Enhancing Hybrid Electric Vehicle Efficiency Through Optimized Battery State of Charge Prediction

[1]Deepak Kumar, [2]Amit Kumar Asthana

[1]M. Tech Scholar, Department of Mechanical Engineering, Truba Institute of Engineering & Information Technology, Bhopal
[2] Professor & Head, Department of Mechanical Engineering, Truba Institute of Engineering & Information Technology, Bhopal
[1]deepakkumar25121989@gmail.com , [2]asthana603@gmail.com

* Corresponding Author: Deepak Kumar

Abstract:

Energy management and performance optimization in Hybrid Electric Vehicles (HEVs) greatly depend on the estimate of the SoC. An accurate SoC estimation allows-off better battery health, vehicle efficiency, and intelligent route planning. The present work is an approach in hybrid modeling that ensures accurate State-of-Charge (SOC) prediction for hybrid electric vehicles, bringing together MATLAB/Simulink-based simulation and advanced optimization algorithms. A hybrid gradient tree swarm optimization (HGTSO) technique is proposed in this study, which essentially capitalizes on the global searching ability of PSO with local searching refinement via Gradient methods. Real driving scenarios are implemented in the method using dynamic speed profiles, and the battery's behavior is assessed under an AI-driven estimation framework. The results establish that HGTSO can bring about significantly better SOC prediction error (0.6605) compared to traditional swarm-based models (0.9606), in turn promoting energy management, battery health, and vehicle performance. Intelligent routing, energy-efficient control strategies, and HEV operational sustainability all prosper along with this paradigm.

Keywords: *State of Charge (SOC) Prediction, Hybrid Electric Vehicles (HEVs), Battery Modeling, Hybrid Gradient Tree Swarm Optimization (HGTSO), Energy Management Systems (EMS).*

I. INTRODUCTION

Battery Electric Vehicles (BEVs) offer the cleaner, more environmentally friendly alternative that erosion ion of the typical combustion engine. These vehicles provide the added advantages of comprising less fossil fuel dependency and being less noisy. Making these vehicles using energy-efficient means went hand in hand with eco-driving techniques, which purport to enhance range, reduce battery deterioration, and improve overall vehicle performance. Fig. 1 represents a schematic diagram of the sensor layout of the in-vehicle power transmission system.

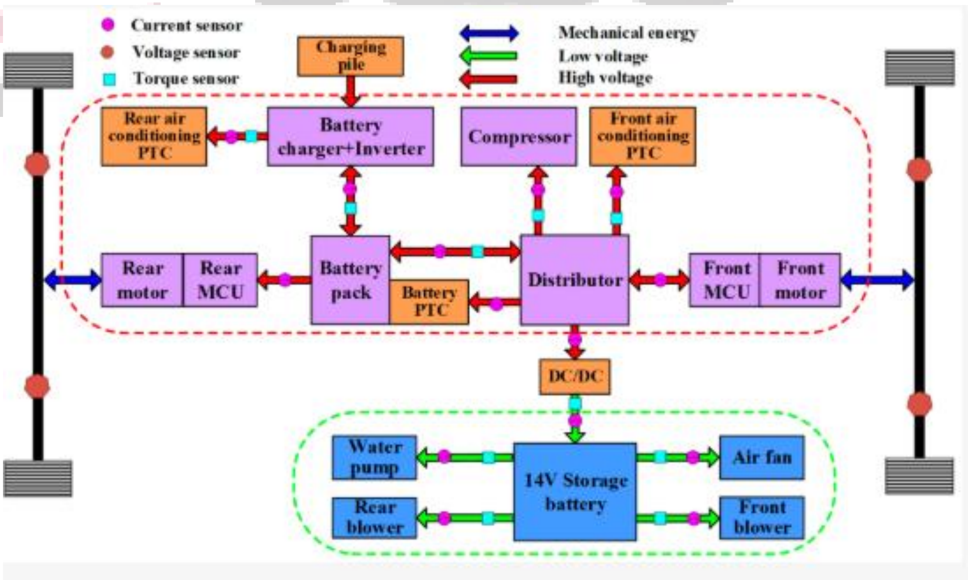

Fig. 1. Schematic of the sensor layout in-vehicle power transmission system [4]

II. Hybrid Electric Vehicle Architecture

The architecture of a hybrid electric vehicle (HEV) bifurcates between an internal combustion engine (ICE) and electric propulsion to achieve improvements in fuel economy and emission control [13]. With two sources available for energy generation, vehicles can use either one source or combine them, depending on driving conditions, load demands, or energy efficiency considerations. Typically, a HEV consists of several major systems: an internal combustion engine, an electrical motor, power electronics, an energy storage system (battery), transmission, and control units; these components work together in different modes such as electric-only drive, engine-only drive, and hybrid drive to maximize energy utilization [14].Intelligent control strategies oversee energy flow management in an energy management system and decide from among using the electric motor, recharging the battery through regenerative braking, or starting the ICE for more power. By monitoring real-time vehicle parameters, the system ensures unnoticeable switching of driving modes and maximizes efficiency [15].

The HEVs can be engineered in various setups: series, parallel, or series-parallel (power-split); in other words, each configuration imparts its characteristic capabilities for efficiency and performance in determining relative complexity. Usually, the choice of a hybridized vehicle configuration depends on its application and vehicle performance targets [16]. Nonetheless, the hybrid type plays a significant role in mitigating the environmental effects of conventional vehicles while still providing power and reliability. Fig. 2 depicts the Hybrid electric vehicle (HEV) configuration: the parallel HEV powertrain configuration. The electric motor and ICE can turn the wheels, either together or apart, through a gearbox [6]. A battery powers the electric motor and is regulated by power electronic equipment, while the fuel tank feeds the ICE. A clutch controls the connection between the ICE and motor, allowing for flexible power flow, while optimizing energy recovery [6]-[7].

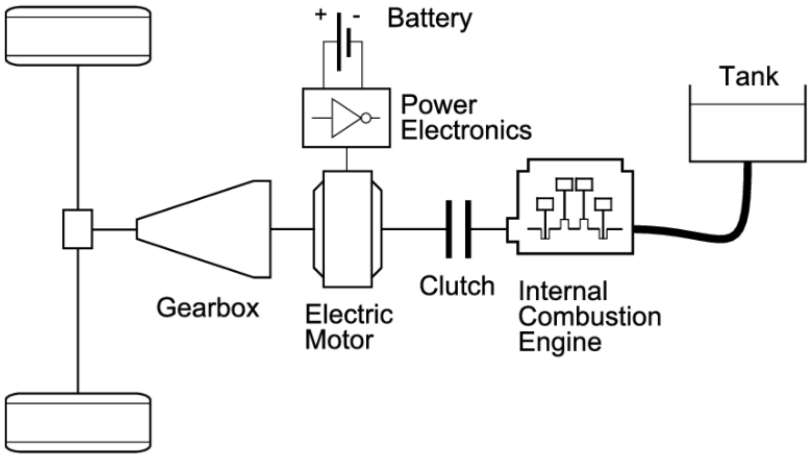

FIG. 2. HYBRID ELECTRIC VEHICLE (HEV) ARCHITECTURE [6]

The study focuses on an integration between Model Predictive Control and Deep Reinforcement Learning toward an energy-efficient eco-drive framework for BEVs. The dual method takes advantage of MPC's predictive capabilities and DRL's learning power to optimize driving behavior for energy consumption [4]. By constantly analyzing real-time data such as speed, acceleration, road gradient, and traffic conditions, the proposed system attempts to minimize energy wastage and thus allow extended ranges for the vehicle [8].
The study, both through simulations and by means of validations in the real world, shows that the proposed hybrid of MPC and DRL optimizes not only the energy efficiency of the BEV but also truly enables the growth of smarter and sustainable solutions for urban mobility. [7]-[8].

III. Battery Modeling Approaches

Battery modeling is an integral part of SOC prediction in an HEV setup. Three broad families of methods are commonly employed in modeling: the Equivalent-Circuit Models, Electrochemical Models, and Thermically based Models. Equivalent-Circuit Models (ECMs) symbolize battery behavior along the dimension of typical electrical components-resistors, capacitors, and voltage sources, to name a few-at a level that retains meaning while being relatively less demanding than computationally on CPU time. ECM options mainly include the Thevenin and Randles forms that symbolize the resistance internal to the battery and the dynamic response characteristics of the battery, respectively. ECMs suit real-time applications and control systems due to their low computational cost and ease of parameter identification.

Electrochemical Models provide a finer, physically more accurate depiction of the battery dynamics. These models stem from the basic electrochemistry-related processes and entail ion transport, electrode kinetics, and diffusion inside a battery. Electrochemical models, while highly accurate, are computationally intensive and require advanced numerical methods for solution in cases. These are primarily used for offline analysis, design validation, or where high-fidelity battery behavior prediction is needed.

Thermal Modeling is needed as battery performance is so much temperature-dependent. When external or internal temperatures deviate, capacity, internal resistance, and even the battery's safety aspects suffer. These thermal models vary from lumped parameter models to detailed finite element analysis, enabling an engineer to predict temperature distribution and integrate thermal management strategies.That triplication of modeling strategies gives a full scope to battery behavior and will lead to improved SOC estimation and energy management in HEVs.

IV. LITERATURE REVIEW

Shi et al. [1] (2025) formulated an adaptive energy management strategy with real traffic data and BP neural networks and attained fuel consumption having only a 2.24–4.31% disadvantage over the global optima.

Bin Chen et al. [2] (2025) presented a hierarchical eco-driving EMS with an improved TD3-ITD3 algorithm that decreases battery degradation by 4.39–35.31% and energy consumption by 2.41–19.35%.

Xiuyong Shi et al. [3] (2025) designed a novel RL algorithm using experience augmentation to save 18.9% fuel while converging 40–45% better in comparison to TD3.

Jinhai Wang et al. [4] (2025) proposed BO-NRTD3 combining Bayesian optimization and TD3 with better robustness and 98.15% DP accuracy.

Xiuyong Shi et al. [5] (2025) reduced training time by 72.7% and engine usage by 5.92% through curriculum learning and random action injection.
Fan Wang et al. [6] (2025) did a comprehensive review of EMS strategies and concluded that optimized EMS saves ~6% fuel, while a learning-based EMS can save 5.2–17% fuel.

In [7] (2025), Xiaoyu Li et al. implemented a MADRL framework using MADDPG for multi-agent EMS, reducing fuel consumption by 26.91% (WLTC) and 8.41% (HWFET).

Leipengyun Deng et al. [8] (2025) tried to regulate SOC and optimize fuel efficiency through fuzzy logic control, attaining digestion reductions of hydrogen by up to 9.81%.

Xinyou Lin et al. [9] (2025) enhanced the robustness and efficiency of an EMS-based on self-learning stochastic velocity Markov prediction.

Siddhesh Yadav et al. [10] (2025) proposed a hierarchical fuzzy plus H-infinity controller for power distribution under uncertainties.

Jian Wang et al. [11] (2025) created a fuzzy-DP hybrid EMS for a battery and supercapacitor, with a 16.68% reduction in battery degradation.

Hegazy Rezk et al. [12] (2025) authored a hybrid PIFLC that outperformed PI by 3.43% and FLC by 9.10%.
Yu-Hsuan Lin et al. [13] (2025) have a PSO-based EMS/TMS system that yields energy savings of between 12.33% and 24.19% and improves thermal stability.

Chun Wang et al. [14] (2025) proposed a real-time NN EMS dynamic programming approach based on RBF networks, which reduced energy loss by up to 16.02%.

R. Khujamberdiev et al. [15] (2025) described the emphasis placed on ANN in modeling diesel engines for biodiesel performance prediction.They advocated for bridging the theoretical gap with ANN and big data and furthering green engine development.

K. Sudhapriya et al.[16] (2025) attempted to propose the HAI-BMS, which combines control methods with AI and RL for EVs.Simulation results showed improved battery life, better decision-making, and energy efficiency.

Lamine Rebhi et al. [17] (2025) modified the MBO using FEM and RBF network to maximize reliability-based optimization of robotic structure.It maximizes the high fatigue reliability while minimizing mass due to random base excitation.

Ipseeta Satpathy et al. [18] (2025) described AI in transport pertaining to traffic management and generative vehicle design.They exhibited customization and eco-efficiency through AI-based real-time control systems.

Joris Jaguemont et al. [19] (2025) proposed MPCANN for Li-ion SoC estimation with a 94% reduction in compute time. The method does require a bit of refinement at high temperatures but supports real-time control feasibility.
The BCA-CAR is a blockchain-AI collision avoidance system with SVR put forth by **Fatma M. Talaat et al. [20] (2025).** It provides enhanced vehicular safety, risk management, and secure communication in IoV environments.
Sadiq M. Sait et al. [21] (2025) put forward a robust engineering optimization method via adversarial learning, MPROA. It surpassed all previous methods in crash and structural analysis with strong capability of handling constraints.

Vito Antonio Nardi et al. [22] (2025) presented an enhanced approach to trajectory planning using Hybrid A*, SVMs, and LSTMs.This approach achieves a 28% reduction in computational time for vehicle motion planning.

Ho Tung Jeremy Chan et al. [23] (2025) improved the SoC estimation technique through the use of real-world data and xAI for signal pruning.Their method allowed them to reduce the input by 25% while not compromising on accuracy, and it has yielded an MSE value of 3 × 10^-4.

Chao Feng et al. [24] (2025) developed UAV-assisted action recognition through AM-E3D-LSTM for sports analytics. Their model gives 7% higher accuracy, with real-time delays of below 100 ms.

Divya Garikapati et al. [25] (2024) elaborated on integration and lifecycle development of AI in autonomous vehicles. The authors discussed autonomy levels, privacy profiles, and optimization trends along vehicle software systems.

III. Research Objectives

IV. Research Methodology

In a hybrid electric vehicle, energy flows in two directions: power is supplied dynamically by the electrochemical batteries for energy storage, and energy is regenerated during braking. Parallel hybrid configuration allows customization of engine size and total weight of the drivetrain by adjusting the output power ratio between the internal combustion engine (ICE) and electric motor(s), through a mechanical coupling device for torque.

1) Swarm Algorithm Implementation and process Description

Particle Swarm Optimization (PSO) is a population-based metaheuristic set in place by the collective intelligence of natural swarms, working in a stochastic way to scan complex solution spaces. A particle moves up in position, on one hand, based on its own best position pbest and a swarm's best gbest on the other hand, thus maintaining a balance between exploration and exploitation. With a small set of control parameters and no gradient information needed, PSO has become popular among engineering applications such as battery modeling and energy management in HEVs.
In a nutshell, the major steps of the standard PSO can be summarized as follows:
Initialization: Randomly initialize the positions and velocities of all particles within the bounds.
Evaluation: Evaluate the fitness value of each particle by using the objective function.
Update the pbest and gbest: For each particle, update the pbest if the current position's fitness value is better. Update the gbest depending on the best fitness value among all of the particles.
Velocity and Position Updates: This step updates the velocity of the particle according to the inertia, because of cognitive learning toward pbest, and because of social learning toward gbest, and then the position gets updated accordingly.
Termination Check: Until some stopping criterion is met (e.g., maximum number of iterations or convergence threshold), keep performing.
By alternating and refining trajectories of particles using their combined knowledge and experience, PSO ultimately acts as an invaluable solution to handle a variety of difficult optimization problems with the highest reliability and efficiency.

The algorithm follows a systematic approach outlined as follows:

A. Step 1: Initialize the particles

Initialize the position array by assigning random numbers with a uniform distribution.

$$X = U_{rand}(r_{lowerlim,}r_{upperlim}) \quad (1)$$

Assign this initial positon to best known position array.

$$P = X \qquad (2)$$

Initialize particle Velocity

$$V = X \qquad (3)$$

If there are Num_p particles, then X represents an array of particle positions with size Num_p. Similarly, P denotes an array of pbest positions with size Num_p, and V signifies an array of particle velocities with size Num_p.

B. Step 2: Evaluate the optimization fitness function

$$E_x = F(X) \text{ and } E_p = F(P) \text{ and } e_g = f(gbest) \qquad (4)$$

The fitness evaluation array for X and P are denoted by E_x and E_p respectively. Meanwhile, e_g represents the function evaluation at the global best solution (gbest).

C. Step 3: Update pbest value for each particle of the population

$$if\ E_x(i) < E_p(i)\ then\ P(i) = X(i) \qquad (5)$$

D. Step 4: Update gbest value for the entire population –

$$if\ E_p(i) < e_g\ then\ gbest = P(i) \qquad (6)$$

E. Step 5: Update the velocity and position of the particles

$$V(i) = wV(i) + c_1 u_{rand}(0,1)\big(P(i) - X(i)\big) + c_2 u_{rand}(0,1)\big(gbest - X(i)\big) \qquad (7)$$

$$X(i) = X(i) + V(i) \qquad (8)$$

Where, ω represents the inertial weight, while c_1 denotes the cognitive parameter and c_2 represents the social parameter.

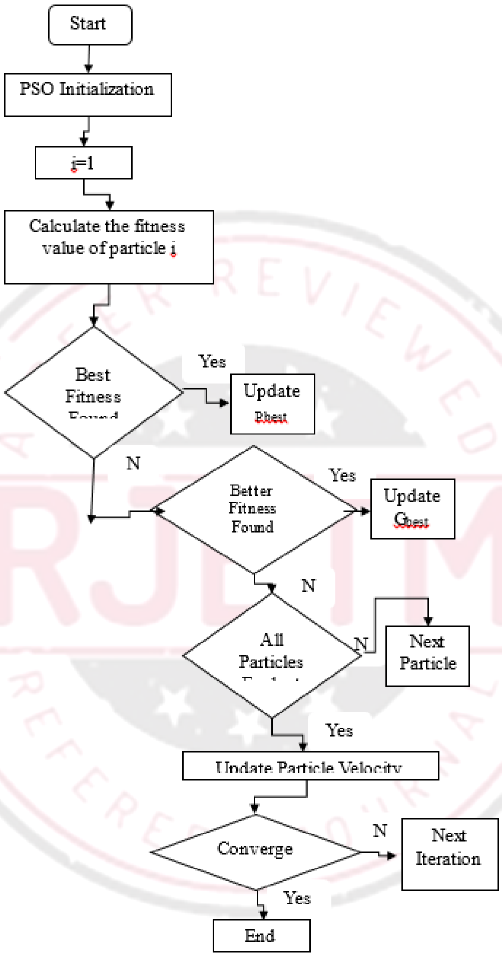

Fig. 3. PSO- controller Technique implemented in MATLAB/SIMULINK

The SOC estimation framework based on Particle Swarm Optimization is shown in Figure 4.6. The proposed methodology utilizes the PSO algorithm in conjunction with real-time measurements of battery voltage and current to optimize internal states of the model. The main aim is to minimize the error between the measured terminal voltage and the estimated voltage of the model for a given input current.

1) Hybrid Gradient Tree swarm Optimization (HGTSO)

The algorithm is based on the concept that any weak learner or base learner could be efficiently 'boosted' into a strong learning algorithm. This means that algorithm works by repeatedly running a weak learner on different versions of the training data and combining the classifier into a single strong classifier. The model can be written on the form

$$f(x) = \sum_{m=1}^{M} \beta_m \emptyset(x: a_m) \tag{9}$$

Being hybrid, this optimization processing combines the global search of PSO with the local-purifying capacity of the GRG method for better convergence accuracy. After every run of PSO, GRG improves upon the best solution achieved by PSO until convergence or until the maximum number of iterations has been reached.

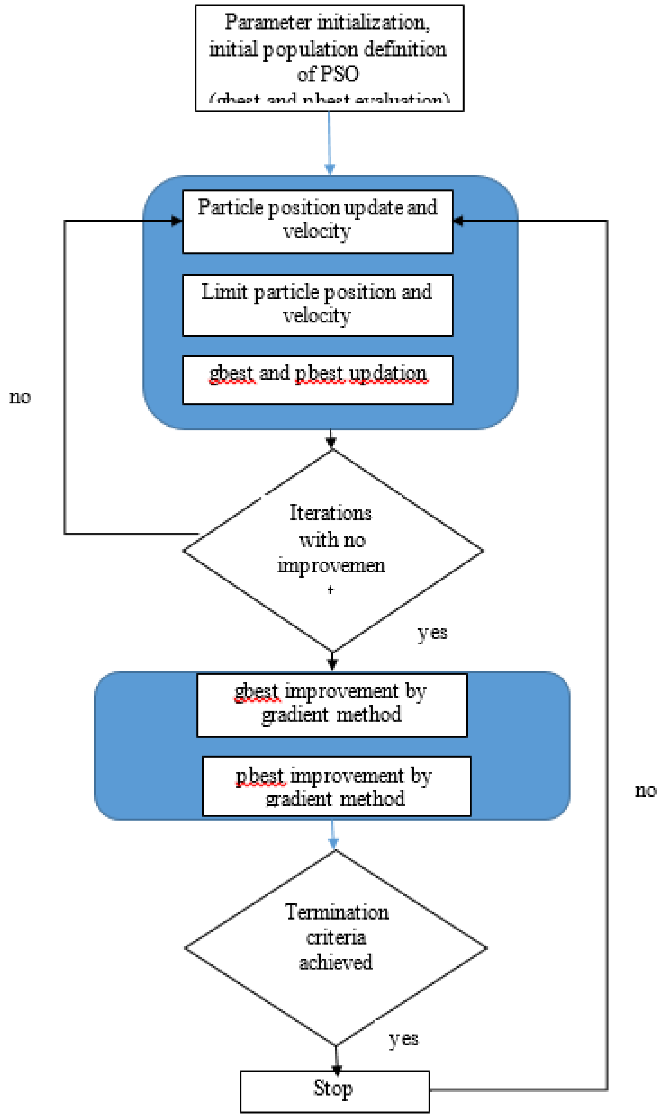

Fig. 4. Working flow of hybrid gradient tree swarm optimization (HGTSO)

PSO inputs are easy to set up and change according to the problem considered and solution sought. In the original research article, the authors insist that a PSO usually provides a good global search in the early stages of the optimization. Also, solutions pass through further local searches in the late stages; the particles determined in the previous step are subjected to local optimization. After fine-tuning with GRG, these solutions can now be precisely optimized. Premature convergence and stagnation in local optima are sometimes problematic. Thus, the hybrid PSO-GRG framework enhances the solutions' accuracy and convergence speed by balancing global search (PSO) and local search (GRG). The collaborative technique produces better optimized results, ensuring consistency and efficacy throughout search phases.

V. Result and Discussion

SOC accurate estimation is critical for researching driving behavior and SOC prediction in improving battery health and EV performance and planning. It enables fleet operation optimization by initiating intelligent routing and minimizing idle charging time. RMSE is used for assessing the accuracy of SOC prediction, and lower values signify better prediction. The formula for RMSE is as follows:

$$RMSE = \sqrt{\sum(Predicted - Actual)^2/n} \tag{10}$$

This work proposes an advanced SOC prediction method for hybrid systems by means of the HGTSO algorithm which combines global search with refinement algorithms locally, thus achieving better precision under different driving conditions. Through taking speed profiles and battery responses analyzed by AI, the system captures the nonlinear dynamics between driving behavior and battery status. With higher accuracy in SOC prediction based on RMSE, measures can be taken to prevent overcharging or deep charging drop, thereby enhancing battery lifetime and consequently reducing HEV ownership cost. Fig. 5 describes Vehicle speed reference

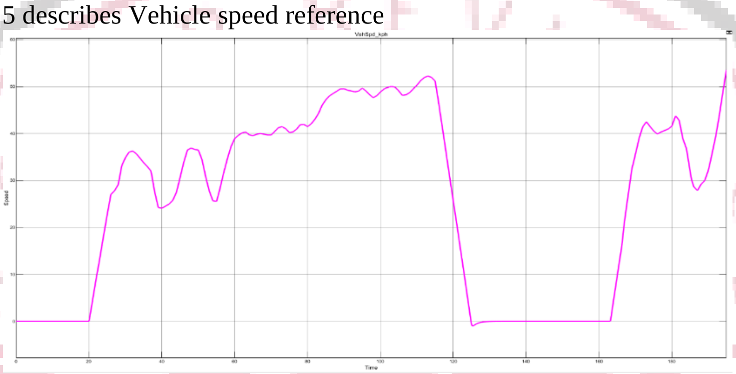

Fig.5: Vehicle speed reference

The speed reference model portrays the dynamic acceleration of the Hybrid Electric Vehicle (HEV), with the acceleration period commencing at 20 seconds into the simulation time. The speed isn't uniform, as other common driving patterns are being channelized through the simulated speed curves. The deceleration period hits roughly at 115 seconds after which the vehicle halts for a very brief moment.

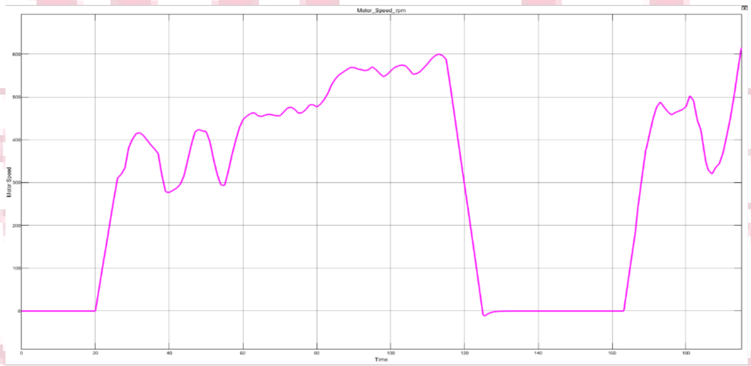

Fig.6: Motor running rpm

During run conditions, the response of the motor in driving mode in an HEV is linked with the vehicle speed during those running conditions and, therefore, having a bearing on the drivetrain mechanism shown in fig.6..

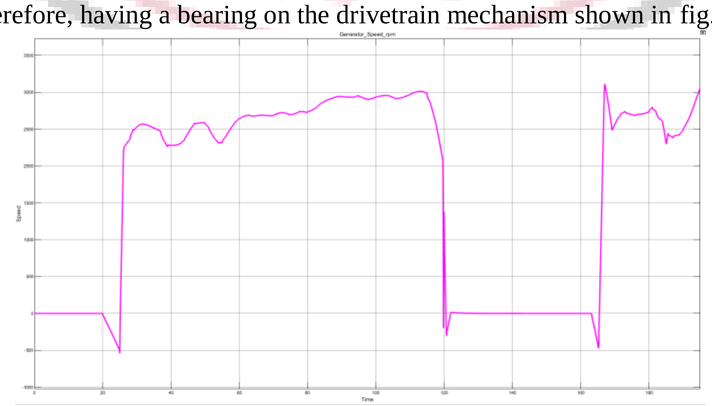

Fig.7: Generator Speed Response under the provided running condition in Hybrid Electric Vehicle

Fig.7 shows the speed response for the driving condition. The speed of the vehicle also affects rpm of the generator. One can observe that the rpm irregularly varies with time intervals corresponding to speeds.

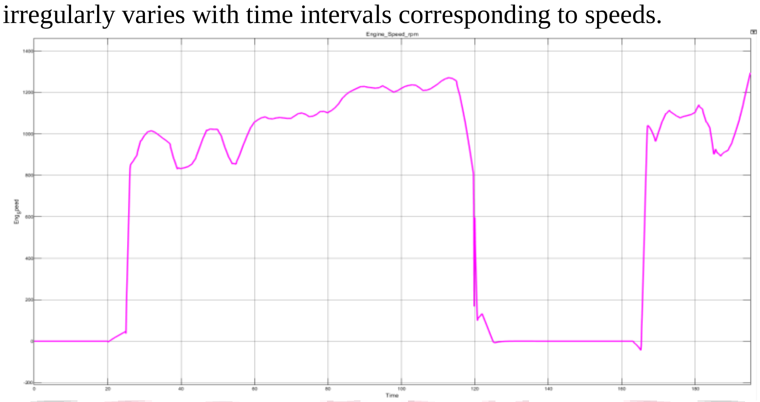

Fig.8. For driving condition the engine speed response

Shown in fig.8 for a certain driving cycle, the engine speed in an HEV is under influence from varying power demand generated in moving the vehicle. At higher vehicle speeds or whenever there is additional power required for acceleration or climbing, the increase in power demand would increase engine speed, as is generally seen in fig.8.

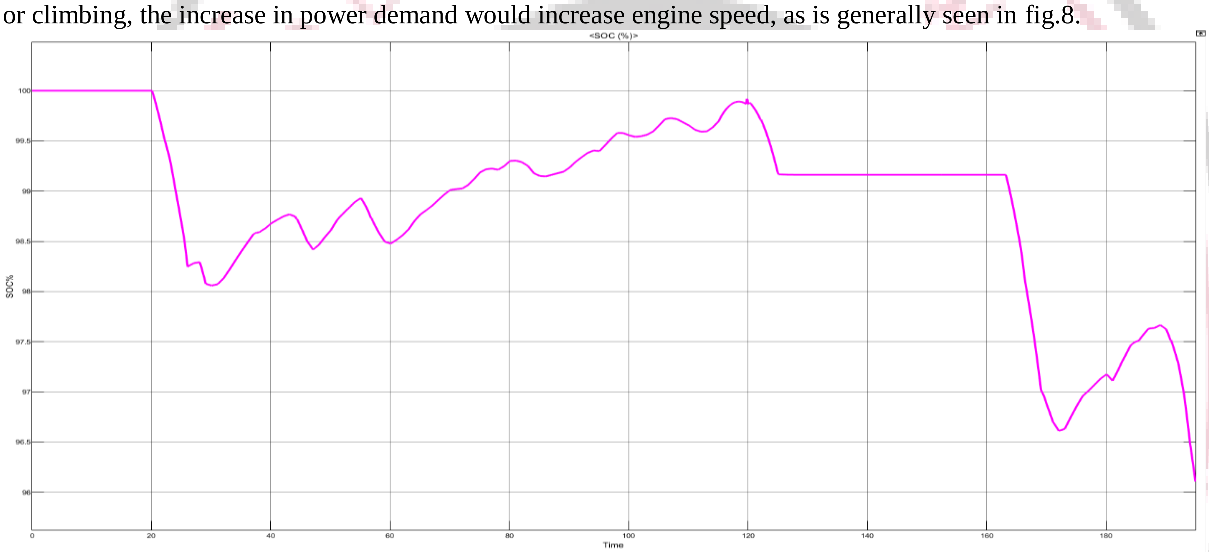

Fig.9: The variation in battery state of charge % as per the driving condition

It is observed that when the motor rpm hits zero, the battery State of Charge (SOC%) remains constant. On analyzing the behavior for various speeds inside the speed reference frame, a few key observations come to the forefront. Fig.9 shows the plots used to draw the conclusions presented here. These observations offer important insights into how the hybrid electric vehicle system behaves under different speed conditions, which in turn helps in honing and optimizing the system performance for better efficiency and reliability.

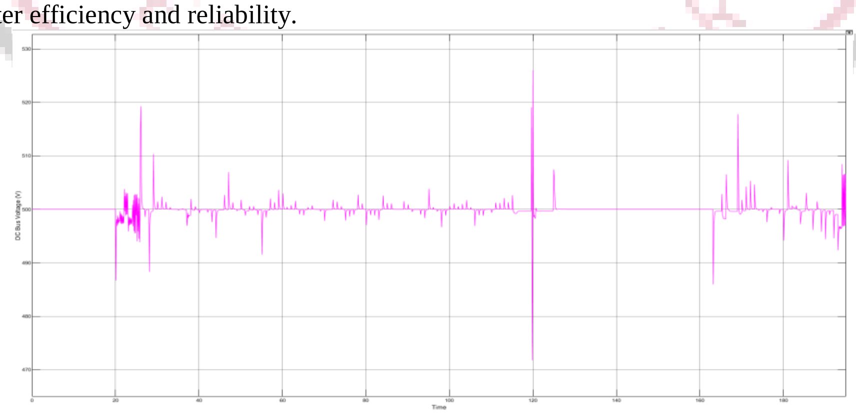

Fig.10. DC bus voltage in the controller of the modelled EV

During the control of the EV model for various running conditions the variation in the DC bus voltage has been shown in fig.10.

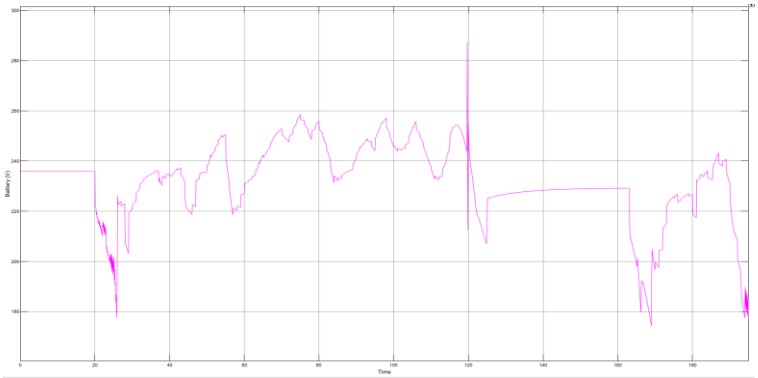

Fig.11. The battery voltage in the EV for the provided non uniform driving condition

This fig.11 shows the battery voltage condition in hybrid electric vehicle, which only comes into existence under non-uniform driving conditions. The voltage was highly non-uniform under this driving condition of the hybrid electric vehicle.

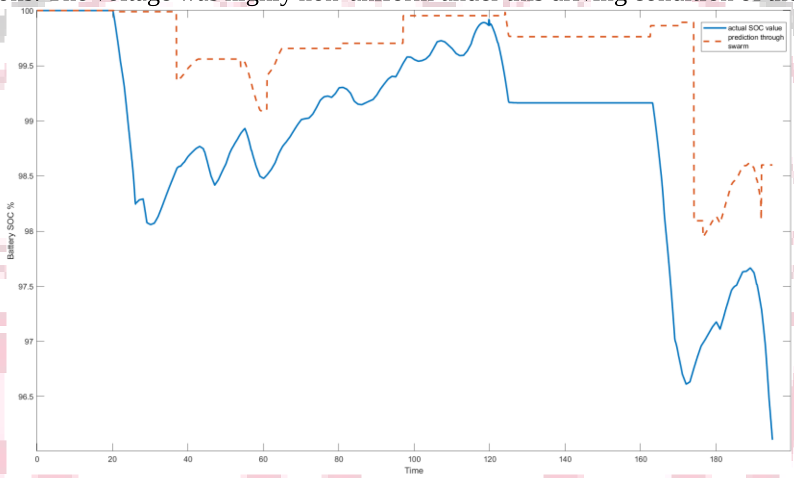

Fig. 12. Comparison of the battery SOC % and predicted SOC in the driving condition using prediction model 1

Fig.12 shows the real SOC of the battery as represented by the blue graph in non-uniform driving conditions. The red graph is a prediction done by the swarm optimization technique, and the error between these two states is evaluated to be 0.9606.

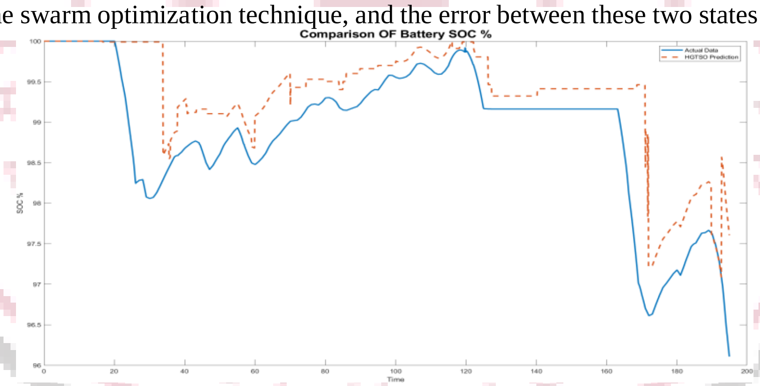

Fig.13: Comparison of the battery SOC % and predicted SOC in the driving condition using prediction model 2

In fig.13, under the non-uniform driving condition, the blue graph shows the real battery SOC %. The predicted charge state by the hybrid Gradient Tree swarm Optimization (HGTSO) algorithm technique is shown by the red graph, and from these two states, the error has been evaluated as 0.6605.

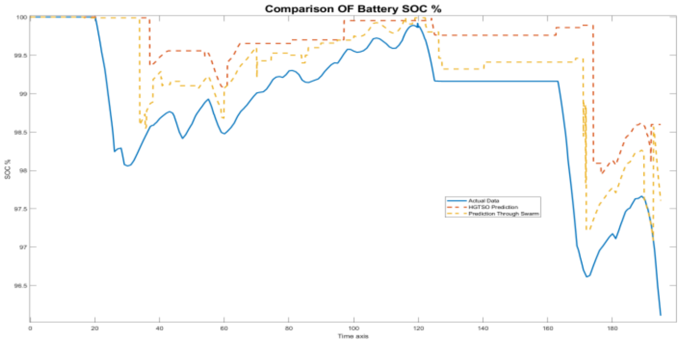

Fig.14: Comparison of the battery SOC % and predicted SOC in the driving condition using two different prediction models

The outcomes, as represented in fig.14, show the juxtaposition between the actual battery SOC values and the predicted battery SOC values of various algorithms in a simulation analysis of the Battery State of Charge (SOC) Prediction System. The red curve is the predicted SOC% by the swarm-based prediction mechanism, which has a maximum error of 0.9606 from the actual corresponding battery SOC%, which is the blue curve. This difference gives an idea of the type of deviation or error level usually encountered when employing standard swarm intelligence for estimating SOC.

Table 1 Comparative Table of Prediction Errors by two Algorithms

S No.	Prediction Models	Prediction Error
1	Swarm Based Prediction	0.9606
2	HGTSO	0.6605

It can be deduced from the table given that the prediction error for the HGTSO model was 0.6605. This result implies that, on average, the predictions formed by this model varied 0.6605 with respect to the dependent variable in actual measurement. Therefore, to recapitulate, both of the prediction approaches employed here-the swarm-based prediction model and the HGTSO model-have prediction errors that inform potential improvement in their predictive capabilities. Table 1 contains the numerical values for the errors.

V. CONCLUSION

The design of the HEV and its simulation involved MATLAB along with the prediction of battery Charge State (SOC%). Hybrid Electric Vehicle design and simulation with MATLAB, along with battery State of Charge (SOC%) prediction, has therefore been a milestone for efficient energy management and sustainable transportation. The key to accomplishing energy flow management is SOC% prediction. This was realized by employing the Swarm Optimization and Hybrid Gradient Tree Swarm Optimization (HGTSO) methods. On the one hand, Swarm Optimization gave 0.9606 as the prediction error; HGTSO provided more accurate results, thereby reducing prediction error to 0.6605, proving the method's efficiency in improving prediction and battery management.In the future, the SOC prediction can be broadened with incorporating state-of-the-art machine learning methodologies such as deep-learning-based approaches and reinforcement learning. These can analyze huge datasets for complex trends to create adaptive models that dynamically adjust to real-time driving and environment conditions. Further injection of context-aware inputs such as weather, traffic, and driver behavior will allow even better SOC prediction, as in the smart generation of HEV systems that are dependable and energy-efficient.

.REFERENCES

[1] D. Shi, S. Li, H. Xu, S. Wang, and L. Wang, “Design and test of adaptive energy management strategy for plug-in hybrid electric vehicle considering traffic information,” *Energy*, vol. 325, p. 136093, 2025, doi: https://doi.org/10.1016/j.energy.2025.136093.

[2] B. Chen *et al.*, “A hierarchical cooperative eco-driving and energy management strategy of hybrid electric vehicle based on improved TD3 with multi-experience,” *Energy Convers. Manag.*, vol. 326, p. 119508, 2025, doi: https://doi.org/10.1016/j.enconman.2025.119508.

[3] X. Shi, D. Jiang, Y. Liang, H. Liu, and X. Hu, “Reinforcement learning with experience augmentation for energy management optimization in hybrid electric vehicles,” *Appl. Therm. Eng.*, vol. 274, p. 126561, 2025, doi: https://doi.org/10.1016/j.applthermaleng.2025.126561.

[4] J. Wang et al., “Bayesian optimization for hyper-parameter tuning of an improved twin delayed deep deterministic policy gradients based energy management strategy for plug-in hybrid electric vehicles,” *Appl. Energy*, vol. 381, p. 125171, 2025, doi: https://doi.org/10.1016/j.apenergy.2024.125171.

[5] X. Shi, D. Jiang, H. Liu, and X. Hu, "Research on energy management optimization of hybrid electric vehicles based on improved curriculum learning," *Energy*, vol. 324, p. 136061, 2025, doi: https://doi.org/10.1016/j.energy.2025.136061.

[6] F. Wang, Y. Hong, and X. Zhao, "Research and Comparative Analysis of Energy Management Strategies for Hybrid Electric Vehicles: A Review," *Energies*, vol. 18, no. 11, 2025, doi: 10.3390/en18112873.

[7] X. Li, Z. Zhou, C. Wei, X. Gao, and Y. Zhang, "Multi-objective optimization of hybrid electric vehicles energy management using multi-agent deep reinforcement learning framework," *Energy AI*, vol. 20, p. 100491, 2025, doi: https://doi.org/10.1016/j.egyai.2025.100491.

[8] L. Deng, M. A. M. Radzi, S. Shafie, and M. K. Hassan, "Optimizing energy management in fuel cell hybrid electric vehicles using fuzzy logic control with state machine approach: Enhancing SOC stability and fuel economy," *J. Eng. Res.*, 2025, doi: https://doi.org/10.1016/j.jer.2025.03.007.

[9] X. Lin, Y. Ren, and X. Xu, "Stochastic velocity-prediction conscious energy management strategy based self-learning Markov algorithm for a fuel cell hybrid electric vehicle," *Energy*, vol. 320, p. 135167, 2025, doi: https://doi.org/10.1016/j.energy.2025.135167.

[10] S. Yadav and F. Assadian, "Robust Energy Management of Fuel Cell Hybrid Electric Vehicles Using Fuzzy Logic Integrated with H-Infinity Control," *Energies*, vol. 18, no. 8, 2025, doi: 10.3390/en18082107.

[11] J. Wang, C. Pan, and Z. Li, "Energy management strategy that optimizes battery degradation for electric vehicles with hybrid energy storage system," *Sci. China Technol. Sci.*, vol. 68, no. 2, p. 1220104, 2025, doi: 10.1007/s11431-024-2766-3.

[12] H. Rezk and A. Fathy, "Combining proportional integral and fuzzy logic control strategies to improve performance of energy management of fuel cell electric vehicles," *Int. J. Thermofluids*, vol. 26, p. 101076, 2025, doi: https://doi.org/10.1016/j.ijft.2025.101076.

[13] Y.-H. Lin and Y.-H. Hung, "Integrated thermal and energy management systems using particle swarm optimization for energy optimization in electric vehicles," *Case Stud. Therm. Eng.*, vol. 71, p. 106136, 2025, doi: https://doi.org/10.1016/j.csite.2025.106136.

[14] C. Wang, H. Mou, and H. Huang, "Optimization of power distribution in electric vehicle hybrid energy storage system based on RBF neural network and dynamic programming," *J. Energy Storage*, vol. 130, p. 117319, 2025, doi: https://doi.org/10.1016/j.est.2025.117319.

[15] R. Khujamberdiev and H. M. Cho, "Artificial Intelligence in Automotives: ANNs' Impact on Biodiesel Engine Performance and Emissions," *Energies*, vol. 18, no. 2, 2025, doi: 10.3390/en18020438.

[16] K. Sudhapriya and S. Jaisiva, "Implementation of artificial intelligence techniques in electric vehicles for battery management system," *Int. J. Low-Carbon Technol.*, vol. 20, pp. 590–604, 2025, doi: 10.1093/ijlct/ctaf022.

[17] Rebhi L, Khalfallah S, Hamel A, Bouzar Essaidi A. Design optimization of a four-wheeled robot chassis frame based on artificial neural network. *Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science*. 2025;239(12):4756-4773. doi:10.1177/09544062251316755

[18] I. Satpathy, A. Nayak, and A. Khang, "Transformative Impact of Generative Artificial Intelligence (Gen AI) on Smart Transportation System," in *Driving Green Transportation System Through Artificial Intelligence and Automation : Approaches, Technologies and Applications*, A. Khang, Ed. Cham: Springer Nature Switzerland, 2025, pp. 563–579. doi: 10.1007/978-3-031-72617-0_29.

[19] J. Jaguemont, A. Darwiche, and F. Bardé, "Model Predictive Control Using an Artificial Neural Network for Fast-Charging Lithium-Ion Batteries," *World Electr. Veh. J.*, vol. 16, no. 4, 2025, doi: 10.3390/wevj16040231.

[20] F. M. Talaat and A. A. Hamza, "Blockchain-enhanced artificial intelligence for advanced collision avoidance in the Internet of Vehicles (IoV)," *Neural Comput. Appl.*, vol. 37, no. 6, pp. 4915–4936, 2025, doi: 10.1007/s00521-024-10842-7.

[21] Sait, Sadiq M., Mehta, Pranav, Yıldız, Betül Sultan and Yıldız, Ali Rıza. "Artificial neural network–infused polar fox algorithm for optimal design of vehicle suspension components" *Materials Testing*, vol. 67, no. 8, 2025, pp. 1400-1408. https://doi.org/10.1515/mt-2025-0043

[22] V. A. Nardi, M. Lanza, F. Ruffa, and V. Scordamaglia, "An Artificial Intelligence Approach for the Kinodynamically Feasible Trajectory Planning of a Car-like Vehicle," *Appl. Sci.*, vol. 15, no. 2, 2025, doi: 10.3390/app15020795.

[23] H. T. J. Chan *et al.*, "Explainable Artificial Intelligence for State of Charge Estimation of Lithium-Ion Batteries," *Appl. Sci.*, vol. 15, no. 9, 2025, doi: 10.3390/app15095078.

[24] C. Feng and L. Wang, "Football Action Recognition Based on Explainable Artificial Intelligence Assisted by Unmanned Aerial Vehicles," *IEEE Trans. Consum. Electron.*, p. 1, 2025, doi: 10.1109/TCE.2025.3571434.

[25] D. Garikapati and S. S. Shetiya, "Autonomous Vehicles: Evolution of Artificial Intelligence and the Current Industry Landscape," *Big Data Cogn. Comput.*, vol. 8, no. 4, 2024, doi: 10.3390/bdcc8040042.