represents an advanced approach to hybrid vehicle design, combining the strengths of various energy sources to create a vehicle that is both environmentally friendly and capable of meeting modern transportation demands. Figure 11 illustrates the proposed vehicle structure design, incorporating a combination of PV, WE, FC, and SC sources along with an Energy Storage System (ESS). A lithium-ion battery was used for this research work because of its light weight and enhancing performance.

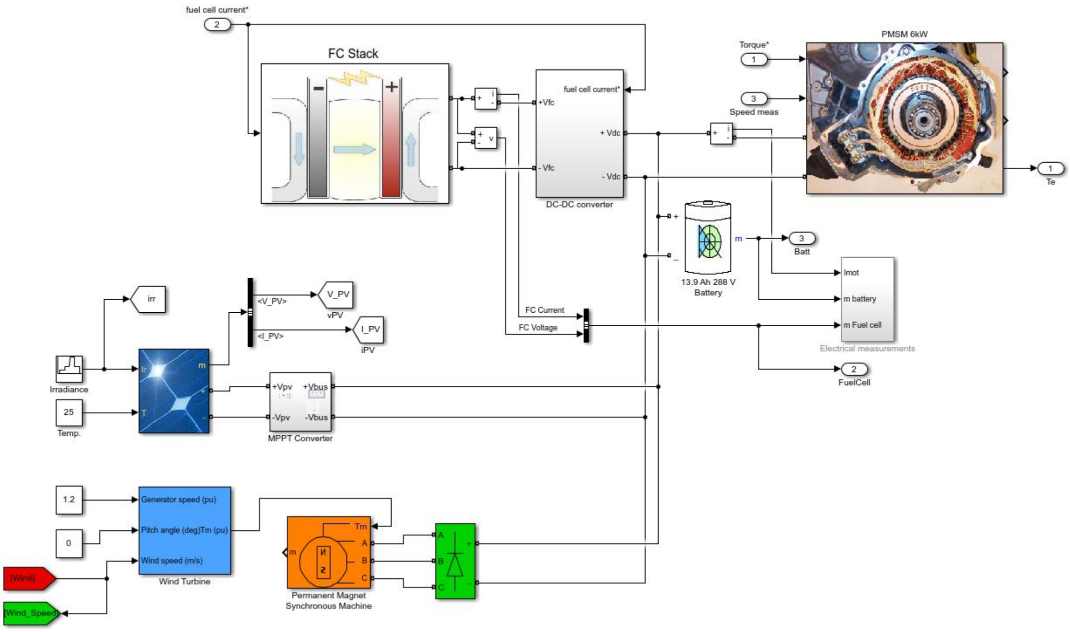

Figure 11: The electrical system of a PVWFCHEV

RESULTS AND DISCUSSION

Electric Vehicle with Battery Simulation Results

Figure 12 shows the speed and speed feedback when using the FTP75 drive cycle source for 1500 second. Figure 12 demonstrate the simulation driving cycle at different time for a simulation period of 1500 seconds. Figure 13 show the battery state of charge (SOC) as the vehicle move for a distance covered around 12.56 Km in 1500 Seconds as shown in Figure 14 that means Average Speed was around 30 km/hr. The battery discharge with respect to the distance covered over a period of time.

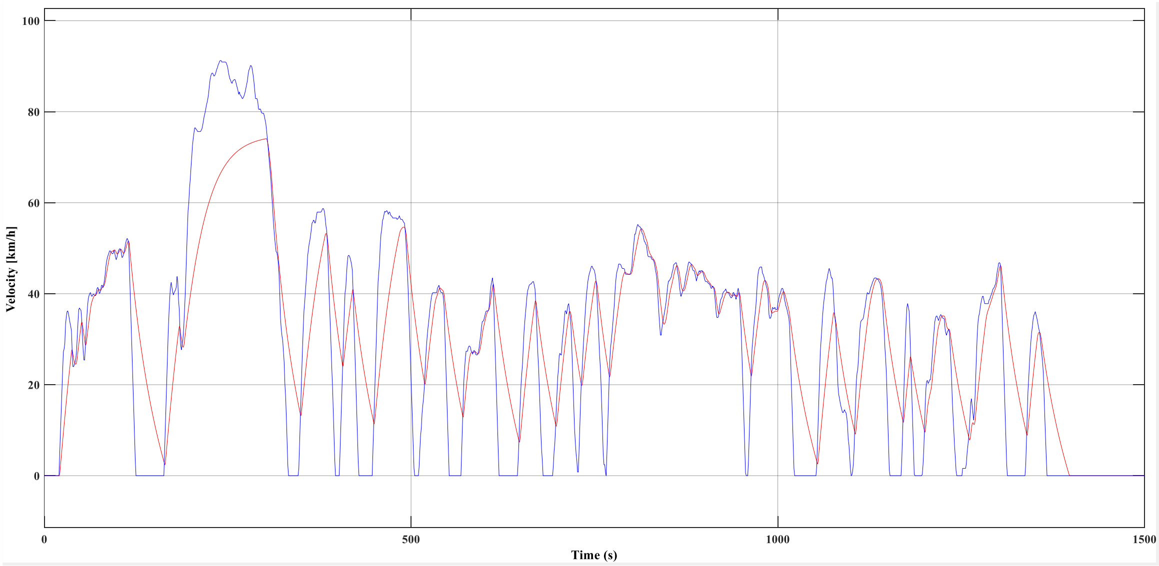

Figure 12: Speed Vs Speed feedback plot

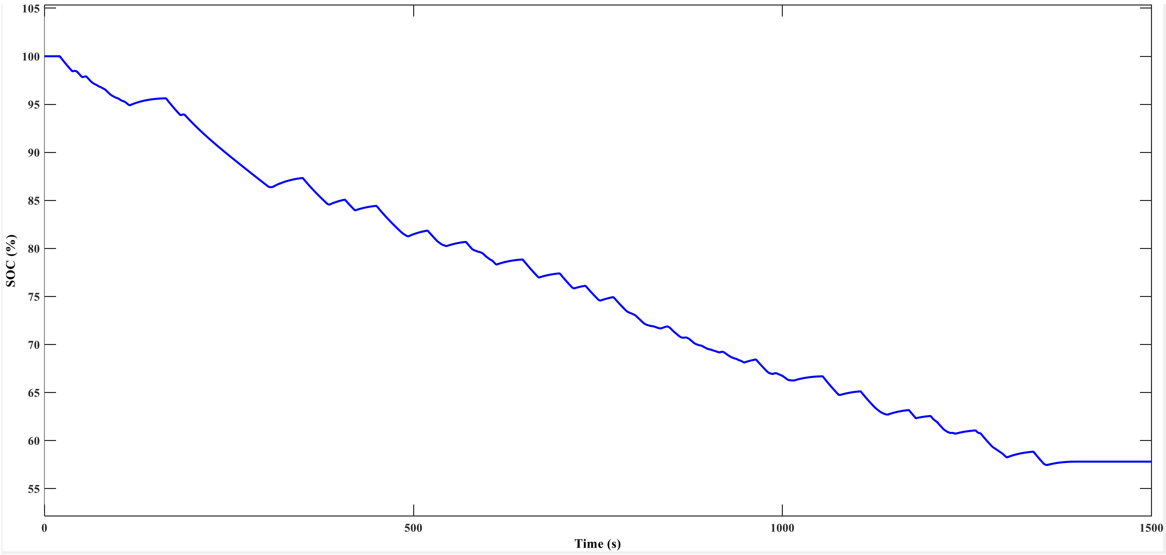

Figure 13: Battery State of Charge

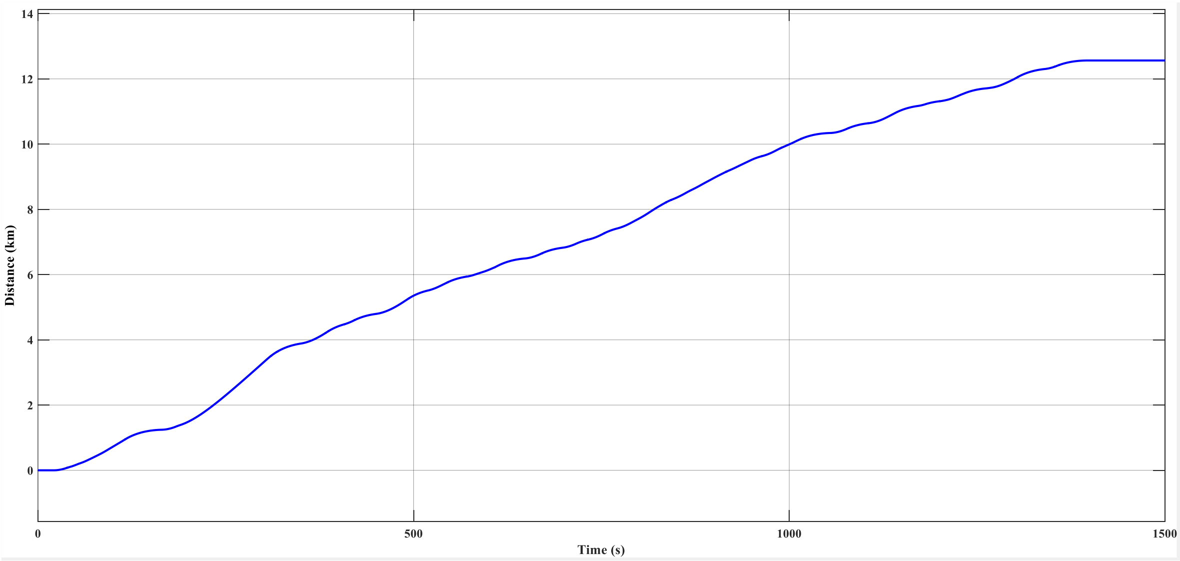

Figure 14: Distance cover

Electric Vehicle with Battery and PV Simulation Results

The output power from the PV panel is a function of the solar irradiance, Figure 15 shows different solar irradiance ranging from 200W/m2 to 1000W/m2. The higher the solar irradiance the higher the output power and vice versa. Figure 16 shows the battery current, whenever the current is positive at that point the battery is discharging and whenever the battery current is negative the battery is charging which clearly describes the state of charge of the battery as shown in Figure 17. Figure 17 shows the effectiveness of the Fuzzy-EMS deployed in this work.

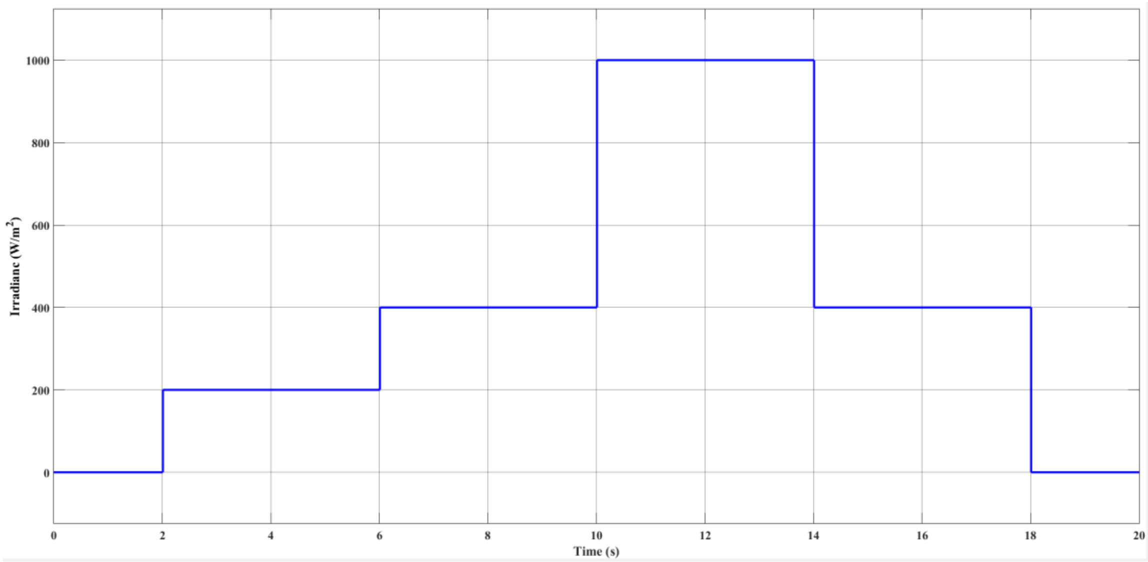

Figure 15: Solar irradiance varation

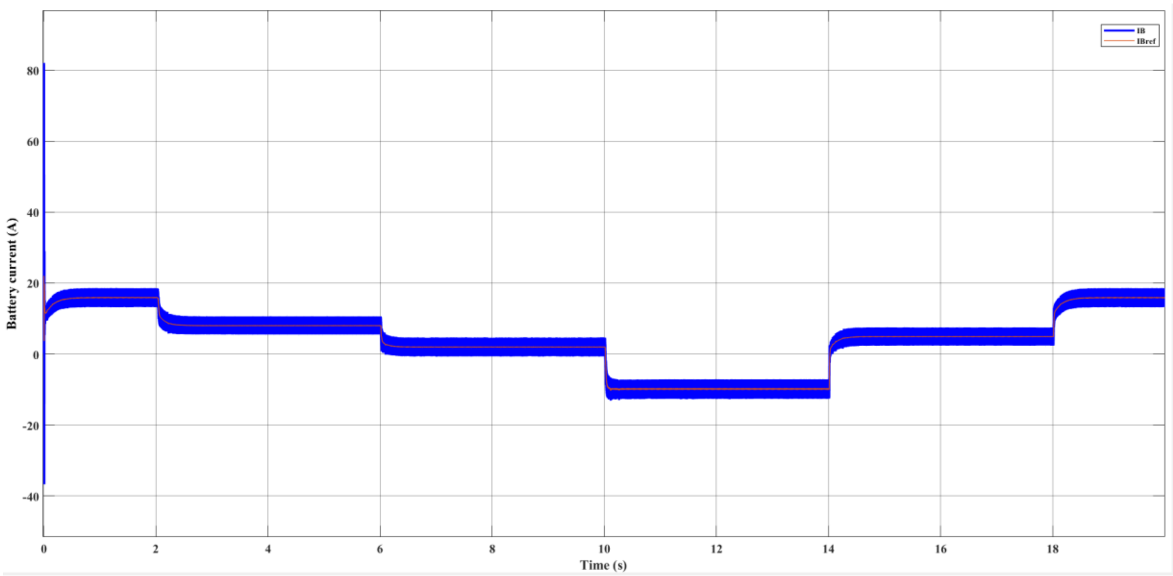

Figure 16: Battery current variation

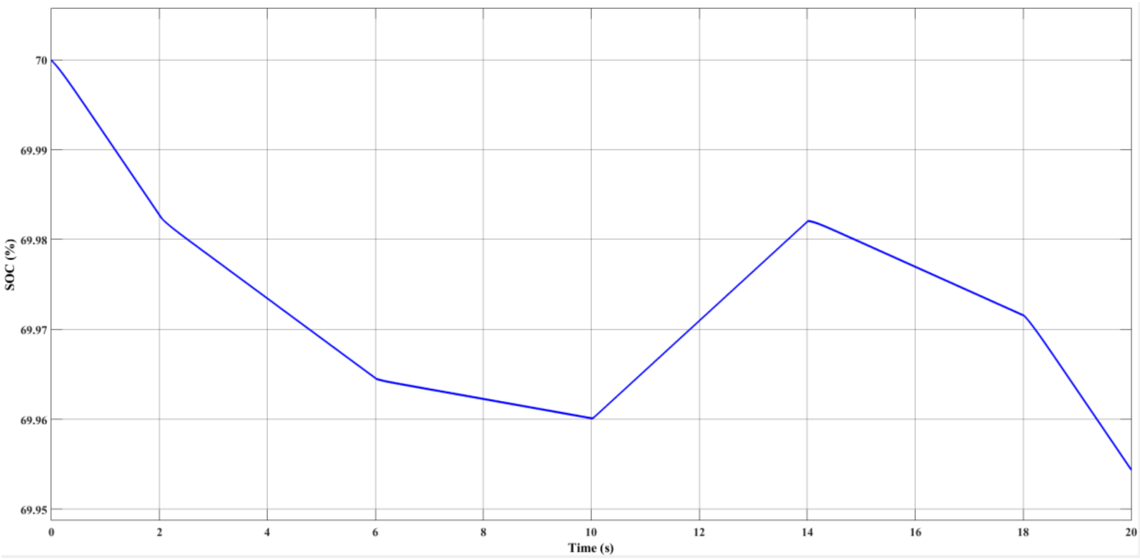

Figure17: Battery State of Charge

PVWFCHEV Simulation Results
At t = 0 s, the FCV is stopped and the driver pushes the accelerator pedal to 70% as shown in Figure 18. The battery provides the motor power till the fuel cell starts. At t = 0.7 s, the fuel cell begins to provide power but is not able to reach the reference power due to its large time constant as seen in Figure 19. That's why the battery continues to provide the electrical power to the motor as depicted in Figure 19. At t = 4 s, the accelerator pedal is released to 25%. The fuel cell cannot decrease its power instantaneously; therefore, the battery absorbs the fuel cell power in order to maintain the required torque. At t = 8 s, the accelerator pedal is pushed to 85%. The battery helps the fuel cell by providing an extra power at that point the battery is discharging. At t = 8.05 s, the total power (fuel cell and battery) cannot reach the required power due to the fuel cell response time. Hence the measured drive torque is not equal to the reference. At t = 8.45 s, the measured torque reaches the reference. The fuel cell power increases so the battery power is progressively reduced. At t = 10.9 s, the battery SOC becomes lower, therefore the battery needs to be recharged. The fuel cell shares its power between the battery and the motor. At t = 12 s, the accelerator pedal is set to -70% (regenerative braking is simulated). The motor acts as a generator driven by the vehicle's wheels. The kinetic energy of the FC is transformed into electrical energy which is stored in the battery.

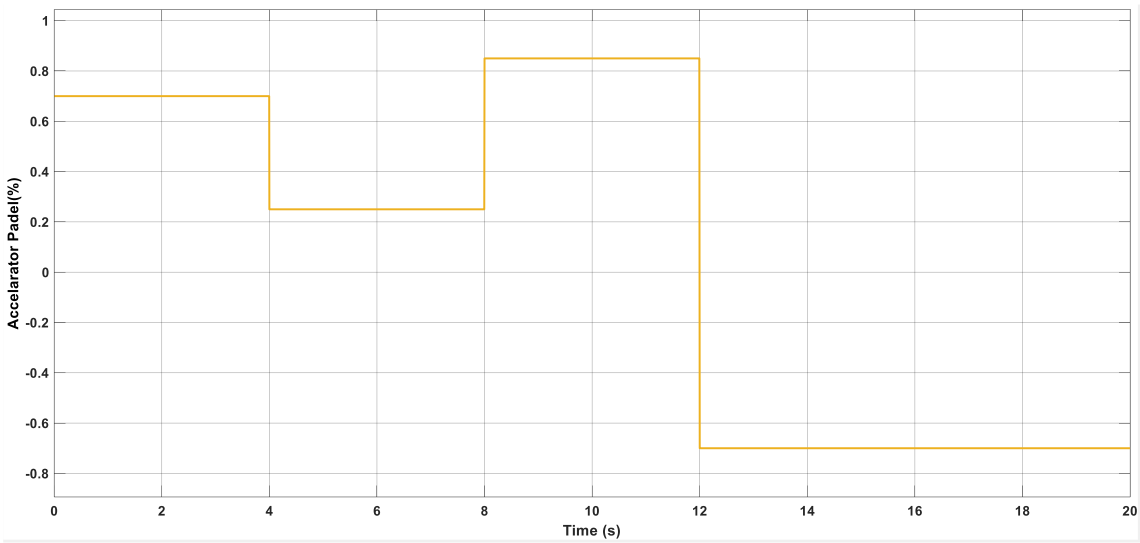

Figure 18: Pedal Position

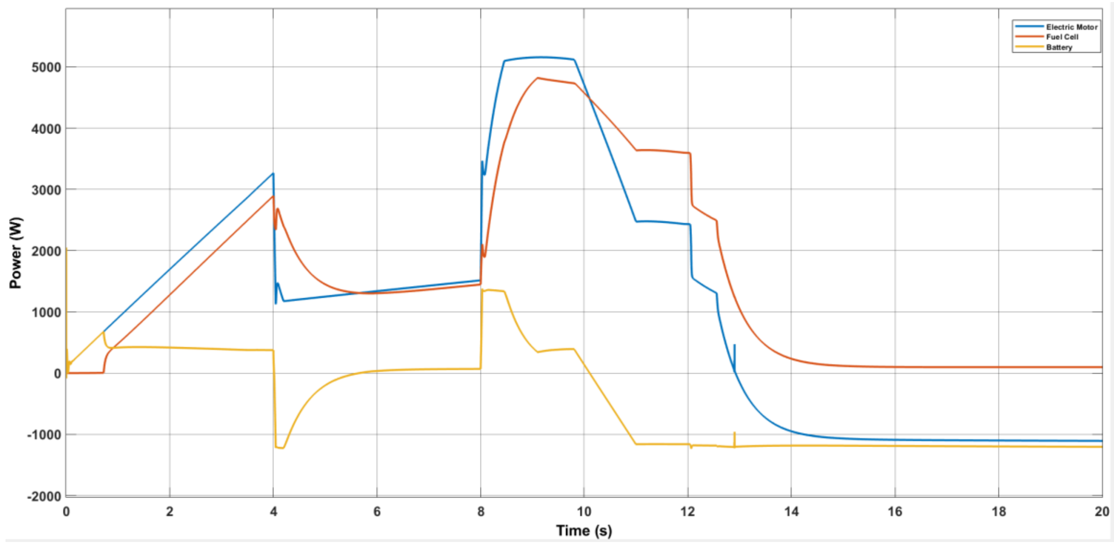

Figure 19: Power flow of the PVWFCHEV

Figure 20 demonstrates how the PVWFCHEV system adapts to low irradiance (200 W/m²) with a moderately charged battery (SOC = 75%). The PV panel contributes limited power, while the fuel cell and battery collaborate to meet load demands. The SOC trend, power split, and system efficiency in the figure provide insight into the control strategy's effectiveness under suboptimal solar conditions.

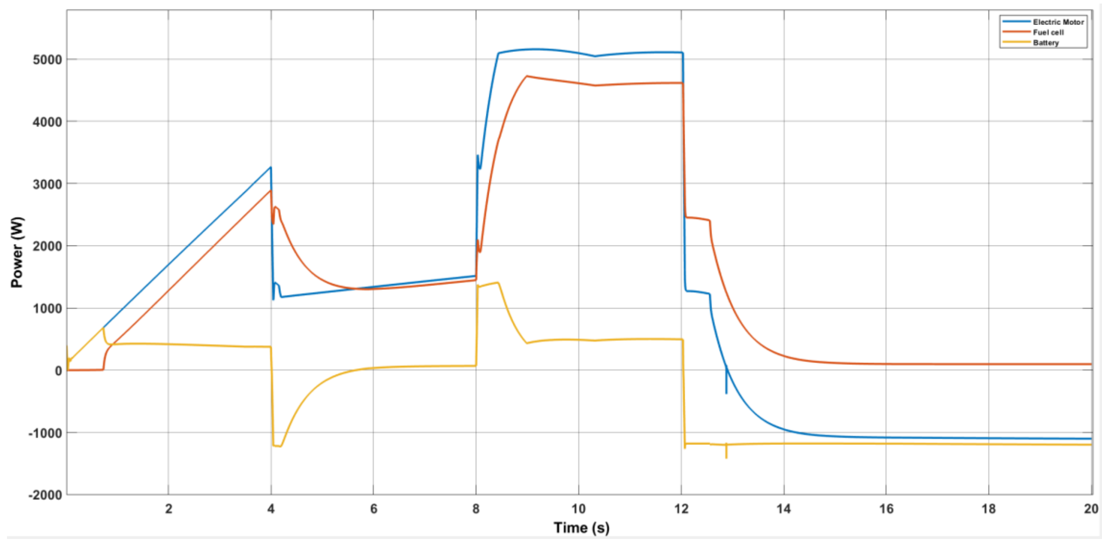

Figure 20: Performance of PVWFCHEV at 200W/m2 Solar irradiance and battery initial SOC of 75%

Figure 21 highlights how the PVFCHEV system performs under high solar irradiance (1000 W/m²) with a low battery SOC (35%). The PV array delivers maximum power, allowing the battery to recharge rapidly while meeting the load. The fuel cell remains inactive or minimally active, illustrating an efficient renewable-dominant operational mode that promotes battery recovery and fuel economy.

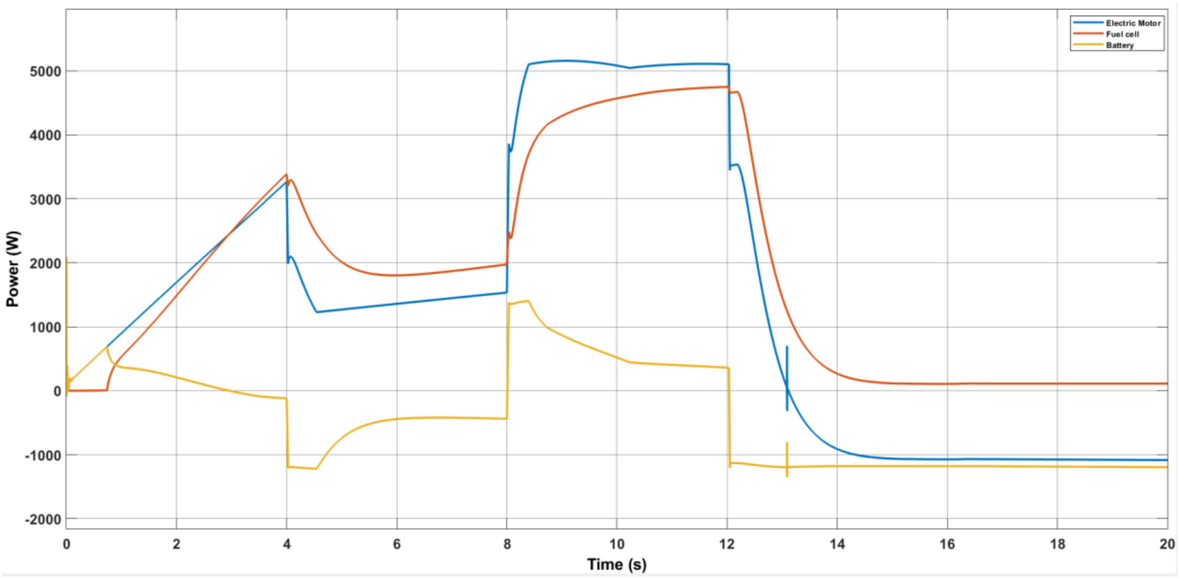

Figure 21: Performance of PVWFCHEV at 1000W/m2 Solar irradiance and battery initial SOC of 35%

Figure 22 shows the PVFCHEV system's performance under challenging conditions: low solar irradiance (200 W/m²) and a depleted battery (SOC = 35%). The PV provides minimal power, and the battery is near its lower limit. Consequently, the fuel cell becomes the dominant power source, ensuring the load is met and possibly initiating battery recovery. This scenario demonstrates the hybrid system's robustness and the importance of the fuel cell under low-renewable and low-storage situations.

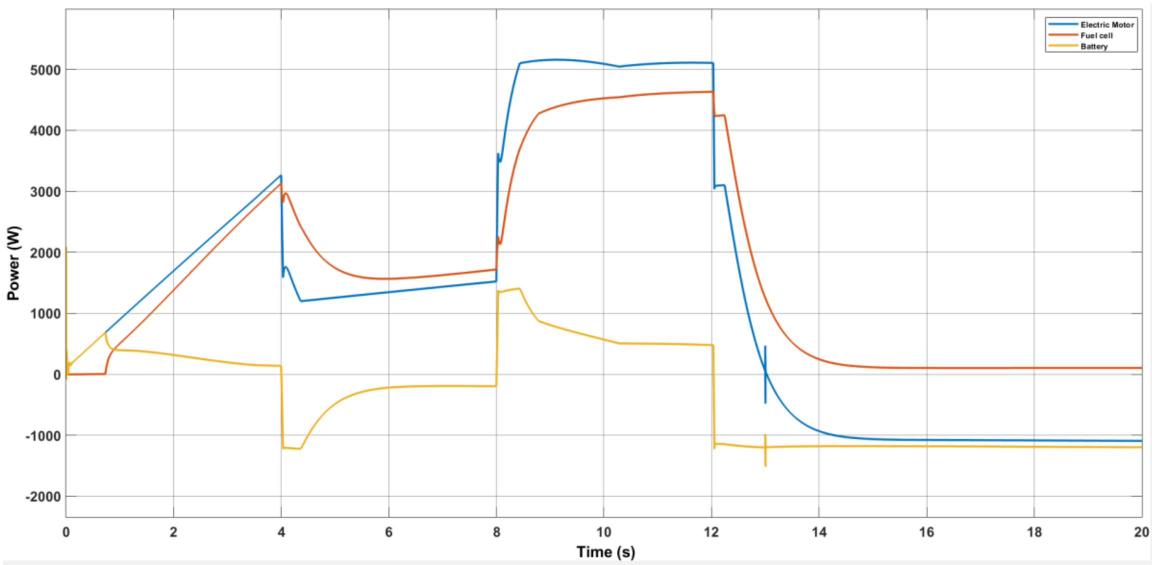

Figure 22: Performance of PVWFCHEV at 200W/m2 Solar irradiance and battery initial SOC of 35%

When the PVWFCHEV runs in the nighttime in which the PV array is off and only the FC and battery work in which there is a probability of the battery been low, the performance of a PVFCHEV using FLC based Energy Management System (EMS) can be compared with a simple FC EV using power-following control (PFC) strategy. In Figure 23, the vehicle using Power Following Control (PFC) strategy consumes 1.21-liter more amount of hydrogen than that using Fuzzy Logic Control (FLC) strategy in the driving cycle. The proposed EMS based on FLC possesses a better fuel economy than commonly used PFC, mainly because that FLC renders the FC working at the high-efficiency area, while the PFC merely regulates the FC to follow the motor power, thus reducing the energy efficiency of the system.

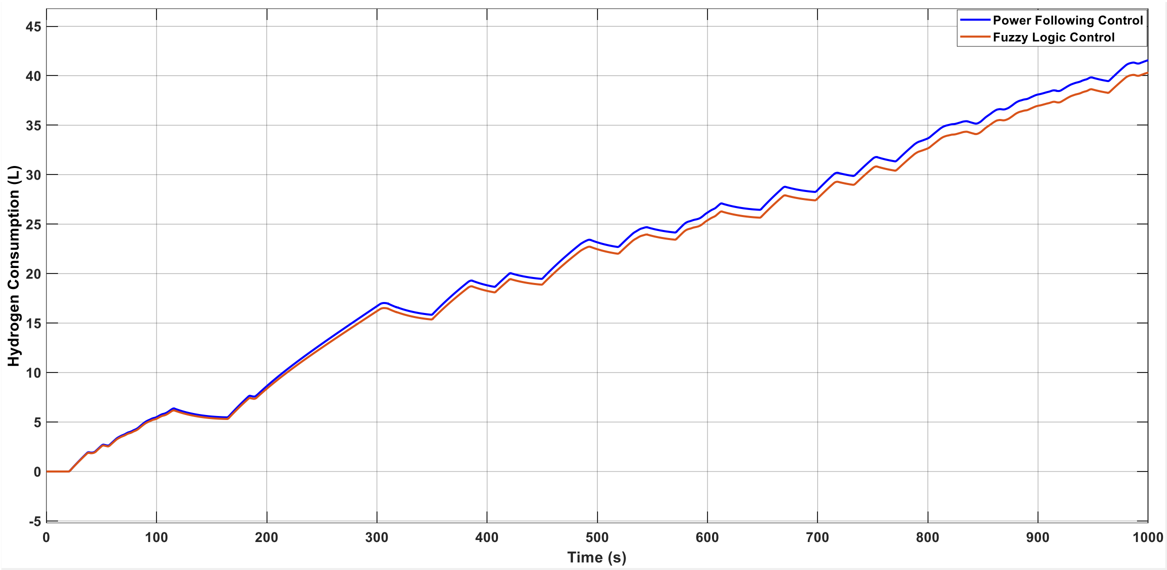

Figure 23: Hydrogen consumption comparison

At night when the PV solar irradiance is zero, and the battery state of charge (SOC) is moderate, the wind energy will need to be high as shown in Figure 24. The FC acts as the primary power source and charges the battery to recover its SOC in a short time. Since wind velocity is intense, it is necessary to reserve some capacity of the battery for storing wind energy. Thus, when the motor reaches its peak power, the battery is set to provide a small part of the demand power, which also helps the FC work at relatively high efficiency.

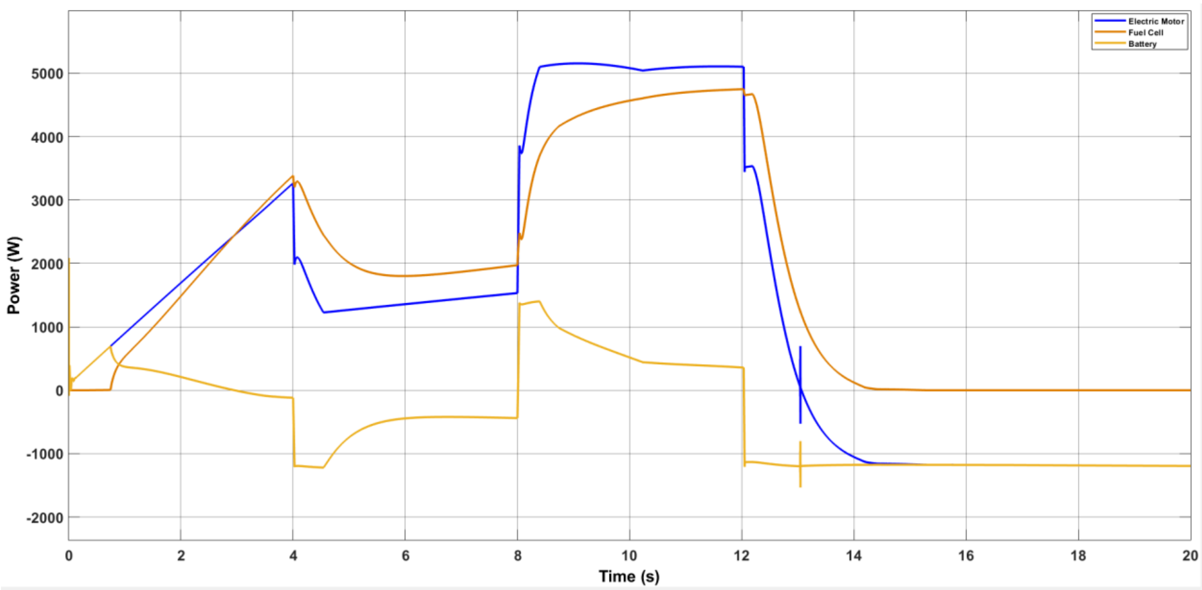

Figure 24: Performance of PVWFCHEV at 0W/m2 Solar irradiance and battery initial SOC of 35%

CONCLUSION

This research work proposes a Hybrid electric vehicle (HEV) concept powered by multiple energy sources. The design integrates solar photovoltaic (PV) energy, wind power, a fuel cell (FC), and a (PV + FC) to generate electrical energy. The system uses a proton exchange membrane (PEM) fuel cell and a supercapacitor to meet high torque demands. The vehicle also includes a battery pack paired with the supercapacitor to handle power requirements, while the fuel cell serves as a backup energy source. Additionally, an alternator is connected to the turbine blades to harness wind energy as the vehicle moves, generating electricity to recharge the battery. This design achieves zero carbon emissions and enhances energy efficiency. An energy management system based on fuzzy logic technique is employed for monitoring, controlling and optimizing energy usage. Modelling and simulation for each subsystem is carried on MATLAB/SIMULINK 2023a. This prototype demonstrates feasibility for localized deployment in urban or campus mobility applications.

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