https://doi.org/10.48047/AFJBS.6.14.2024.9704-9718

AFJBS

African Journal of Biological Sciences

Journal homepage: http://www.afjbs.com

Research Paper Open Access

Improved Grey Wolf Optimization based Energy Management System for HEVs with Hybrid Power Sources

Kedar Albanna[1], Vikas Kulkarni[2]

[1]Student, Department of Electrical, AISSMS College of Engineering, Pune, India, 411012

[2] Assistant Professor, Department of Electrical, AISSMS College of Engineering, Pune, India, 411012

Corresponding Author Email Id: kedar_ali2@rediffmail.com

Volume 6, Issue 14, Aug 2024

Received: 15 June 2024

Accepted: 25 July 2024

Published: 15 Aug 2024

doi: 10.48047/AFJBS.6.14.2024.9703-9718

ABSTRACT

Future transportation advancements are anticipated to be dependent on electric cars (EVs). The performance of batteries in terms of power density and energy density, however, remains a barrier to the widespread use of electric cars. The energy management system (EMS) of a hybrid electric vehicle (HEV) is necessary for the conversion from a conventional automobile to a pure electric vehicle (PEV). As hybrid electrical sources are often used to power HEVs, choosing the best one is essential for improving HEV performance, cutting fuel use, and lowering nitrogen oxide and hydrocarbon emissions. This research introduces the improved Grey Wolf Optimization (GWO), which replaced weak member strategy and spiralized learning scheme to enhance the exploitation and solution diversity of the proposed GWO approach to control the power sources in HEVs based on power demand and economy. The recommended GWO-based EMS provides economical, pollution-free HEV management in addition to effective power source switching.

Keywords: Hybrid Electrical Vehicle, Energy Management System, Grey Wolf Optimization, Fuel Cell

1. INTRODUCTION

Because of the growing global population and improving living standards in emerging nations, there are now significantly more cars on the road. On the other hand, owing to the depletion of fossil fuels and the rise in air pollution brought on by the creation of hazardous gases, traditional diesel/petrol vehicles are becoming less efficient and less popular. The primary source of air pollution and global warming is CO2, which is emitted by conventional internal combustion engine-based vehicles. Due to their reduced cost, efficiency, and absence of pollution, electric cars have lately seen a boom in popularity. Despite this, all-electric vehicle adoption is difficult [5], [11], [13] due to their short range.

The current generation of electric vehicles can only drive 150–200 kilometres on a single battery charge, which limits their ability to travel large distances. By combining an internal combustion engine (ICE) with electrical power sources to power the vehicle, hybrid electric vehicles increase HEV performance in high-stakes situations. Researchers have created allied tiny power sources for HEV in addition to batteries since battery size and number are significant HEV restrictions. The rechargeable battery in plug-in hybrid electric vehicles (PHEVs) may be plugged in to boost battery capacity. PHEVs need both electrical and mechanical energy. Thus, in PHEVs, an EMS is needed to maintain the battery's and ICE's operational states (EMS). According to the different connection topologies between the electric motor, the battery, and the internal combustion engine, PHEVs are divided into three groups: series, parallel, and series-parallel (EM). Flexible operating modes in series-parallel PHEVs may lead to reduced emissions and greater driving performance as compared to series or parallel PHEVs. A well-designed EMS for series-parallel PHEVs lowers emissions while increasing fuel economy (FE). The objective of EMS design is to maintain high efficiency with minimal complexity [9],[12],[14].

In a HEV, the primary objective of an EMS is to satisfy power requirements while using the least amount of fuel, creating the fewest emissions, and creating the most effective vehicle feasible. HEVs provide a difficult challenge for EMS because of their intricate design. EMSs are helpful in assessing the fuel economy of HEVs because they can accurately predict the power distribution of the engine and motors [15]. Fuzzy Rule-based EMSs are easy to set up and maintain. It can handle spoken and numerical data at the same time. Fuzzy logic control (FLC) has readily adjustable parameters and provides a high degree of control flexibility. Conventional fuzzy control, predictive fuzzy control, and adaptive fuzzy control are the three types of fuzzy rule-based EMS [6]. For parallel HEVs, Bathaee et al. [1] developed a fuzzy-based torque controller. The necessary battery SOC and ICE torque define the ICE operating points. According to Li et al. [3], the power distribution between the battery and the ice may be calculated using an FLC-based method, allowing the HEV engine to run more efficiently and emit less pollutants. The operating points for the PHEV's engine and motor were also created using fuzzy logic-based EMS. Fuel consumption as well as CO, CO2, and NOx emissions decreased as a result [7]. Using a rate limiter and fuzzy controller, Akar et al. [8] proposed EMSs for battery/ultra-capacitor EVs with multi-objective converters.

Better results for the EMS of HEVs have been achieved because of the optimization algorithms' ability to handle multiple targets. Based on the different driving circumstances, Ramadan et al. [22] presented GWO and Artificial Bee Colony (ABC) for energy management in the Fuel Cell HEV (FCHEV). Although GWO-based optimization yields superior results in dynamic contexts, ABC offers more commercially feasible options. With plug-in HEVs, it's essential to seamlessly go from conventional vehicle mode to pure EV mode (PHEVs). Ding et al. [18] looked into a Genetic Algorithm (GA) and a rule-based control method for the EMS of PHEVs. Nitrogen oxide and hydrocarbon emissions are reduced using the suggested strategy. The surrounding environment and possible driving conditions are very unpredictable in real-world settings. Conventional EMS systems depend on rigid energy management standards, which are useless for solving problems right now [10]. Without any previous knowledge of driving or vehicle data, reinforcement learning (RL) algorithms are capable of developing EMS systems based on real-time driving conditions. Therefore, parametric research is necessary in order to increase fuel economy and develop a universal EMS model that can be used with any kind of HEV model [16]. The deep learning-based EMS for HEVs is slower because of the drawn-out training process and complicated topologies. Lian et al. [17] looked into the deep deterministic policy gradient (DDPG), which uses the expertise of the expert to lower the EMS method's training expenses. It featured a general approach that could be used to any kind of HEV, more stable operation, more fuel economy, speedier EMS algorithm training, and more. In an emergency, the fuel cell may be thought of as a reliable, effective, and portable source of power, but repeated usage will raise the system's cost [2],[4]. The EMS of HEVs has recently been subjected to a range of optimisation strategies, with promising outcomes in a number of dynamic situations. Nevertheless, there is a need to concentrate on the speedier management of EMS systems for HEVs with diverse power sources that give maximum power, longer battery life, cheaper cost, and can handle dynamic driving scenarios, road conditions, and environmental variables [19], [23-26].

The energy regulation in HEVs using hybrid electrical sources is discussed in this work. The following is a summary of the paper's main contributions:

• Performance assessment of suggested optimization approach for various vehicle dynamics and restrictions.
• For HEVs with hybrid electrical sources, an effective multi-objective improved Grey Wolf Optimization-based energy management technique is designed.

The subsequent portions of the article are structured as follows: In Part 2, the proposed GWO-based EMS for HEVs is covered in great length. The simulation results are thoroughly documented in Section 3, and several parametric modifications and their effects on the proposed control strategy are explored. Section 4 presents ideas and future plans for improving the planned EMS system.

2. METHODOLOGY

A. System Development

The proposed GWO-based control approach is shown in Fig. 1. Three hybrid electrical sources, including a battery bank, a fuel cell, and ultra-capacitors, power the HEV under consideration. The ultra-capacitor and fuel are connected to the DC connection using the recommended method's bidirectional buck-boost converter and unidirectional boost converter. It had a transmission model and a DC-AC converter for supplying electricity to the vehicle's engine.

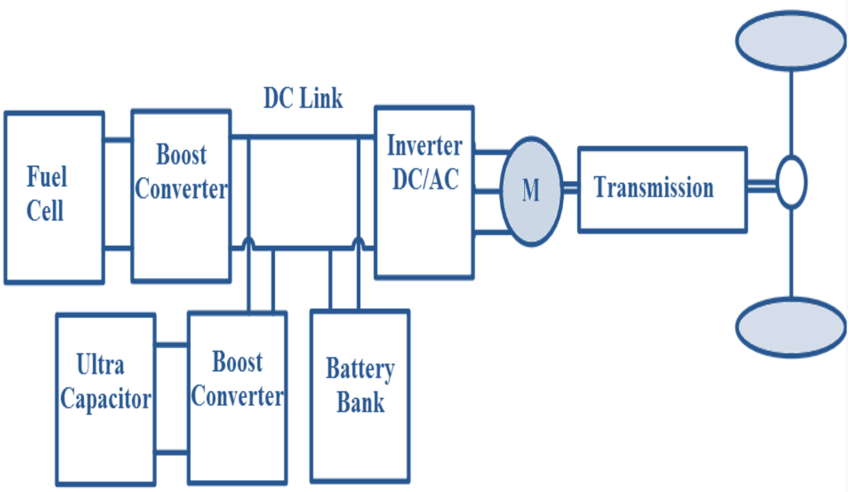

Fig. 1: *Configuration of Different Power Sources for HEV*

B. Fuel Cell Model

This research takes into account the Proton Exchange Membrane Fuel Cell (PEMFC) model, which converts the chemical energy of the reactant into electrical energy. The most common hydrogen and air-fueled fuel cell stacks may be represented using the universal fuel cell stack model provided by the Fuel Cell Stack block. The graphic below depicts a fuel cell electrical model that is dependent on fuel flow rate. A fundamental model and a comprehensive model are the two main parts of the stack model.

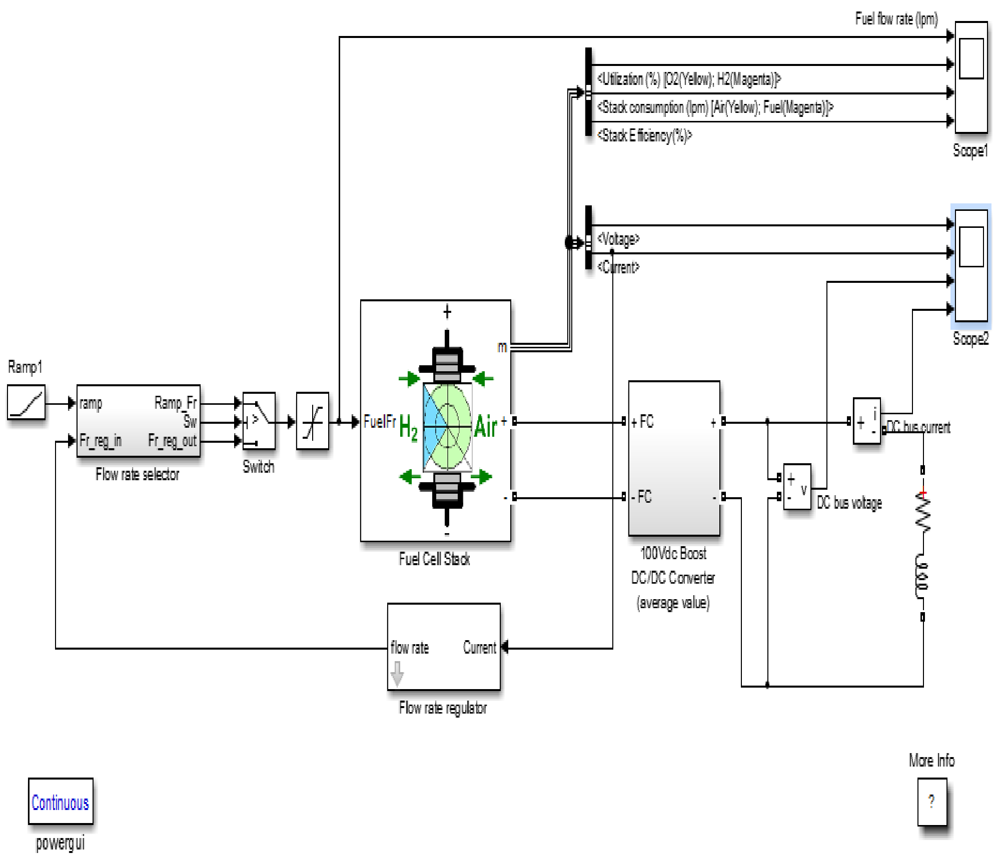

Fig. 2: Simulink Model for Fuel cell

To switch between the two models, choose the level in the mask located under Model Detail Level in the block dialogue box. The Simulink model and the fuel cell equivalent circuit are shown in Fig. 2 and 3, respectively.

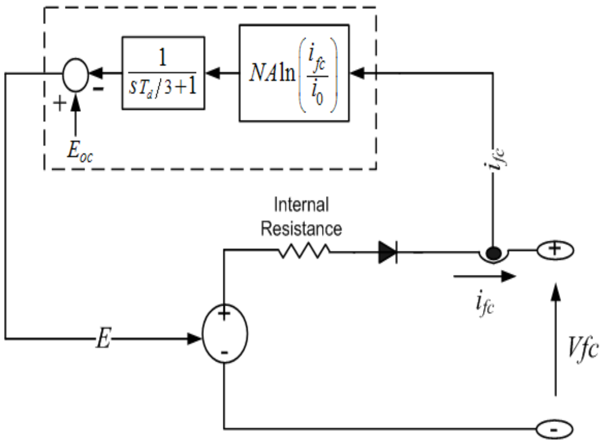

Fig. 3: Equivalent Circuit of Fuel Cell

C. GWO for EMS

The grey wolf is a member of the canid family. Grey wolves are the top predators in the food chain due to their position as apex predators. Grey wolves like to live in harmony with the other wolves in their pack. A wolf pack normally consists of 5 to 12 wolves. The complicated social dominance structure they have is fascinating to see. A male and a female serve as the alphas or leaders. The alpha wolf often is in charge of things like waking times, hunting plans, and sleeping arrangements. The pack is governed by the alpha's judgements. A fascinating social characteristic of grey wolves is group hunting, which they engage in in addition to their social hierarchy.

The first chase, encirclement, and hounding of the prey until it stops moving are the three primary stages of grey wolf hunting. The following pursuit, encirclement, and approaching assault are the next three phases. Equations 1 and 2 depict the grey wolf around its prey.

$$\vec{\mathrm{E}} = \left|\overrightarrow{\mathrm{OB}}.\overrightarrow{\mathrm{X_p}}(\mathrm{k}) - \vec{\mathrm{X}}(\mathrm{k})\right| \tag{1}$$

$$\vec{\mathrm{X}}(\mathrm{k}+1) = \overrightarrow{\mathrm{X_p}}(\mathrm{k}) - \vec{\mathrm{D}}.\vec{\mathrm{E}} \tag{2}$$

Where, k represent the iteration count, *OB* stands for the coefficient vector representing the obstacle in hunting, *D* stands for the distance related coefficient vector, X gives wolf's position and X_p denotes prey position. Equations 3 and 4 are used to calculate the coefficient vectors ($\vec{\mathrm{D}}$ and $\overrightarrow{\mathrm{OB}}$) needed for encirclement.

$$\vec{\mathrm{D}} = 2 \times \vec{\mathrm{l}} \times \overrightarrow{\mathrm{r_1}} - \vec{\mathrm{l}} \tag{3}$$

$$\vec{\mathrm{O}} = 2 \times \overrightarrow{\mathrm{r_2}} \tag{4}$$

The GWO algorithms aims for reduction in the cost function as given in equation 5 and 6.

$$Fitness_{MG} = Fit_B + Fit_{FC} + Fit_{UC} \tag{5}$$

$$Fitness_{MG} = \alpha_1 P_B + \alpha_2 P_{FC} + \alpha_3 P_{UC} \tag{6}$$

Here $\alpha_1, \alpha_2, and\ \alpha_3$ are cost coefficient of battery, fuel cell and ultra-capacitor respectively, P_B, P_{FC} and P_{UC} denotes battery power, fuel cell power and ultra-capacitor power respectively. The algorithm for GWO based HEV EMS system is described as follow.

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
Apply weak member replacement strategy
Apply spiralized learning scheme
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)*

3. SIMULATION RESULTS AND DISCUSSIONS

On a personal computer running Windows, the described system is simulated using MATLAB-Simulink. The simulation parameters for the various energy sources are summarized in Table1.

Table 1: *Parameter Configurations*

Parameter	**Value**
Battery Specification	
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
Fuel Cell 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 %

Fig. 4 and 5, respectively, indicate the performance of the FC and battery. The voltage and power rating of the FC are shown in Fig. 4. The voltage and SOC of the battery as determined by simulation of the battery model are shown in Fig. 5.

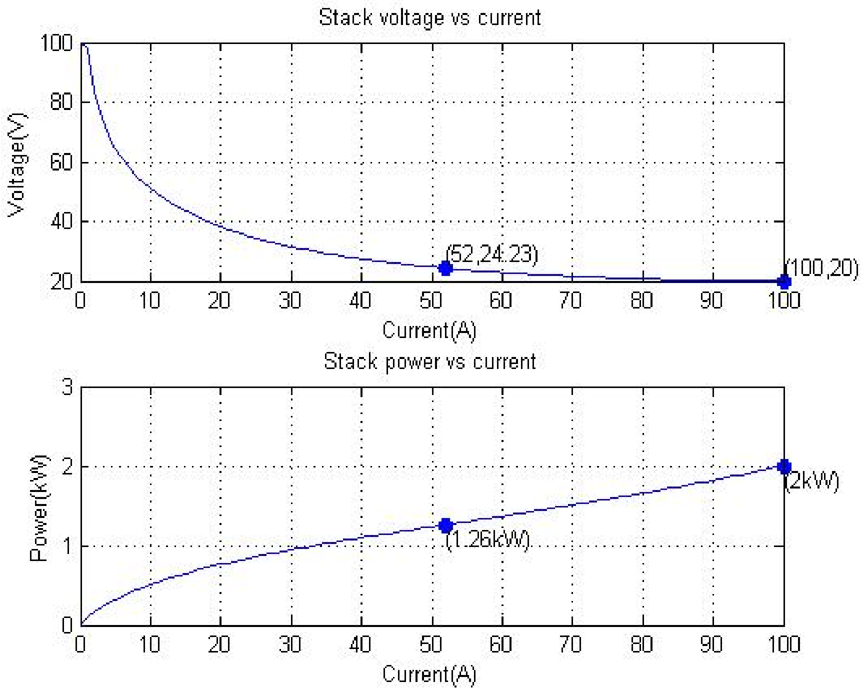

Fig. 4: *Performance of FC*

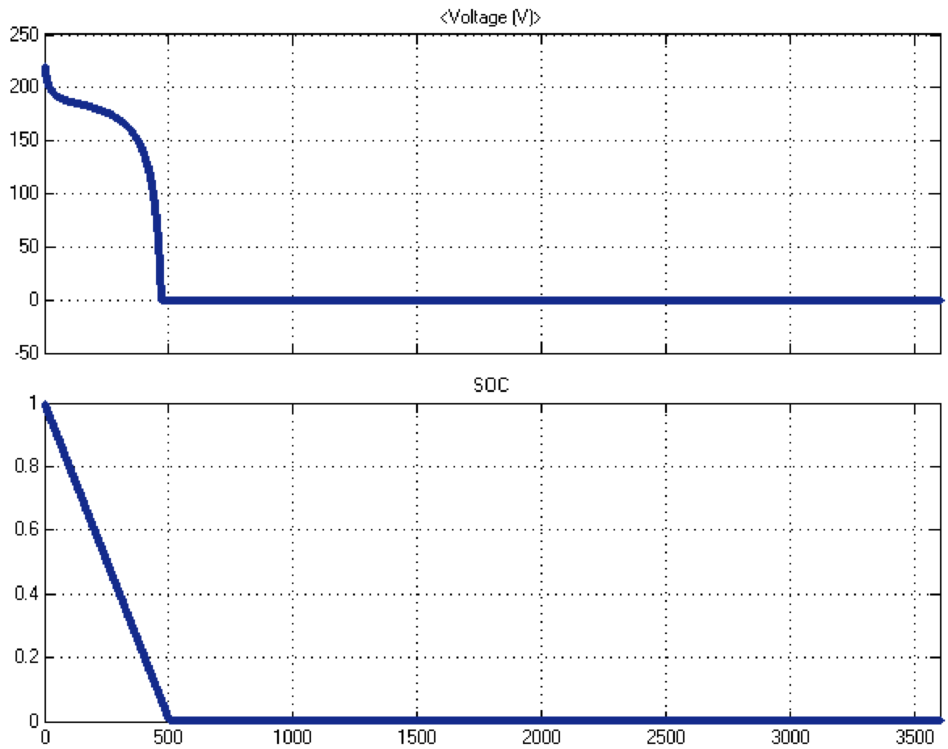

Fig. 5: *Performance of Battery*

It is discovered that the suggested EMS model can power the HEV for a longer amount of time, as shown in Fig. 6, when the findings are confirmed for different values of the battery state of charge, ultra-capacitor charging, the need for FC power, and the demand for load. Since the system only utilises the FC power source in emergencies, petrol prices are decreased.

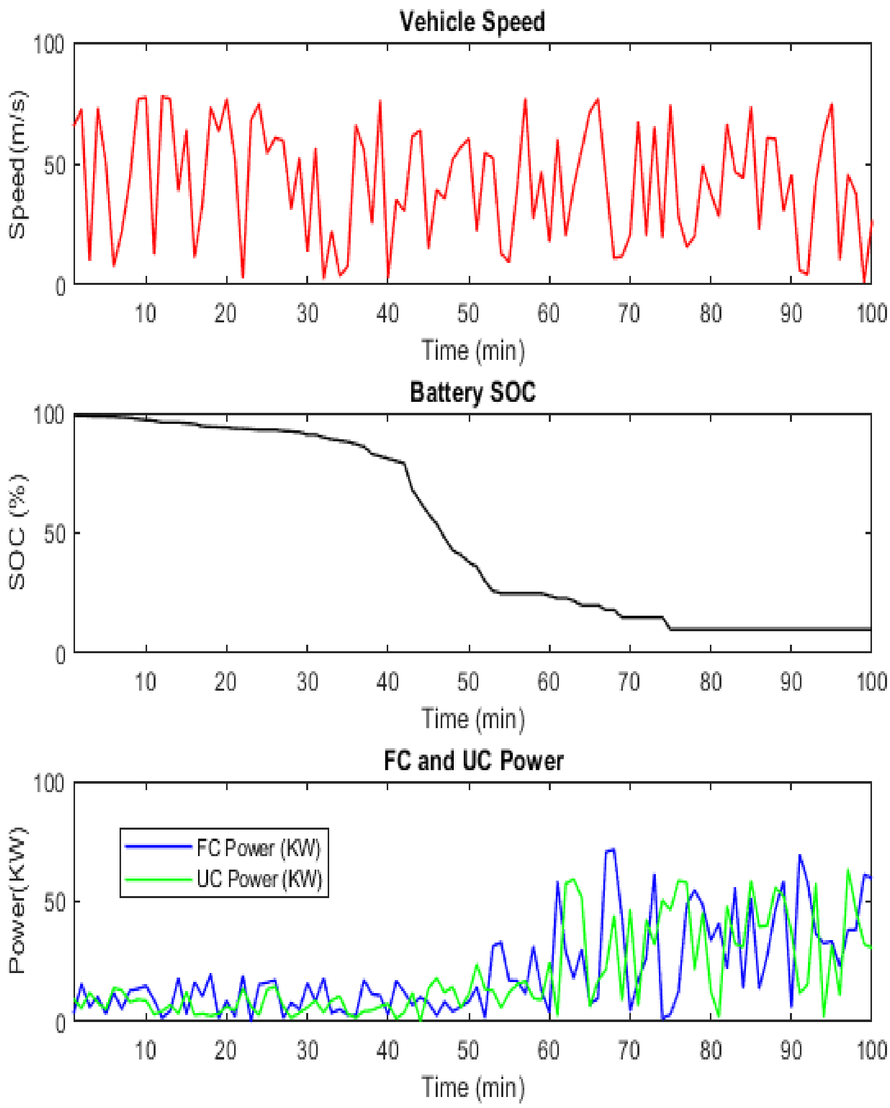

Fig. 6: *Simulation Results for GWO-Based EMS*

Less FC power is often used when the battery SOC is higher, according to observations. Nonetheless, FC power is often used to power HEVs when the battery SOC falls below 40% of the battery's entire capacity. Results from the simulation are done under dynamic vehicle and environmental conditions at different speeds. The simulation findings show that during the battery's discharge state, the recommended GWO aids in providing power to the HEV to meet its electrical needs. The GWO can manage the unpredictable behaviour of the driving cycle and offers the greatest control of power source selection at the lowest cost. By offering a variety of pollution-free sources for the vehicle's fuel, it also demonstrates the HEV's zero-emission status. Deep learning algorithms have shown amazing contributions in a number of signal processing applications in recent years [27-30] because of their rapid conversions, high accuracy, reliability, and effectiveness. Future deep learning-based systems may be utilised to improve driving and vehicle condition data in order to provide synthetic data for simulations using the currently constrained datasets [21-33]. Once again, it may be used to improve accuracy, reduce control time, handle multiple EMS control objectives, and provide universal EMS for varied HEV types.

The performance is compared based on the drop in the battery SOC and % energy efficiency. The energy efficiency is computed based on total power provided by the hybrid power sources divided by total power requirement. It is observed that the battery drop is sharp in fuzzy logic based EMS techniques [123] but small in GA tuned Fuzzy Logic [26], Deep Q-learning [101] and proposed GWO. The proposed GWO presents the energy efficiency of the 92.50 % which has shown the 1.6 % -15% improvements in the energy efficiency over traditional techniques.

Thus, it is observed that the optimization based EMS schemes performs better compared with traditional techniques and fuzzy logic based EMS under various conditions. It is powerful to provide the optimal solution in the dynamic control variables and helps to attain the pollution-free, reliable and robust EMS scheme for the HEVs to improve its performance.

The outcomes of the proposed EMS are compared with several traditional EMS approaches and it is found that the proposed approach provides better performance compared with existing state of arts for the EMS of the HEVs as given in Table 2.

Table 2: Comparative analysis of proposed scheme with existing EMS schemes

Author and Year	**Method**	**SOC Drop**	**% Energy Efficiency**
Mohammad Suhail *et al.*, 2021 [34]	Fuzzy Logic control	Sharp	88 %
Jichao Liu *et al., 2017 [35]*	Genetic Algorithm & PSO	Small	89.20%
Yue *et al.*, 2019, [36]	Genetic algorithm based Fuzzy Logic	Small	90 %
Tang *et al.*, 2022 [37]	Deep Q-Learning	Small	91.04 %

Fuzzy logic based EMS	Fuzzy Logic	Sharp	89 %
Proposed GWO based EMS	GWO	Small	92.50 %

It is observed that the proposed algorithm provides significant improvement over the traditional EMS in terms of fuel efficiency. It provides 5.11%, 3.93%, 2.77%, 1.64%, and 3.93% improvement in the fuel efficiency over FLC, GA-PSO, GA-Fuzzy, Deep Q-learning and Fuzzy logic control respectively. The proposed GWO helps to attain the dynamic control over the different conditions to provide the optimal power to the EV. Further, the drop in the battery SOC much lower compared to the existing state of arts.

4. CONCLUSIONS AND FUTURE SCOPE

Hence, this paper advises using a GWO-based hybrid energy source for the EMS of HEVS in order to satisfy the power need and decrease pollution caused by the emission of hydrocarbon and nitrogen oxides, based on the cost profile. The suggested GWO provides an inexpensive and green solution to raise the efficiency of the HEVs while taking into consideration the various driving scenarios. The suggested EMS may be enhanced in the future by accounting for various real-time environmental conditions and driving patterns. Several deep learning algorithms may be used to the EMS for various HEVs for data augmentation and control to improve the system's performance under a variety of driving and environmental conditions. HEVs may be included to the plan while also taking into account renewable energy sources.

Declarations

Funding: Not applicable

Conflict of Interest: The authors declares no conflict of interest

Data Availability: The data will be made available on reasonable request to authors

REFERENCES

[1] Bathaee, S. M.T., Gastaj, A.H., Emami, S.R., et al.: A fuzzy-based supervisory robust control for parallel hybrid electric vehicles. Vehicle Power & Propulsion IEEE, Chicago, IL, USA, September 2005, pp. 694–700, (2005).

[2] Steward, D., G. Saur, M. Penev, and T. Ramsden. *Lifecycle cost analysis of hydrogen versus other technologies for electrical energy storage*. No. NREL/TP-560-46719. National Renewable Energy Lab.(NREL), Golden, CO (United States), 2009.

[3] Li, S.G., Sharkh, S.M., Walsh, F.C., et al.: Energy and battery management of a plug-in series hybrid electric vehicle using fuzzy logic. IEEE Trans. Veh. Technol. 60, 3571–3585, (2011).

[4] Ourimi, Seyyed Reza Mousavi, and Behzad Asaei. "Optimization of fuel cell stack, ultra-capacitor, and battery banks based on cost function minimization for fuel-cell electric vehicles." In *2014 14th International Conference on Environment and Electrical Engineering*, pp. 17-22. IEEE, 2014.

[5] Sabri, M. F. M., Kumeresan A. Danapalasingam, and Mohd Fuaad Rahmat. "A review on hybrid electric vehicles architecture and energy management strategies." *Renewable and Sustainable Energy Reviews* 53 (2016): 1433-1442.

[6] Ramadan, H. S., Becherif, M., Claude, F.: Energy Management Improvement of Hybrid Electric Vehicles via Combined GPS/Rule-Based Methodology. IEEE Transactions on Automation Science and Engineering 14(2), 586-597, (2017).

[7] Gujarathi, P.K., Varsha, S., Makarand, L.: Fuzzy logic based energy management strategy for a converted parallel plug-in hybrid electric vehicle. IEEE 8th Control and System Graduate Research Colloquium, Shah Alam, Malaysia, pp. 185–190, (2017).

[8] Akar, F., Tavlasoglu, Y., Vural, B.: An Energy Management Strategy for a Concept Battery/Ultracapacitor Electric Vehicle With Improved Battery Life. IEEE Transactions on Transportation Electrification 3(1), 191-200, (2017).

[9] Ali, Ahmed M., and Dirk Söffker. "Towards optimal power management of hybrid electric vehicles in real-time: A review on methods, challenges, and state-of-the-art solutions." *Energies* 11, no. 3 (2018): 476.

[10] Hu, Yue, Weimin Li, Kun Xu, Taimoor Zahid, Feiyan Qin, and Chenming Li. "Energy management strategy for a hybrid electric vehicle based on deep reinforcement learning." *Applied Sciences* 8, no. 2 (2018): 187.

[11] Zhou, Yang, Alexandre Ravey, and Marie-Cécile Péra. "A survey on driving prediction techniques for predictive energy management of plug-in hybrid electric vehicles." *Journal of Power Sources* 412 (2019): 480-495.

[12] Zhang, Fengqi, Xiaosong Hu, Reza Langari, and Dongpu Cao. "Energy management strategies of connected HEVs and PHEVs: Recent progress and outlook." *Progress in Energy and Combustion Science* 73 (2019): 235-256.

[13] Zhang, Fengqi, Lihua Wang, Serdar Coskun, Hui Pang, Yahui Cui, and Junqiang Xi. "Energy management strategies for hybrid electric vehicles: Review, classification, comparison, and outlook." *Energies* 13, no. 13 (2020): 3352.

[14] Tran, Dai-Duong, Majid Vafaeipour, Mohamed El Baghdadi, Ricardo Barrero, Joeri Van Mierlo, and Omar Hegazy. "Thorough state-of-the-art analysis of electric and hybrid vehicle powertrains: Topologies and integrated energy management strategies." *Renewable and Sustainable Energy Reviews* 119 (2020): 109596.

[15] Yang, C., Zha, M., Wang, W., Liu, K., Xiang, C.: Efficient energy management strategy for hybrid electric vehicles/plug-in hybrid electric vehicles: review and recent advances under intelligent transportation system. IET Intelligent Transport Systems 14(7), 702-711, (2020).

[16] Xu, Bin, Dhruvang Rathod, Darui Zhang, Adamu Yebi, Xueyu Zhang, Xiaoya Li, and Zoran Filipi. "Parametric study on reinforcement learning optimized energy management strategy for a hybrid electric vehicle." *Applied Energy* 259 (2020): 114200.

[17] Lian, Renzong, Jiankun Peng, Yuankai Wu, Huachun Tan, and Hailong Zhang. "Rule-interposing deep reinforcement learning based energy management strategy for power-split hybrid electric vehicle." *Energy* 197 (2020): 117297.

[18] Ding, N., K. Prasad, and T. T. Lie. "Design of a hybrid EMS using designed rule-based control strategy and genetic algorithm for the series-parallel plug-in hybrid electric vehicle." *International Journal of Energy Research* 45, no. 2 (2021): 1627-1644.

[19] Du, Guodong, Yuan Zou, Xudong Zhang, Lingxiong Guo, and Ningyuan Guo. "Heuristic energy management strategy of hybrid electric vehicle based on deep reinforcement learning with accelerated gradient optimization." *IEEE Transactions on Transportation Electrification* 7, no. 4 (2021): 2194-2208.

[20] Bhangale, Kishor, Piyush Ingle, Rajani Kanase, and Divyashri Desale. "Multi-view multi-pose robust face recognition based on VGGNet." In *International Conference on Image Processing and Capsule Networks*, pp. 414-421. Springer, Cham, 2021.

[21] Li, Weihan, Han Cui, Thomas Nemeth, Jonathan Jansen, Cem Uenluebayir, Zhongbao Wei, Lei Zhang et al. "Deep reinforcement learning-based energy management of hybrid battery systems in electric vehicles." *Journal of Energy Storage* 36 (2021): 102355.

[22] Ramadan, Haitham S., Islam A. Hassan, and Hassan Haes Alhelou. "Robust control for techno-economic efficient energy management of fuel cell hybrid electric vehicles." *IET Renewable Power Generation* (2022).

[23] Min, Dehao, Zhen Song, Huicui Chen, Tianxiang Wang, and Tong Zhang. "Genetic algorithm optimized neural network based fuel cell hybrid electric vehicle energy management strategy under start-stop condition." *Applied Energy* 306 (2022): 118036.

[24] Yang, Chao, Kaijia Liu, Xiaohong Jiao, Weida Wang, Ruihu Chen, and Sixiong You. "An adaptive firework algorithm optimization-based intelligent energy management strategy for plug-in hybrid electric vehicles." *Energy* 239 (2022): 122120.

[25] Fan, Likang, Yufei Wang, Hongqian Wei, Youtong Zhang, Pengyu Zheng, Tianyi Huang, and Wei Li. "A GA-based online real-time optimized energy management strategy for plug-in hybrid electric vehicles." *Energy* 241 (2022): 122811.

[26] Zhu, Di, Ewan Pritchard, Sumanth Reddy Dadam, Vivek Kumar, and Yang Xu. "Optimization of rule-based energy management strategies for hybrid vehicles using dynamic programming." *arXiv preprint arXiv:2207.06450* (2022).

[27] Bhangale, Kishor Barasu, and Mohanaprasad Kothandaraman. "Survey of Deep Learning Paradigms for Speech Processing." *Wireless Personal Communications* (2022): 1-37.

[28] Bhangale, Kishor, and K. Mohanaprasad. "Speech emotion recognition using mel frequency log spectrogram and deep convolutional neural network." In *Futuristic Communication and Network Technologies*, pp. 241-250. Springer, Singapore, 2022.

[29] Bhangale, Kishor B., Pranoti Desai, Saloni Banne, and Utkarsh Rajput. "Neural Style Transfer: Reliving art through Artificial Intelligence." In *2022 3rd International Conference for Emerging Technology (INCET)*, pp. 1-6. IEEE, 2022.

[30] Bhangale, Kishor, and Mohanaprasad Kothandaraman. "Speech emotion recognition based on multiple acoustic features and deep convolutional neural network." *Electronics* 12, no. 4 (2023): 839.

[31] Bhangale, Kishor B., and Mohanaprasad Kothandaraman. "Speech emotion recognition using the novel PEmoNet (Parallel Emotion Network)." *Applied Acoustics* 212 (2023): 109613.

[32] Bhangale, Kishor, and Mohanaprasad Kothandaraman. "Speech Emotion Recognition Using Generative Adversarial Network and Deep Convolutional Neural Network." *Circuits, Systems, and Signal Processing* 43, no. 4 (2024): 2341-2384.

[33] Hu, Dong, and Yuanyuan Zhang. "Deep reinforcement learning based on driver experience embedding for energy management strategies in hybrid electric vehicles." *Energy Technology* (2022): 2200123.

[34] Suhail, Mohammad, Iram Akhtar, Sheeraz Kirmani, and Mohammed Jameel. "Development of progressive fuzzy logic and ANFIS control for energy management of plug-in hybrid electric vehicle." *IEEE Access* 9, pp. 62219-62231, (2021).

[35] Qi, X., Wu, G., Boriboonsomsin, K., Barth, M., “Development and Evaluation of an Evolutionary Algorithm-Based On-Line EMS for Plug-In Hybrid Electric Vehicles”, *IEEE Transactions on Intelligent Transportation Systems 18(8),* pp. 2181-2191, (2017).

[36] M. Yue, S. Jemei and N. Zerhouni, “Health-Conscious Energy Management for Fuel Cell HEV Based on Prognostics-Enabled Decision-Making,” *IEEE Transactions on Vehicular Technology, vol. 68, no. 12,* pp. 11483-11491, Dec. (2019), doi: 10.1109/TVT.2019.2937130.

[37] Tang, Xiaolin, Haitao Zhou, Feng Wang, Weida Wang, and Xianke Lin, “Longevity-conscious EMS of fuel cell hybrid electric Vehicle Based on deep reinforcement learning,” *Energy* 238, pp. 121593, (2022).