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Grey Wolf Optimization Based Energy Management Strategy for Hybrid Electrical Vehicles

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ABSTRACT- Electric vehicles (EVs) are seen as a necessary component of transportation's future growth. However, the performance of batteries related to power density and energy density restricts the adoption of electric vehicles. To make the transition from a conventional car to a pure electric vehicle (PEV), a Hybrid Electric Vehicle's (HEV) Energy Management System (EMS) is crucial. The HEVs are often powered with hybrid electrical sources, therefore it is important to select the optimal power source to improve the HEV performance, minimize the fuel cost and minimize hydrocarbon and nitrogen oxides emission. This paper presents the Grey Wolf Optimization (GWO) algorithm for the control of the power sources in the HEVs based on power requirement and economy. The proposed GWO-based EMS provides optimized switching of the power sources and economical and pollution free control of HEV.

Keywords: Energy Management System, Fuel Cell, Grey Wolf Optimization, Hybrid Electrical Vehicle, State of Charge.

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1. INTRODUCTION

The massive growth in the global population and rising living standards in emerging nations have caused a spike in the number of automotive vehicles. Traditional diesel/petrol cars, on the other hand, are becoming less efficient and less popular as a result of the scarcity of fossil fuels and the rise in air pollution caused by the release of dangerous gases. CO2 is emitted by classic inter combustion engine-based cars, which is the primary cause of global warming and air pollution. Because of their pollution-free nature, cheaper cost, and efficiency, electric vehicles have seen a recent surge in popularity. Despite this, the adoption of a completely electric car is difficult due to its restricted range [26], [19], [14].

The present electric car can only drive 150-200 kilometres on a single charge of the battery, limiting the vehicle's long-distance capacity. To increase HEV outcomes in critical situations, hybrid electric vehicles employ a combination of the internal combustion engine (ICE) and electrical power sources to power the vehicle. Because battery size and quantity are key constraints in HEV, researchers have worked on allied small power sources for HEV in addition to batteries. By incorporating a plug-in rechargeable battery, plug-in hybrid electric vehicles (PHEVs) increase battery capacity. Both mechanical and electric power is required by PHEVs. As a result, in PHEVs, an EMS is required to maintain the operating states of the ICE and the battery. PHEVs are classified as series PHEVs, parallel PHEVs, or series-parallel PHEVs based on the different connection topologies between the ICE, the battery, and the electric motor (EM). Flexible operating modes in series-parallel PHEVs can produce lower emissions and greater driving outcome than series or parallel PHEVs. An EMS for series-parallel PHEVs that is well-designed reduces emissions while enhancing fuel efficiency (FE). The goal of EMS design is to acquire minimum complexity while maintaining high efficiency [15], [20], [21].

In HEV, the primary purpose of an EMS is to fulfill power demand with the least amount of fuel, the least number of emissions, and the greatest potential vehicle outcome. HEVs are tough to EMS because of their intricate architecture. Because they can accurately estimate the power distribution of the engine and motors, EMSs are useful in measuring HEV fuel economy [16]. Fuzzy Rule-based EMSs are easy to set up and maintain. It can handle both spoken and statistical data at the same time. The parameters of fuzzy logic control (FLC) are simple to change, allowing for a lot of control flexibility. The three forms of fuzzy rule-based EMS are conventional fuzzy control, predictive fuzzy control, and adaptive fuzzy control [25]. Bathaee et al. [30] developed a fuzzy-based torque controller for parallel HEVs. The ICE operational points are determined by the required battery SOC and ICE torque. Li et al. [28] suggested an FLC-based method for calculating the power split between the ice and the battery, allowing the HEV engine to run more efficiently and generate fewer pollutants. The engine and motor operation points of the PHEV were also determined using a fuzzy logic-based EMS. It resulted in decreased fuel consumption and emissions of CO, CO2, HC, and NOx [24]. Akar et al. [23] introduced EMSs for battery/ultra-capacitor EVs with multi-objective converters using rate limiter and fuzzy controller.

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The optimization algorithms have shown superior results for the EMS of HEVs because of their multi-objective constraints handling capability. Ramdan et al. [1] presented GWO and Artificial Bee Colony (ABC) for the energy management in the Fuel Cell HEV (FCHEV) based on the various driving conditions. The GWO based optimization provides better results in dynamic conditions whereas ABC provides more economical feasibility. In Plug-in HEV (PHEV) it is essential to switch efficiently from the conventional vehicle mode to pure EV mode. Ding et al. [10] explored a rule-based control strategy along with a Genetic Algorithm (GA) for the EMS of PHEV. The suggested method is used to minimize hydrocarbon and nitrogen oxides emissions. The environmental conditions and future driving conditions are highly unpredictable in real life scenario. Traditional EMS systems use predefined rules for energy management that fails to provide effective solution in real time conditions [22]. The reinforcement learning (RL) algorithms are capable of designing EMS systems based on real time driving conditions without any prior knowledge of driving and vehicle parameters. However, parametric study is vital to attain better fuel economy and design a generalized EMS model that can be adaptable to any type of HEV model [17]. The deep learning-based EMS for HEVs is slower because of its extensive training process and the complexity of the architectures. Lian et al. [18] explored deep deterministic policy gradient (DDPG) that utilizes the expert's knowledge to minimize the training overheads of the EMS strategy. It provides better stable operation, fuel economy, faster training of EMS algorithm and a generalized approach that can be employed for any type of HEVs. The fuel cell can be seen as a reliable, efficient, and portable source of power under critical conditions; however, it increases the cost of the system if used regularly [29], [27]. Various optimization strategies have been employed for EMS of HEV in recent years which has given promising performance under different dynamic scenarios. Still, there is a need to focus on the faster control of EMS systems for HEVs with multiple power sources that provide maximum power, longer lifetime of the battery, lower cost, and can deal with dynamic driving conditions, road conditions, and environmental conditions [2-5], [11].

This paper presents energy control in HEV with hybrid electrical sources. The major contributions of the paper are summarized as follows:

- Design of effective multi-objective Grey Wolf Optimization based energy management strategy for HEVs with hybrid electrical sources.
- Performance evaluation of proposed optimization technique for different vehicle dynamics and constraints.

The rest of the paper is organized as follows: *Section 2* provides the proposed GWO based EMS for HEVs in detail. *Section 3* gives detailed description of the simulation results and discussions of various parametric variations and their effect on the proposed control strategy. *Section 4* depicts the conclusions, merits and future planning for the improvement of the proposed EMS scheme.

2. SYSTEM MODEL

The suggested GWO based control strategy is described in *Figure 1*. The considered HEV model consists of three hybrid electrical sources such as a battery bank, fuel cell and ultra-capacitors to power the HEV. In the proposed model the ultra-capacitor and fuel are connected to the DC link through an interleaved bidirectional buck-boost converter and unidirectional boost converter. It included a DC-AC converter and transmission model that transfer power to drive the vehicle.

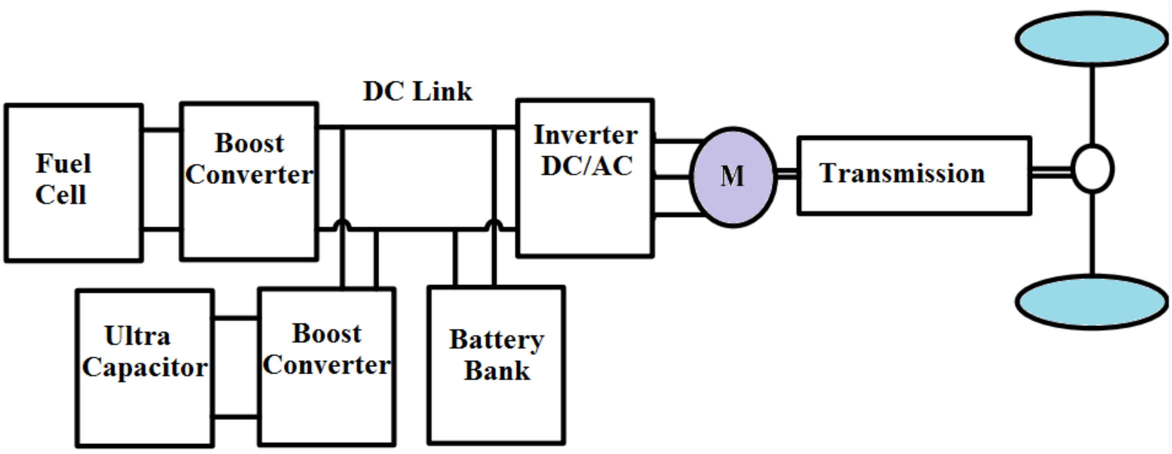

Figure 1: The configuration of the different power sources for HEV

2.1 Modeling of Fuel Cell

In this work, Proton Exchange Membrane Fuel Cell (PEMFC) model is considered that converts the reactant's chemical energy into electricity. The general fuel cell stack model offered by the Fuel Cell Stack block may be used to represent the most widely used hydrogen and air-fueled fuel cell stacks. An electrical model of a fuel cell that relies on fuel flow rate is shown in the diagram below. The two building components of the stack model are a fundamental model and a comprehensive model. Select the level in the mask under Model detail level in the block dialogue box to switch between the two models. *Figure 2 and 3* show the fuel cell equivalent circuit and SIMULINK model, respectively.

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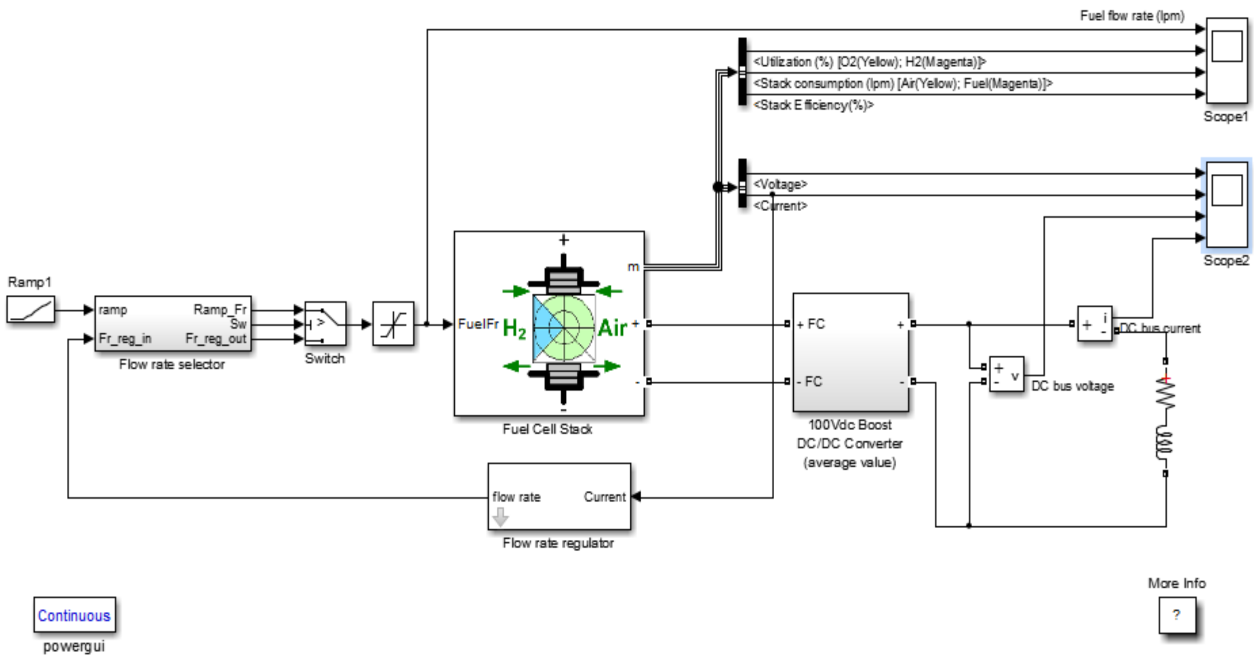


Figure 2: Simulink Modelling of Fuel cell

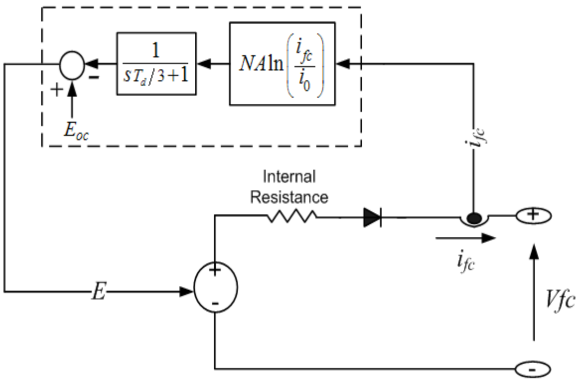


Figure 3: Equivalent circuit of fuel cell

The simulation of the voltage power relationship of the fuel cell is shown in the *Figure 4*.

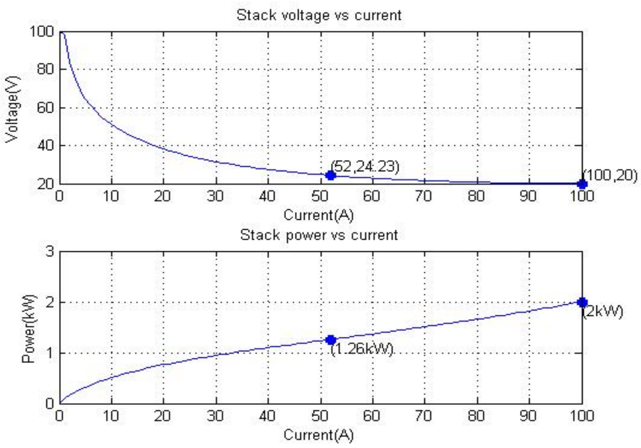


Figure 4: Outcome curve for single FC

It is observed that the FC provides large efficiency at low current. For limited fuel flow rate, the current efficiency and fuel utilization is very low. Increase in current leads to reduction in voltage because of over potential, internal resistance and concentration effects. The parameter selected for the simulation of the FC are described in the *table 1*. The offered system consider stack of 8 fuel cell to fulfill the power requirement.

Table 1: Fuel cell simulation parameters

Parameter	Specification
Type of cell	PEMFC
Number of Cells	8
Nominal Stack efficiency (%)	55 %
Voltage range	98- 100 V
Operating temperature (Celsius)	65 degree
Nominal Air flow rate (lpm)	300
Nominal fuel supply pressure (bar)	1.5 bar
Nominal air supply pressure (bar)	1 bar
H_2	99.92 %
O_2	21 %
H_2O	1 %

2.2 Modeling of Battery

A general dynamic model that depicts the most common kinds of rechargeable batteries are implemented by the battery block. *Table 2* lists the battery configurations. The charging and discharging equations for the Lithium battery are given in *equation 1 and 2*.

Discharge Model($i^* > 0$):

$$f_1(it, i*, i) = E_0 - K\frac{Q}{Q - it}i * - K\frac{Q}{Q - it}it - A.e^{-B.it} \quad (1)$$

Charging Model ($i^* < 0$):

$$f_1(it, i*, i) = E_0 - K\frac{Q}{Q - 0.1Q}i * - K\frac{Q}{Q - it}it - A.e^{-B.it} \quad (2)$$

The SIMULINK model for battery and output voltage and SOC for the Lithium battery considered for the modeling of proposed HEV EMS system are given in *figure 5* and *figure 6* respectively.

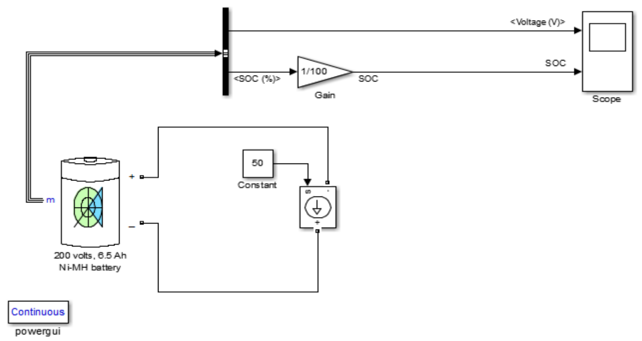


Figure 5: Simulink model for battery

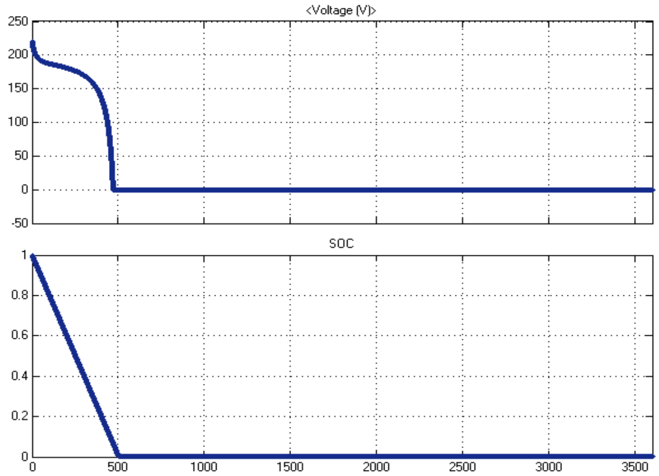


Figure 6: Simulation results for the battery - a) Battery voltage vs time b) Battery state of charging (SOC) vs time

Table 2: Battery Specifications

Parameter	Value
Rated Capacity	6.5 Ah
Internal Resistance	2 mΩ
Nominal Voltage	1.18 V
Rated Capacity	6.5 Ah
Maximum Capacity	7 Ah
Fully Charged Voltage	1.39 V
Nominal Discharge Current	1.3 A
Capacity @ Nominal Voltage	6.25 Ah
Exponential Voltage	1.28 V
Exponential Capacity	1.3 Ah

3. GWO FOR EMS IN HEV

The Canidae family includes the grey wolf (Canis lupus). Grey wolves are peak predators which indicate that they are the top predators in the food chain. Grey wolves desire to be with other wolves in a pack. The typical wolf pack size is between 5 and 12 wolves. They have a complex social dominance system, which is fascinating. A male and a female are the alphas, or leaders. The alpha wolf is habitually in charge of sleeping arrangements, hunting, and waking times, among other things. The pack is dictated by the alpha's judgments.

Grey wolves engage in group hunting, which is an interesting social characteristic in addition to their social hierarchy.

The three key stages of grey wolf hunting the first stage is as following, encircling, and pestering the prey until it stops moving, the second phase is tracking, pursuing, and impending the prey, and the final stage of attacking the prey.

After searching for the prey, the pack of grey wolves encircles the prey which can be mathematically represented by equation 3-4.

$$\vec{E} = |\vec{O}.\vec{X_p}(i) - \vec{X}(i)| \quad (3)$$

$$\vec{X}(i+1) = \vec{X_p}(i) - \vec{B}.\vec{E} \quad (4)$$

Where, i represents current iteration, $\vec{B}$ stands for the coefficient vector representing distance the between the two wolfs, $\vec{O}$ denotes the coefficient vector representing the obstacle in hunting path when the wolves reaching towards the prey, $\vec{X_p}$ describes the position of prey and $\vec{X}$ depicts the position of the grey wolf.

The coefficients vectors ($\vec{B}$ and $\vec{O}$) required for encirclement are calculated using *equation 5 and 6*.

$$\vec{B} = 2 \times \vec{l} \times \vec{r_1} - \vec{l} \quad (5)$$

$$\vec{O} = 2 \times \vec{r_2} \quad (6)$$

Where, the component $\vec{l}$ reduces linearly from 2 to 0 at the time of iterations and $\vec{r_1}$ and $\vec{r_2}$ represents random vectors in the interval [0, 1].

After encirclement of the prey, α, β, and δ wolf guides the other members for attacking the prey. The α wolf provides the best decision among α, β, and δ wolves. The hunting behavior of the grey wolf is mathematically represented using *equation 7-13*.

$$\vec{E_\alpha} = |\vec{O_1}.\vec{X_\alpha}(i) - \vec{X}(i)| \quad (7)$$

$$\vec{E_\beta} = |\vec{O_2}.\vec{X_\beta}(i) - \vec{X}(i)| \quad (8)$$

$$\vec{E_\delta} = |\vec{O_3}.\vec{X_\delta}(i) - \vec{X}(i)| \quad (9)$$

$$\vec{X_1} = \vec{X_\alpha}(i) - \vec{B_1}.\vec{E_\alpha} \quad (10)$$

$$\vec{X_2} = \vec{X_\beta}(i) - \vec{B_2}.\vec{E_\beta} \quad (11)$$

$$\vec{X_3} = \vec{X_\delta}(i) - \vec{B_3}.\vec{E_\delta} \quad (12)$$

$$\vec{X}(i+1) = \frac{(X_1 + X_2 + X_3)}{3} \quad (13)$$

The main goal of the suggested GWO based EMS to minimize the fitness to acquire the power requirement of HEV for the given driving cycle with minimum cost and less pollution. Equation 14 provides the fitness function for the suggested GWO based

$$Fitness_{MG} = Fit_B + Fit_{FC} + Fit_{UC} + Fit_{ICE} \quad (14)$$

3.1 Cost Function for Battery

The cost function for battery is given by equation 15. The suggested simulation considered 500 kW battery for the simulation. The changing mode of the battery is considered as the load of about 3 MW.

$$Fit_B = \alpha_1 P_B \quad (15)$$

Where, P_B stands for the battery power (MW), Fit_B is cost fitness function of battery, α_1 represents cost coefficient for the battery energy (300 $/kW).

3.2 Cost Function for Fuel Cell

The cost function for fuel cell is also typically considered as a function of quadratic approximation is given in equation 16.

$$Fit_{FC} = \alpha_2 P_{FC} \quad (16)$$

Where, Fit_{FC} is cost fitness function of fuel cell, and α_2 stands for the cost coefficients of the fuel cell (340$/KW) [29], [27].

3.3 Cost Function for Ultra-Capacitor

The cost function for the ultra-capacitor considering cost per unit of ultra-capacitor power (α_3 =200$/KW) is given in equation 17.

$$Fit_{UC} = \alpha_3 P_{UC} \quad (17)$$

The algorithm for the GWO based EMS for the HEV system is given as:

Algorithm: GWO based HEV EMS

Step 1: Initialization Phase

Initialize the grey wolf population Xi (i = 1, 2, ..., n)
N: Number of energy sources(FC, UC, and BT)
Initialize a, A, and C
Initialize the distributed generator parameters
Initialize costing parameters of the generators

Step 2: Calculate the fitness using equation 1 for each wolf

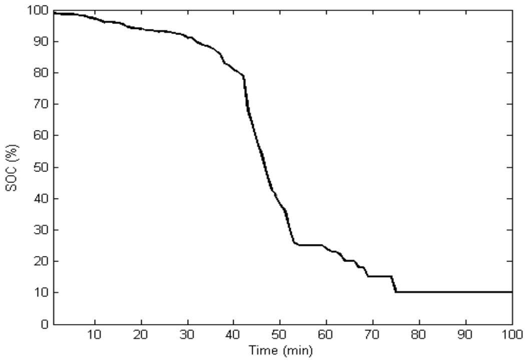
$X_\propto$ =*the best wolf (search agent)*
X_β =*the second best wolf (search agent)*
X_δ =*the third best wolf (search agent)*

Step 3: while (t < Max number of iterations)

for each wolf (search agent)
Update the position of the current search agent by above equations
end for
Update a,A and C
Calculate the fitness of all search agents
Update $X_\propto$, X_β, *and* X_δ
t=t+1
end while
return $X_\propto$*(Best Solution)*

4. SIMULATION RESULTS AND DISCUSSIONS

The suggested system is simulated using MATLAB-Simulink on the personal computer with the windows environment. The outcome of the suggested EMS model is validated for the different values of the battery state of charging, ultra-capacitor charging, requirement of FC power and Load demand and it is observed that it is able to provide the power to the HEV for longer duration as shown in *figure 7*. The system utilizes the FC power source in critical conditions only that helps to minimize the fuel cost.



(a)

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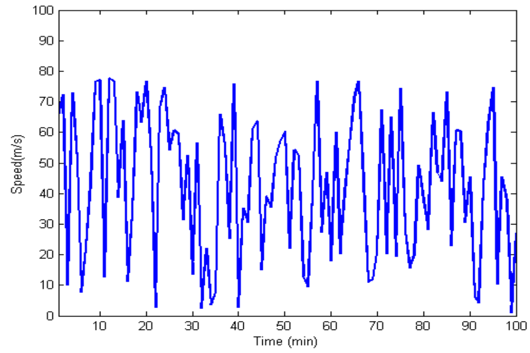

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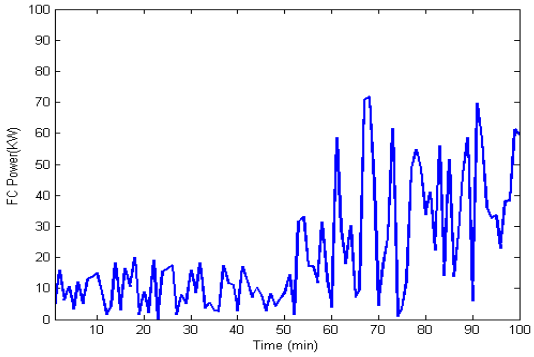

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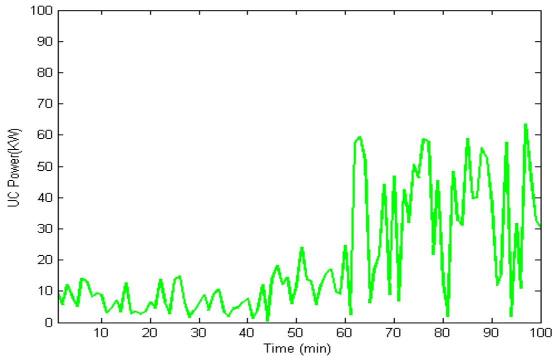

(d)

Figure 7: Simulation results for the GWO based EMS a) Battery SOC b) Speed of vehicle c) FC power d) UC power

It is noted that when the battery SOC is higher than the FC power is less frequently used. However, FC power is frequently used for powering HEV when battery SOC drops below 40% of its maximum capacity. The simulation results are carried out for varying speeds with dynamic vehicular and ambient conditions. The simulation results depicts that the suggested GWO helps to provide the power to the HEV during the discharge condition of the battery to fulfill the power demand. The GWO is able to handle the unpredictable behavior of the driving cycle and provides the best control of the power source selection with the minimum cost. Also, it provides the pollution free nature of the HEV by selection of pollution free sources for the powering the HEV. In recent years, deep learning algorithms have shown noteworthy contributions in various signal processing applications because of their faster conversions, high accuracy, reliability, and effectiveness [6], [7], [12]. In the future, various deep learning-based systems can be employed for driving and vehicle condition data augmentation to create the synthetic data for the simulation using available limited datasets [8], [9], [13]. Again, it can be used to improve accuracy; minimize control time; handle multiple objectives for EMS control; and provide generalized EMS for different types of HEVs.

5. CONCLUSION AND FUTURE SCOPE

Thus, this article presents GWO based hybrid energy source selection for the EMS of HEVs based on the cost profile to fulfill the power requirement and minimize the pollution occurred due to emission of hydrocarbon and nitrogen oxides. The suggested GWO considers the various driving conditions and provides the economical and pollution free solution to attain the higher efficiency of the HEVs. In future, the outcome of the suggested EMS can be improved by considering various real time environmental parameters and driving patterns. Various deep learning algorithms can be used for the EMS for different HEVs for driving conditions data augmentation and control of EMS to improve the performance of the system under various driving and environmental conditions. Also, the approach can be extended for the HEVs considering the renewable power sources.

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