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Enhancing Performance of Hybrid Electric Vehicle Using Optimized Energy Management Methodology

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ABSTRACT

The fuel consumption and the fuel management strategy (PMS) of the hybrid electric vehicle are closely linked (HEV). In this study, a hybrid power management technique and an adaptive neuro-fuzzy inference (ANFIS) method are established. Artificial intelligence represents a huge improvement in electricity management across different energy sources (AI). The main energy source of the hybrid power supply is a proton exchange membrane fuel cell (PEMFC), while its electrical storage devices are a battery bank and an ultracapacitor. The hybrid electric vehicle's power management strategy (PMS) and fuel consumption are closely related (HEV). In this paper, an adaptive neuro-fuzzy inference and hybrid power management strategy (ANFIS) approach is developed. A significant advance in electricity management across multiple energy sources is artificial intelligence (AI). The proton exchange membrane fuel cell (PEMFC) serves as the primary energy source of the hybrid power supply, and the ultracapacitor and battery bank serve as its electrical storage components.

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1. INTRODUCTION

The three most important and well-known engineering topics are fresh water, electricity, and the atmosphere because of their interdependence. Key issues that have been addressed include resource limitations and global warming. As a result, manufacturing processes and technical communities are rapidly changing their approach to energy-efficient applications, and the growth of the transportation industry is driven by economic and environmental factors [1]. Most fossil fuels used in transportation result in greenhouse gas emissions. Several attempts have been made in this field to increase the need for fuel cells (FCs) as a sustainable source of electrical energy that produces no greenhouse gases in transportation applications [2]. Fuel cells are a clean source of fuel for transportation and contribute to environmental protection when used in electric cars, trains, aeroplanes, etc. [3]. New energy conversion technologies such as fuel cells outperform conventional devices in many ways, including great energy efficiency, small size, environmental safety, long life, and many others. Because of its high power generation density and low heat generation—both essential in transportation applications—the proton exchange membrane fuel cell (PEMFC) appears to be the most suitable form for use in automotive applications. The limited dynamic response of fuel cells is their main disadvantage in transport applications. This means that the fuel cell is unable to respond adequately to sudden load changes because it lags behind the load changes.

As a result, the battery storage and ultracapacitor (UC) should be connected to the fuel cell [4]; while the battery storage seems to have high power density, it also has several disadvantages, including low energy capacity and long charging time. , high price and short life. The most effective method to address these concerns is to use a hybrid FC/B/UC network. Hybrid sources can take advantage of their special qualities with this combination. The ultracapacitor provides short bursts of peak power while the battery acts as an energy buffer. A power management scheme (PMS) is necessary to achieve some hybridization, and the main goal is to spread load demands across power sources. PMS successfully maintains hydrogen consumption and improves energy efficiency by limiting fuel cell output to wider operating levels. A set of traditional PMS [5] has been implemented to manage the system load between these integrated input sources.

They are Equivalent Consumption Minimization Scheme (ECMS), Fuzzy Logic Control (FLC), External Energy Minimization Scheme (EEMS), PI Control, State Machine Control (SMC) and Equivalent Consumption Minimization Scheme. Several other contemporary optimization-based techniques have also been developed. The battery bank, fuel cell, and ultracapacitors are included in the state machine control (SMC) power management technique that Wang et al. proposed in [6]. The authors of [7] implemented power management using the proportional-integral (PI) technique to control the energy flowing between photovoltaics (PV), fuel cells (FC), batteries and supercapacitors (SC). In [8], a rule-based energy management strategy was used to operate a hybrid device with B/SC/FC in many operating modes. Jiang et al. in Ref. [9] proposed a dynamic programming (DP) strategy to reduce the amount of hydrogen used in a hybrid power system that uses a fuel cell, battery, and supercapacitor to power the drivetrain. For the purpose of powering an electric car [10], a unique consumption control technique using rule-based fuzzy logic control with a number of multi-input sources, i.e. initially, the input sources consist of FC/B and later input sources. consist of B/SC/FC.

The authors present in [11] an adaptive neuro-fuzzy inference system (ANFIS) for efficient power management between FC and battery, which is often used to power electric vehicles. (EV). To improve the output power in an electric car using neural networks, a power management technique with two sections – wavelet-based and radial-based solutions was developed in [12]. In order to control the power between FC, B, SC and EV, the authors developed a new power control mechanism that focuses on wavelet transform techniques. By Djerioui et al., the grey wolf optimizer (GWO) was created. A hybrid power system for electric vehicle applications that considers FC/B/UC [13]. For parallel HEVs, an FLC-based method was developed to optimize the SoC, improve fuel efficiency, reduce NOx emissions, and guarantee better drivability. An FLC-based Intelligent Energy Management Agent (IEMA) was created to distribute energy among available resources. Energy requirements, vehicle speed, SoC and FLC were constructed in [14] to improve system performance.

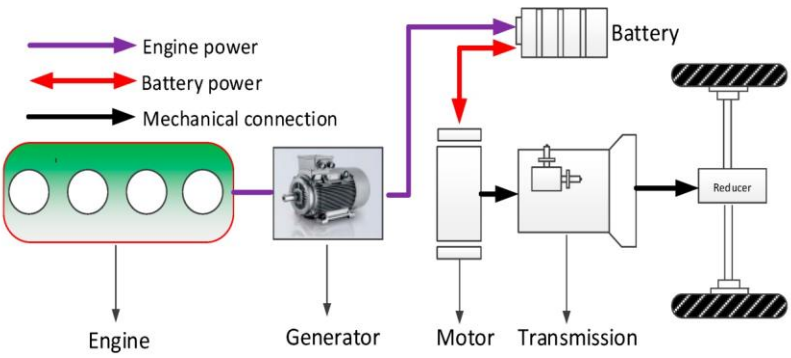

Figure 1. Conventional diagram of Hybrid E-Vehicle

[15] Presents a number of power management options for FC-powered EVs. Bison et al. proposed a new optimization strategy based on a two-dimensional mechanism that describes the fuel efficiency of hybrid vehicles. [16] used wavelet transform and fuzzy logic methodologies to improve the energy management of hybrid trams. The main goal of the project is the development of an ideal EMS to reduce hydrogen consumption and loss of FC functionality. No optimization problems are fully solved by any of the different algorithms. This is consistent with the No Free Lunch Scientific Theory, which is explored in [17], and shows that there is a real need for new optimization techniques in the study of EV power management. One important problem that could be solved is the measurement of hydrogen consumption using a hybrid DC bus energy storage system. In addition, it combines each DC/DC converter into a single device. In this research paper, an innovative hybrid power management system that incorporates ANFIS and serves as an adaptive control system is described. This control system is modelled using MATLAB/Simulink software to reduce hydrogen consumption in the FC and to keep the battery level (percentage of SoC) as high as possible in

terms of life cycle costs and maintenance. With FC/B/UC and PMS settings, a hybrid power control scheme is proposed to improve the fuel economy of a hybrid electric vehicle, as shown in Figure 1.

The essay is structured as follows. The literature review was described in Section 2 in relation to several problem statements. The proposed power management strategy (ANFIS) approach is presented in Section 3. The analysis of the comparative findings and the proposed technique are presented in Section 4. The primary findings that were derived from conducting this proposed work are presented in Section 5 as a final point.

2. LITERATURE SURVEY

MATLAB/Simulink was used to model fuel cells, ultracapacitor fuel cells, and ultracapacitor fuel cell vehicles. Modelling features were included when they significantly affected the optimization goals (e.g. in accurate modelling of DC/DC converters) and excluded otherwise to achieve a good trade-off between accuracy and runtime (e.g. in simplified motor modelling). Based on efficiency, weight, and cost, the optimal powertrain topologies for use in this paper were selected through qualitative analysis. Selected powertrain topologies are shown in Figure 1. All three vehicle types use a DC/DC converter to step up the fuel cell output voltage to match the motor controller input voltage (250–400 V is a common range [18]). This design allows the use of a smaller and, therefore, cheaper fuel cell, as the output voltage of the fuel cell can be lower than 250 V. The number of battery or ultracapacitor cells that can be connected in series with the ESS is limited because they are directly connected to the high-voltage bus (with the exception of the vehicle battery fuel cell-battery-ultracapacitor). This limitation is acceptable because using a different DC/DC converter for the ESS would increase the weight and cost of the car and reduce the efficiency of the system.

2.1. Batteries

Due to their better power and energy density, lithium-ion batteries are currently widely considered to be the best option for energy storage in electric vehicles over lead-acid or nickel-metal hydride batteries [19]. The basis of the battery model used in this work is the high-performance lithium-ion cell ANR26650MI from A123 Systems. This paper exhibits great power density, high efficiency, and low cost compared to batteries used in earlier vehicle studies [20, 21]. The total resistance and the %V -SOC curves are determined by two variables: the number of cells in series and in parallel (batt s and batt p). The %V -SOC curve is a function of the percentage of peak voltage, as in the fuel cell model, allowing it to be applied to different serial numbers of cells. Estimates put Colombian efficiency at 95% [22].

The battery voltage is multiplied by the measured battery current. In order to add the energy entering or leaving the battery to the initial energy in the battery, this energy is integrated and then converted from joules to kilowatt hours (in kilowatt-hours). The SOC of the battery in per cent is then calculated by dividing the current energy output of the battery by its total capacity. This %SOC is converted to voltage using a lookup table based on the information for the ANR26650MI cell [23]. Since the bus voltage rating for the ESS battery is 346.5 volts at 3.3 volts per cell, the number of battery cells in series is fixed at 105 (with room to charge and discharge without exceeding the motor controller voltage limits). The battery voltage is chosen to be lower than the bus voltage for the battery-ultracapacitor ESS, which uses a two-quadrant DC/DC converter between the battery and the high-voltage bus. The maximum number of battery cells in series is 75, which allows the ultracapacitor bank to dissipate at 250 V. The weight of each cell is 70 g. The final weight per cell is 123 g after adding 53 g for packaging and cell balance. $110 was quoted as the price for six articles [24]. It is estimated that the price may drop as low as $100 for higher volume production. A final $15 is added to each group of six cells for cell packing and balancing. Therefore, each cell is expected to cost $19.15. The maximum current allowed is 70A, and the price per kilowatt is expected to be $82.90/kW.

2.2. Fuel Cell Model

In order to vary the voltage of the fuel cell and battery independently of the voltage of the ultracapacitor, DC/DC converters coupled to the fuel cell and battery are essential components of the powertrain. If isolation is not required, as assumed in this paper, and if the voltage gain is not excessive, as in this paper, a non-isolated DC/DC converter is suitable for use in fuel cell automobiles [25]. As a result, the fuel cell-battery-ultracapacitor vehicle uses a straight-line bidirectional converter (see Fig. 5) that connects the battery to the high-voltage bus, and all other types of vehicles use a straight-line unidirectional boost converter (the converter in Fig. 5 with switch S1 removed for ensuring unidirectional energy flow). This article uses basic hard-switching converter models to simplify the modelling and avoid the in-depth topic of comparing different soft-switching methods based on efficiency, complexity, ease of control, weight, and cost. It is common practice to use interleaved and/or softswitch [26] converters at these high power levels.

Since the losses of the dynamic converter will impact the overall fuel consumption of the car [27] and because a high-performance converter can increase the volume and cost of the motor, it is essential to use a precise DC/DC converter. Model. For example, when determining the true benefit of using a smaller fuel cell or battery, it is important to consider how much lighter and less expensive the accompanying DC/DC converter will be.

2.3. Ultracapacitor Vehicle

In a car using an ultracapacitor, the ultracapacitor stores energy from regenerative braking and offers additional power during acceleration. The energy storage capacity of the ultracapacitor is usually insufficient for vehicle movement at low speeds. Therefore, the control approach must guarantee that the energy storage capacity will be used as efficiently as possible. [28] examines three approaches and shows that optimal fuel efficiency is achieved by keeping the sum of the vehicle's kinetic energy and the energy stored in the ultracapacitor constant. This makes intuitive sense because the ultracapacitor will have enough room to absorb regenerative braking energy when the vehicle is braking when its speed is high and its voltage is low. The low-pass coefficient is again chosen as the controller variable. The power supply of the fuel cell and the EZS are separated from the necessary electrical energy by means of a filter. All ESS (transient) power is supplied by the ultracapacitor within its current and voltage limitations. The battery supplies the remaining energy needed in case the voltage of the ultracapacitor drops below its lower limit (250 V). If the fuel cell is unable to provide electricity, or if the current consumption of the fuel cell is less than 7.55%, the battery supplies additional energy.

3. PROPOSED HYBRID POWER MANAGEMENT SYSTEM

A hybrid energy storage system (HESS) consists of a supercapacitor, Li-ion batteries, and a PEMFC. To ensure that the load has sufficient reliable power, these three sources are often considered FCHEVs. Figure 2 shows the hybrid system analysis configuration. The three power sources in this system are the capacitors, the fuel cell and the rechargeable battery. The fuel cell is equipped with a DC/DC boost converter that increases its voltage level to the desired level and maintains it at the outputs. A DC/DC bidirectional power supply device that converts fluctuating power into a fixed voltage is found in batteries. Supercapacitors have been included in bi-directional converters that allow energy to be exchanged in both directions, similar to some other capacitors.

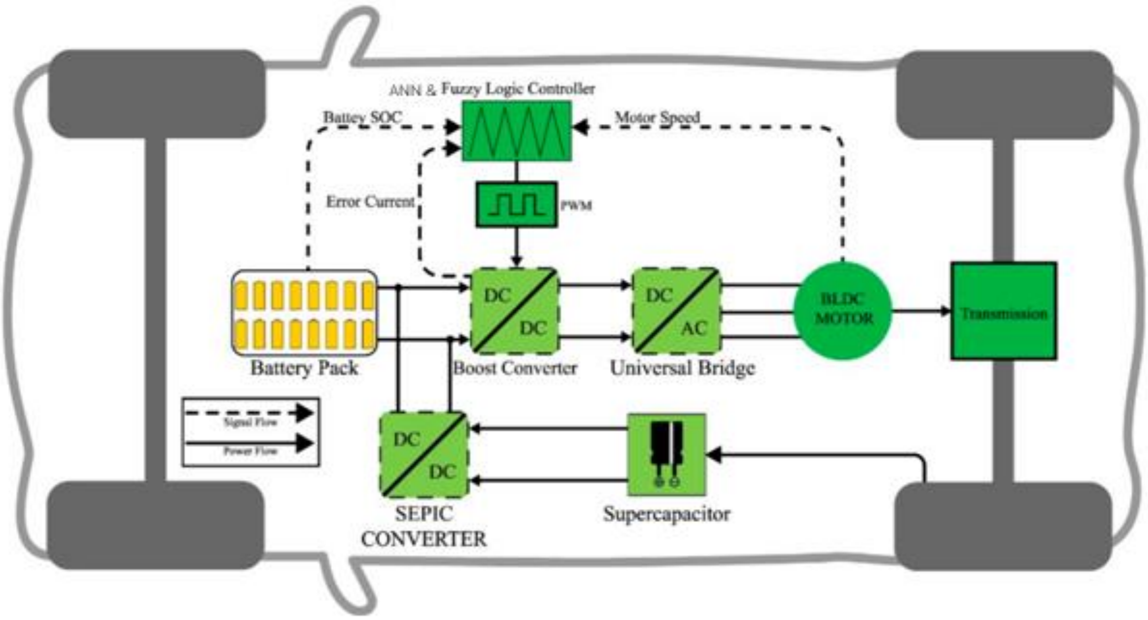

Figure 2. Proposed Hybrid Power Management System

3.1. Fuel Cell

Various fuel cell technologies exist, and they are divided into groups based on the electrolytes they use. Proton exchange membrane fuel cells are a different kind of fuel cell that is frequently utilised in automotive applications (PEMFC). There are a number of novel fuel cell prototypes, each having a unique set of advantages and disadvantages depending on the subject being researched. Any model should be accurate and succinct. Additionally, this study proposes a straightforward electrochemical model that might be utilised to predict how such a fuel cell will behave under both dynamic and static circumstances [29]. The relationship between the fuel cell voltage level and the absolute pressures of hydrogen, water, and oxygen is the basis for the hydrogen fuel design used in this work. Table 1 provides an illustration of the fuel cell stack's specs. The relative pressures of oxygen and hydrogen, the temperature at which the membrane hydrates chemically, and the output current all affect the fuel cell's voltage. Below is the mathematical model.

$$V_{FC=}E_{Nernst} - V_{act} - V_{ohmic} - V_{con} \quad (1)$$

Where E_{Nernst} represents the mean value of thermodynamic potential in every single cell unit.
Here,
V_{act} = Activation voltage drop,
V_{ohmic} = Ohmic voltage drop,
V_{con} = Concentration voltage drop.
Hence, for N number of cells connected in series, the stack voltage V_{stack} is described as

$$V_{stack} = N.V_{FC} \quad (2)$$

Table 1. Fuel Cell Specifications

Fuel Cell Model (Input Parameters)	Specifications
Voltage	53.5V
Number of Fuel Cell	65
Operating temperature	43^{O}C
Nominal efficiency of the fuel stack	55%
Response time of Fuel Cell Voltage	1s
Voltage undershoot	2V

3.2. Supercapacitors

One of the most recent developments in power storage technology, particularly for integrated devices, is the use of supercapacitors. In this configuration, a series resistance (R sc) comparable to a capacitance (C sc) is connected. In Table 2, the UC's specifications are displayed. The supercapacitor voltage (V sc), which results from the SC current (I sc), is calculated using the formula [30].

$$V_{sc} = V_1 - R_{sc} \times I_{sc} = \frac{Q_{sc}}{S_{sc}} - R_{sc} \times I_{sc} \quad (3)$$

An electric vehicle that uses supercapacitors as its storage system must be built with a stack of cells where N S cells are connected in series and N P cells are connected in parallel.

Table 2. Supercapacitor Specifications

Supercapacitor Model (Input Parameters)	Specifications
Surge Voltage	306V
Capacitor number in series	6
Capacitor counts in parallel	1
Rated voltage	290V
Rated Capacitance	14.5F
Operating Temperature	24^{O}C

3.3. Battery

A tiny controlled power supply is built into the battery in series with a fixed resistance like this [21]. Table 3 lists the requirements for Li-ion batteries. The battery voltage Vbat is specified in equation (1).

$$V_{batt} = E - R_{bat}.I_{bat} \tag{4}$$

Table 3. Li-ion Battery Specifications

Battery Model (Input Parameters)	Specifications
Minimal Voltage	48V
Determined capacity	40Ah
Esteemed Capacity	40Ah
Nominal Voltage capacity	35.15Ah
Response time of battery voltage	29s
Fully charged voltage	55.77V

3.4. Adaptive Network-Based Fuzzy Interface System (ANFIS)

Power management techniques have emerged to support industrial purposes, such as fuzzy approaches, which are more popular in systems control, by automating the learning experience. ANFIS is a key method that combines rule-based fuzzy logic control methodology and artificial neural network (ANN) learning ability to develop a complete set of all different kinds of feed-forward neural networks using supervised learning functions [31]. The ANFIS strategy implements a hybrid training procedure based on relevant data, input/output and coupling factors.

The ANFIS architecture is shown in Figure 3 as having only one hidden layer. The input node is represented by Layer 1, the fuzzification nodes are in Layer 2, the result nodes (hidden) are in Layer 3, the defuzzification nodes are in Layer 4, and the output node is represented by Layer 5 [32]. A node can also be updated, at which point it will be divided into dynamic and static categories. Layers 2 and 4 are examples of dynamic nodes, while layers 1 and 3 are examples of stable nodes. The Li-ion battery SoC with three membership functions (MF) and the vehicle energy load represented by Pload are both used as inputs of the ANFIS control technique to predict the output power of the fuel cell [33]. The predicted proportional benefit from the PEMFC level is the result of ANFIS. ANFIS uses proportional variables to quickly measure and change standards.

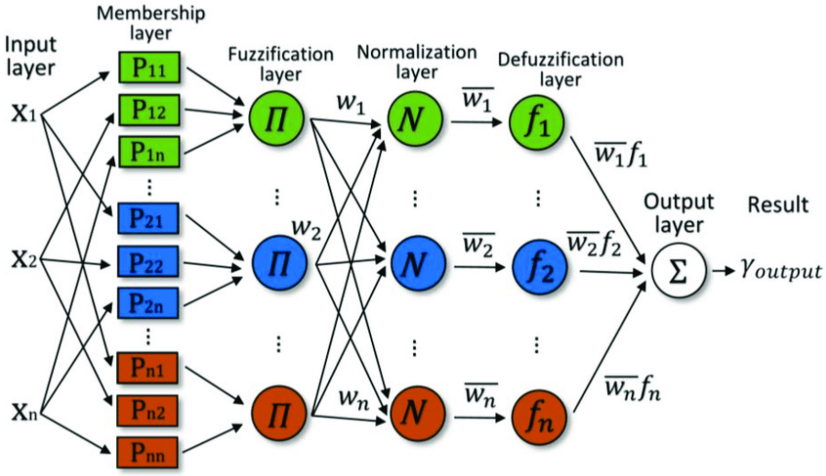

Figure 3. ANFIS five-layer structure

4. RESULTS AND DISCUSSION

The performance of EV driving just with the battery, fuel cell, and supercapacitor has been compared with the performance of EV driving in order to assess the efficacy of the proposed ANFIS energy management method. The primary simulation parameters are listed in Table 4.

Table 4. Comparison Performance [34]

Power Device's	Drive range (km)	Specific Energy Consumption (Wh/km)	Energy saving (%)
Fuel cell	150	93	+13
Supercapacitor	150	91	+15
Battery	150	90	+2.5

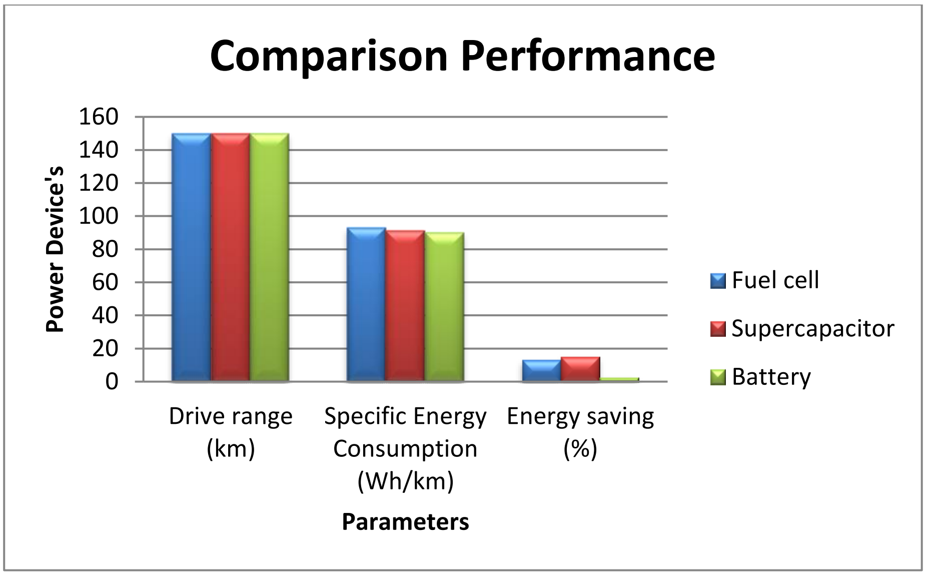

Figure 4. Comparison performance

Table 5. Characteristics of cell present and future battery technologies for EVs [35]

Parameter's	Cell voltage	Ah	Wgt. kg	EV W/kg	HEV W/kg
Batteries	2.8	30	87	140	521
Fuel	2.7	15	60	127	540
Supercapacitor	3.4	20	24	5.5	250
PV	1.5	20	24	40	156

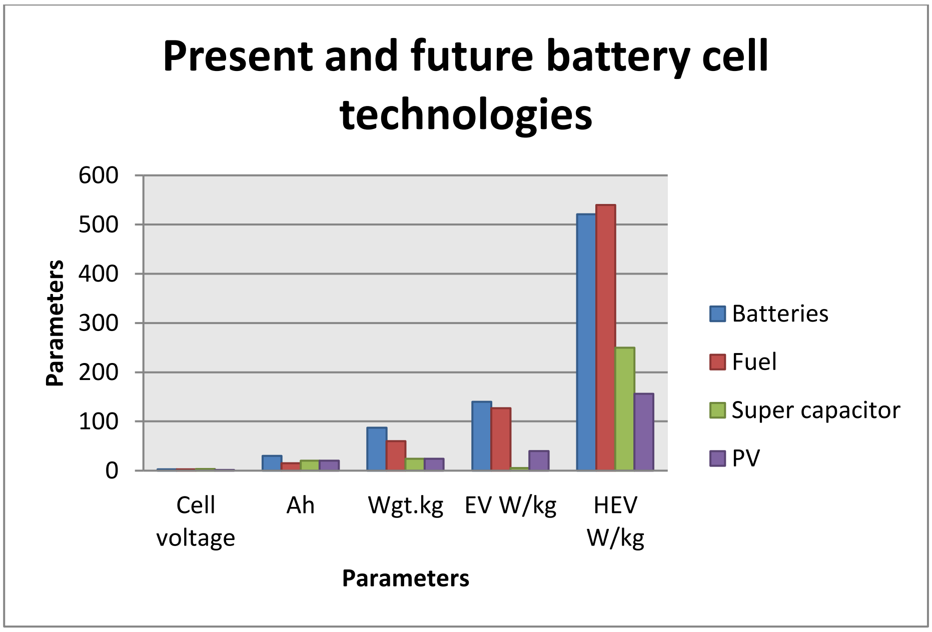

Figure 5. Characteristics of cell present and future battery technologies for EVs

Table 6. The Simulation Results Comparison for Different Driving Cycles [36]

Driving Cycle	Proposed HEV FC/Bat (kW)	Proposed HEV FC/PV/Bat (kW)	Proposed HEV FC/Bat/PV/UC (kW)
UDDS	7.57	7.64	7.85
NEDC	5.28	5.33	5.54
JP	3.43	3.81	3.90

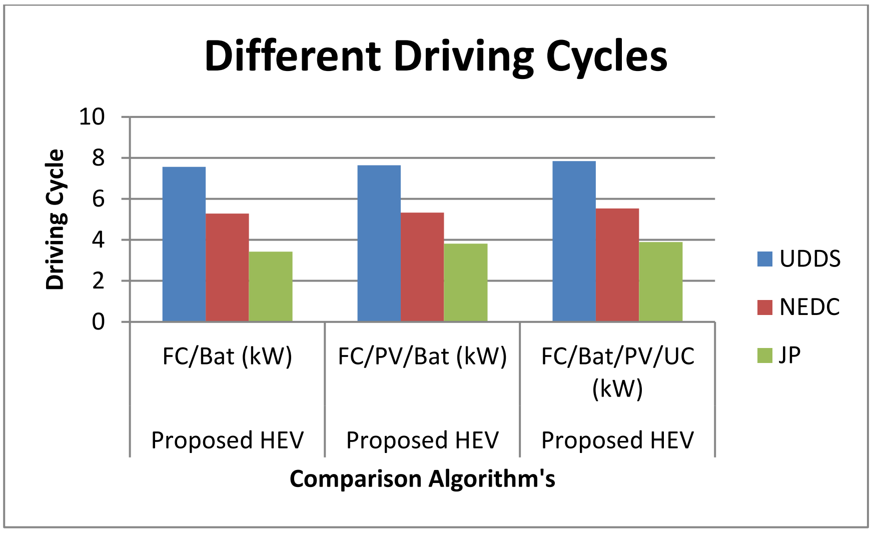

Figure 6. The Simulation Results Comparison for Different Driving Cycles

Moreover, the most successful offline global optimization method, dynamic programming, was compared with the proposed EMS for an online driving cycle in this study. The priority and effectiveness of the proposed approach will be guaranteed by its advantage over the dynamic programming method. In addition, the dynamic programming method does not limit the power generated by the PEMFC to specific operating locations. The simulation results of the proposed strategy are contrasted with the results of the dynamic programming approach, the most successful offline global optimization technique. For example, the fuel consumption in the proposed EMS is 7.64 MPG, while the fuel consumption in the DP strategy is 7.65 MPG in the UDDS driving cycle for an identical FC/battery/UC structure. As a result, the fuel consumption of the proposed EMS is roughly equivalent to that of the DP technique. Table 4 also lists battery power fluctuations. According to the findings, the FC/battery/UC arrangement with the proposed EMS has the least performance variation compared to the alternative tactics.

5. CONCLUSION

In order to save gasoline as much as possible, this study proposes an ANFIS for power management in hybrid electric vehicles, with fuel cell (FC) as the primary energy source and batteries (BB) and ultracapacitors (UC) as secondary sources. The battery SoC is controlled by battery performance penalty coefficients in ECMS, a cost-based optimization approach. UC efficiency is not considered in this optimization strategy. Once the UCs are depleted, they can be recharged with the same power from the battery bank thanks to converters in the battery bank that control the DC bus voltage profile. During the load cycle, the battery and FC balance the load demand. This study recommends ANFIS for power management in hybrid electric vehicles, with fuel cell (FC) as the main energy source and batteries (BB) and ultracapacitors as secondary sources to save as much oil as possible (UC). The battery SoC is controlled by battery penalty coefficients in ECMS, which is a cost-based optimization method. This optimization technique does not consider the utility of UC. The battery bank has converters that regulate the DC bus voltage profile so that if the UCs are depleted, they can be recharged with the same power from the battery bank. The battery and FC balance the load demand during the load cycle.

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