Advancements and Challenges in Electric Vehicle Adoption: A Global Perspective on Policy, Technology and Supply Chain Management

[1]Prasad Telang, [2] Prof. Sachindra Kumar Verma,[3] Dr. P. K. Sharma
[1]Department of Electrical Engineering, NRI Institute of Research & Technology, Bhopal India,
[2] HOD Department of Electrical Engineering, NRI Institute of Research & Technology, Bhopal India,
[3]Principal and Guide, Department of Electrical Engineering, NRI Institute of Research & Technology, Bhopal India
[1]prasadmits@gmail.com

* Corresponding Author: Prasad Telang

Abstract: *Policy makers worldwide are actively developing regulatory frameworks to boost Electric Vehicle (EV) adoption, aiming to reduce carbon emissions in the transportation sector. The EV battery supply chain has become a global arena of competition, driven by EVs' increasing share in passenger vehicle sales. Notably, China, the United States, and the EU lead in global EV markets. The surge in EV demand has intensified competition in the battery supply chain, with projected future demand exceeding current supply levels. Developing countries prioritize socio-economic development, emphasizing robust infrastructure and access to modern energy services. Technological advancements in EVs, particularly in battery management systems (BMS) and charging infrastructure, contribute to their widespread adoption.*

Keywords: *Electric Vehicles, EV Battery Supply Chain, Regulatory Frameworks, Battery Management Systems, Charging Infrastructure.*

I. INTRODUCTION

Policy makers worldwide are actively developing robust regulatory frameworks to bolster the adoption of Electric Vehicles (EVs), with the aim of mitigating carbon emissions from the transportation sector. The EV battery supply chain has emerged as a relatively new arena of global competition within the passenger vehicle industry, with EVs constituting a progressively significant portion of passenger vehicle sales. Notably, China, the United States, and the EU stand out as the top three markets for EV sales on a global scale. Since 2017, the availability of EV-specific trade data on an international scale has facilitated better monitoring of EV import, export, and sales trends. Consequently, there's been a notable surge in demand for the batteries required to power these EVs. The EV battery supply chain has become highly competitive, primarily due to the absence of established suppliers, with projected future demand surpassing current supply levels, both at the cell and material levels. As a result, the structure of this supply chain remains fluid and open to alteration. Many developing countries, such as Ethiopia, India, and Haiti, have large underserved populations, underscoring the importance of prioritizing socio-economic development. Consequently, policymakers in these nations prioritize the development of robust infrastructure and access to modern energy services to address widespread poverty.

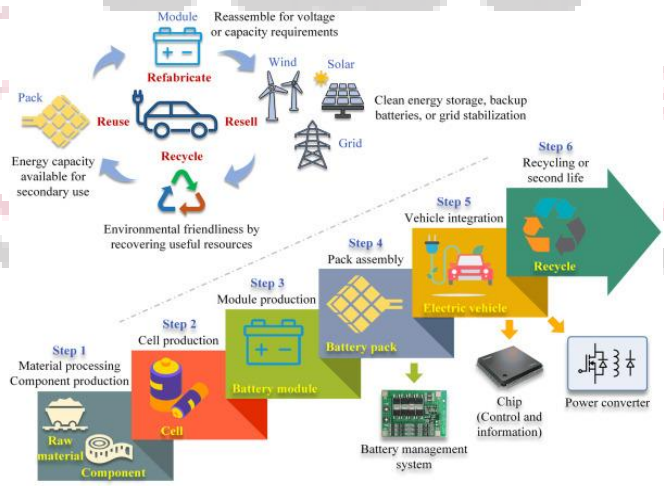

Figure 1. Industrial Value Chain and Rechargeable Battery Circulation in Electric Vehicle Mobility [3]

Electric vehicles (EVs) and hybrid electric vehicles (HEVs) have gained traction as viable alternatives to traditional internal combustion engine vehicles, showcasing significant technological advancements. Central to these vehicles are batteries, offering benefits such as high energy density, eco-friendliness, and long-term reliability. However, effective battery management is crucial due to safety risks associated with mishandling like over-current, over-voltage, or improper charging/discharging, which can hasten degradation and lead to accidents like fires or explosions [4]. Hence, a robust battery management system (BMS) is indispensable for these effort s, a fuzzy inference system-based Power Management Control (PMC) system is being developed, with genetic algorithms (GA) being used to fine-tune the system. The Hybrid Energy Storage System (HESS) total mass is decreased and the overall range of the EV is increased by using the GA offline to optimize the lower and upper membership limitations. Furthermore, there are exciting advancements in sustainable EV charging infrastructure, with the emergence of fully solar-powered charging stations at the forefront of modern technology.

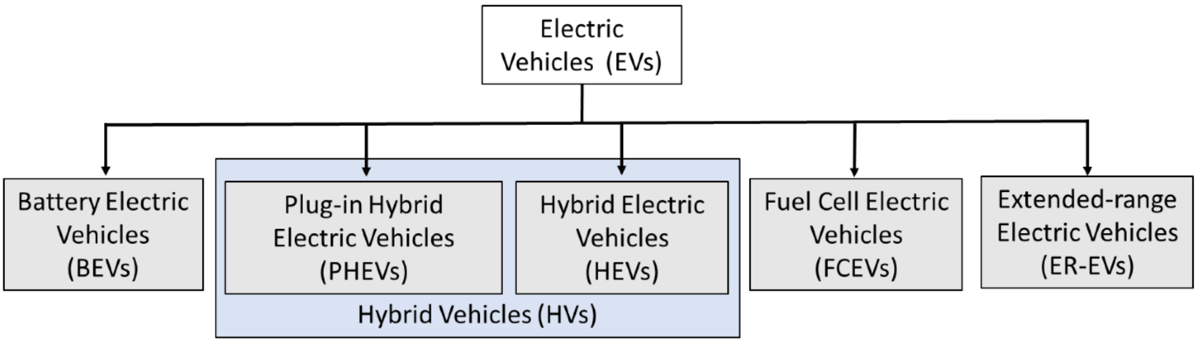

Figure 2 Classification of Electric Vehicles Based on Engine Technologies and Configurations [14]

Electric vehicles (EVs) have garnered significant interest as a promising alternative in today's transportation landscape, driven by their environmental advantages and transformative potential in mobility. These vehicles are broadly categorized into three main types based on their propulsion mechanisms: Plug-in Electric Vehicles (PEVs), Hybrid Electric Vehicles (HEVs), and Fuel Cell Electric Vehicles (FCEVs). HEVs combine electric propulsion with internal combustion engine technology, delivering benefits like enhanced fuel efficiency, lower emissions, and extended mileage compared to traditional internal combustion engine vehicles. This dual propulsion system of HEVs optimizes performance while minimizing environmental impact, meeting the increasing need for sustainable transportation solutions in modern society.

- **Hybrid Electric Vehicle**

Hybrid Electric Vehicles (HEVs) combine the utilization of an Internal Combustion Engine (ICE) alongside a battery system, effectively harnessing both energy sources to drive the vehicle forward. This dual-power-source configuration has earned HEVs the moniker of being dual-power vehicles. Particularly suitable for urban driving, HEVs capitalize on regenerative braking to recharge the battery by harnessing kinetic energy, a process especially beneficial in stop-and-go city driving scenarios.

- **Electric Vehicle (EV)**

Acknowledging the environmental advantages Electric Vehicles (EVs) offer, researchers [18] have shifted from conventional series-parallel hybrid designs to fully electric models. These advanced EVs now integrate real-time EV movement data to accurately predict the State of Charge (SOC). Factors such as road incline, vehicle weight, and wind resistance are taken into account to enhance the precision of SOC predictions.

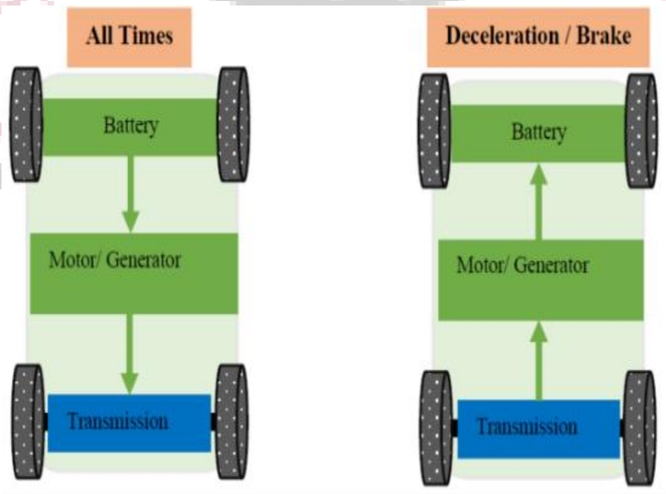

Figure 3 Electric Vehicle mode of operations

- **Fuel Cell Electric Vehicle (FCEV)**

As society progresses and technological innovation advances, there is an increasingly urgent call to tackle the escalating issues of global warming and the irreversible alterations in our climate. This necessitates ongoing developments in engine technologies, with a notable emphasis on exploring alternative fuel-based solutions. Automotive manufacturers are currently directing their efforts towards the development of electric vehicles (EVs), producing a myriad of prototype designs.

A. Battery Capacity and Range for Travel

The performance of a battery is determined by its capacity, which refers to the amount of energy it can store and subsequently discharge. It's important to note that different battery models from various manufacturers exhibit varying capacity levels. Among these, lithium-ion (Li-ion) battery technology stands out for its higher energy density compared to other batteries like lead-acid (Pb-Acid), especially in applications such as electric vehicles (EVs). This means that Li-ion batteries can store more energy within the same physical space, enabling them to provide greater power output and longer operating times. The travel range of an EV is directly influenced by the type and quantity of batteries utilized. While factors like terrain, weather conditions, and driving habits also play a role, the choice of battery type remains a primary determinant. Additionally, energy efficiency is closely linked to battery capacity. Batteries with higher efficiency ratings can utilize a greater percentage of stored energy, leading to faster charging times and the ability to achieve deeper discharge levels. Therefore, batteries with higher efficiency are typically associated with larger capacity, resulting in improved overall performance.

B. Parameters of Battery Performance: Specific Power, Specific Energy, Energy Density, Size and Weight

In the initial stages of electric vehicle (EV) development, lead-acid batteries emerged as the primary power source. These batteries were broadly classified into two main categories: Starting batteries and Deep-Cycle batteries. Among these, Deep-Cycle variants such as VRLA (Valve Regulated Lead Acid), AGM (Absorbent Glass Mat), and Gel batteries gained popularity for EV applications due to their superior energy capacity and longevity. Unlike certain other battery types, lead-acid batteries do not internally generate voltage. Instead, they rely on external sources to either receive or store charge, hence earning them the moniker of "storage batteries" as they retain only a single charge. The storage capacity of batteries, regardless of type, is typically quantified using amp-hour (Ah) or watt-hour (Wh) ratings. Lead-acid batteries are characterized by relatively low specific energy and energy density, typically falling within the range of 35-40 Wh/kg and 80-90 Wh/L [43]. Consequently, early electric vehicles necessitated larger battery sizes to accommodate the power requirements, thereby contributing to the increased curb weight of these vehicles.

C. Operation of Automobile Batteries

Electric traction motors are utilized in all-electric cars instead of traditional gasoline-powered internal combustion engines. These vehicles are dependent on a traction battery pack, usually consisting of lithium-ion batteries, to store the energy needed for the motor to drive the vehicle's wheels. The efficiency of this traction battery pack greatly impacts the vehicle's overall range, requiring intermittent recharging from an external power source. Additionally, plug-in hybrid electric vehicles (PHEVs) are equipped with traction battery packs to drive their electric motors, alongside a combustion engine for added functionality. In PHEVs, when the battery charge becomes depleted, the vehicle seamlessly transitions to the use of the internal combustion engine fueled by gasoline. Recharging the lithium-ion battery pack in both all-electric and plug-in hybrid vehicles is achieved through methods such as plugging into a power source, utilizing regenerative braking, or activating the vehicle's engine. The combination of a battery and gasoline engine in PHEVs allows for a greater driving range compared to all-electric vehicles.

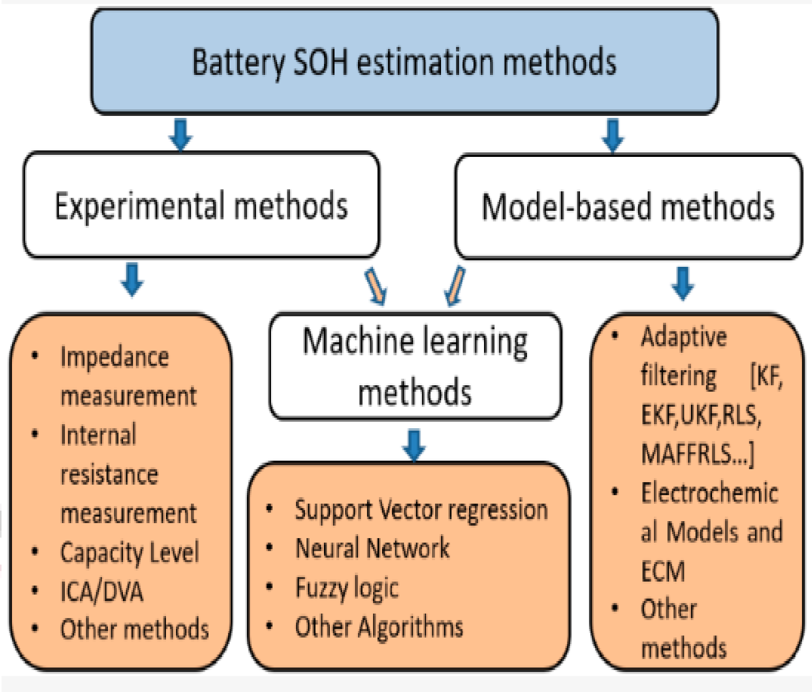

Figure 4. Techniques for Evaluating Battery Health (SOH)

II. LITERATURE REVIEW

Over the past decade, transportation electrification has surged, led by the rising popularity of electric vehicles (EVs), reshaping the automotive landscape and driving a significant expansion in charging infrastructure. Various strategies and methodologies are being developed to address challenges and capitalize on opportunities arising from EV adoption, as highlighted in studies by **Das et al. (2020)** and others. These efforts aim to enhance grid integration, optimize resource utilization, and shape the future of sustainable transportation.

While hybrid electric vehicles (HEVs) have improved fuel efficiency, the focus is shifting towards fully electric vehicles (PEVs). **Li, Khajepour, and Song (2019)** provide a comprehensive review of PEVs, covering their characteristics, energy sources, environmental impacts, and advancements in charging technologies. This reflects a collective push towards mitigating environmental degradation and fostering sustainable transportation solutions.

Battery technology remains a crucial aspect of EV development, with **Arif et al. (2018)** and others emphasizing its significance. Simulation models tailored for electric and hybrid vehicles help optimize battery performance and operational dynamics, driving advancements in EV technology.

Innovative charging methodologies such as Battery Swap Stations (BSS) and Wireless Power Transfer (WPT) are explored in studies by **Arif et al. (2021)** and others, highlighting the evolving landscape of EV charging infrastructure. Standardization efforts and optimization strategies further contribute to efficient resource utilization and infrastructure planning in the EV ecosystem.

The transition to battery electric vehicles (BEVs) is accelerating, driven by advancements in powertrain designs, battery technology, and propulsion mechanisms, as outlined by **Wagh and Dhatrak (2022)**. Despite notable progress, challenges remain, necessitating concerted efforts to drive innovation in the electric vehicle domain.

In India, policy measures are incentivizing EV adoption, with researchers like **Kumar and Chakrabarty (2020)** assessing the Total Cost of Ownership (TCO) for EVs compared to internal combustion engine vehicles. Innovative business models and charging infrastructure planning are crucial for expediting EV adoption.

NVH (Noise, Vibration, and Harshness) issues in EVs are addressed by **Krishna et al. (2023)**, underscoring the importance of enhancing ride comfort for widespread EV acceptance.

As the automotive sector grapples with emissions and energy concerns, the demand for hybrid electric vehicles (HEVs) is rising, offering a transitional solution towards sustainable transportation, as highlighted by **Talari and Jatrothu (2022)**.

Lastly, Zhou et al. (2020) introduce a novel energy management strategy for Fuel Cell Electric Vehicles (FCEVs), aiming to optimize power allocation and prolong the lifespan of power sources. This exemplifies ongoing efforts to enhance the performance and longevity of alternative fuel vehicles.

III. OBJECTIVES

1. To predict and evaluate the variation in maximum energy consumption of battery parameters and to optimizing energy efficiency by using regenerative system.
2. To design energy efficient EV model by using Artificial Intelligence based prediction algorithm to study for the vehicle performance and life.
3. Evaluating the efficacy of the proposed algorithm by conducting a comparative analysis of the errors between the algorithm's output and the actual data.

IV. METHODOLOGY

Hybrid electric vehicles (HEVs) commonly feature an electric drivetrain coupled with a bidirectional energy storage device, allowing for versatile power flow management. Unlike traditional internal combustion engine (ICE) vehicles, which rely solely on unidirectional energy sources, HEVs leverage electrochemical batteries as their primary energy storage solution.

The use of electrochemical batteries in HEVs facilitates efficient power management, enabling the vehicle to adaptively select from multiple power flow paths to meet varying load requirements. Additionally, HEVs boast the capability to recuperate energy during vehicle braking, enhancing overall energy efficiency. The control strategy employed in an HEV can be tailored to serve different objectives, with flexibility in configuring power flow combinations. This adaptability allows for the optimization of vehicle performance, energy utilization, and overall driving experience based on specific driving conditions and user preferences.

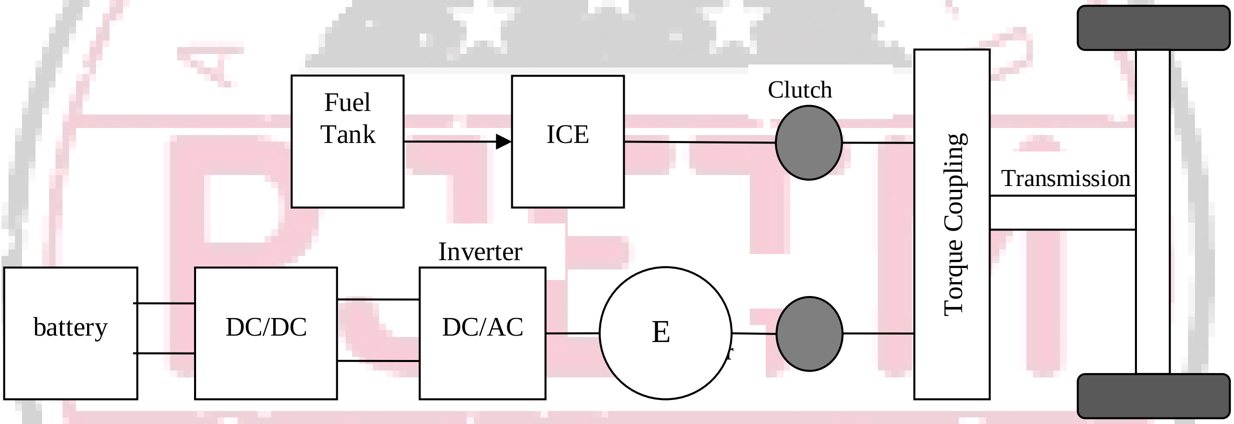

Figure 5. Parallel configuration of hybrid electric vehicle

The energy management controller in hybrid electric vehicles (HEVs) integrates diverse inputs to optimize vehicle performance and efficiency. These inputs encompass power demand from the driver, vehicle speed or acceleration, energy storage state of charge, current road load, and occasionally future traffic conditions gathered from the Global Positioning System (GPS). The primary function of the control strategy in Hybrid Electric Vehicles (HEVs) is to make informed decisions regarding the activation or deactivation of drivetrain components and to adjust their operating points accordingly.

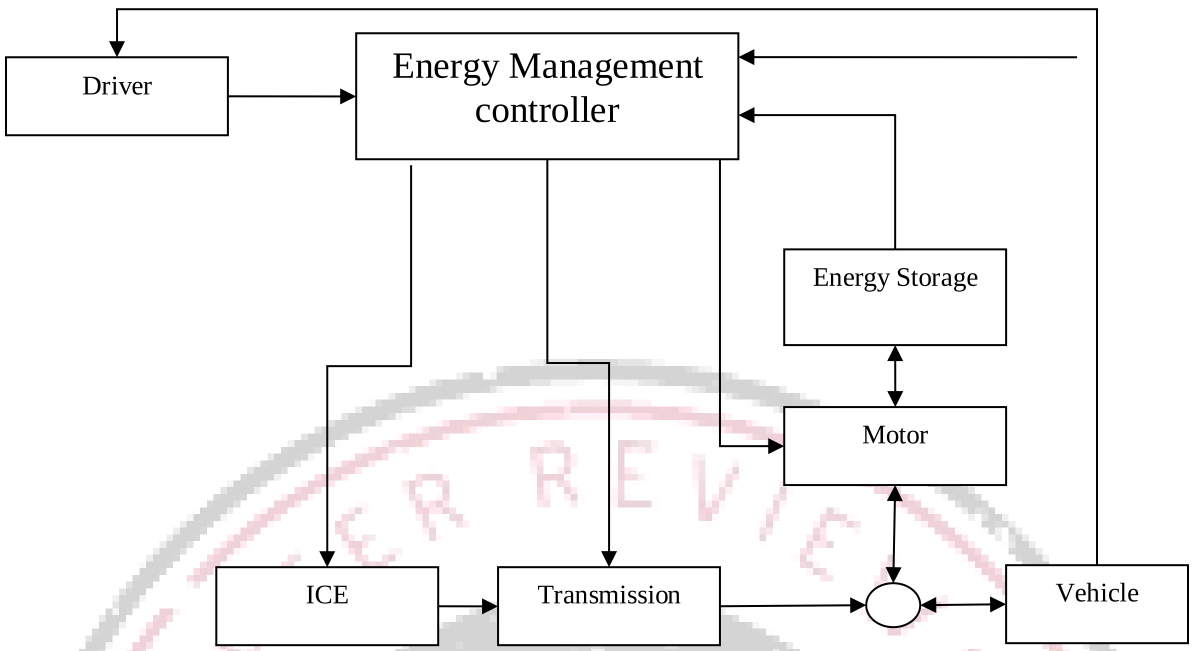

Figure 6. Energy Management Controller Layout for Hybrid Electric Vehicles

A. Storage Units in the hybrid electric vehicles

Hybrid electric vehicles (HEVs) utilize a unique type of battery known as a hybrid battery or traction battery. These batteries play a crucial role in powering the electric components of HEVs and complementing the internal combustion engine. They enable the vehicle to operate efficiently by providing energy for electric motors, regenerative braking, and other auxiliary systems.

HEV batteries are typically a type of rechargeable battery called a nickel-metal hydride (NiMH) battery or a lithium-ion (Li-ion) battery.

The battery pack in an HEV consists of multiple individual battery modules, each containing numerous cells connected in series or parallel configurations to provide the desired voltage and capacity. These modules are designed to be compact and often integrated into the vehicle's chassis or placed in the trunk area.

The primary function of the hybrid battery is to store electrical energy produced via regenerative braking and surplus power from the internal combustion engine. Subsequently, this stored energy is deployed to drive the electric motor during low-speed travel, aid the engine during acceleration, and supply supplementary power as required.

As state of charge (SOC) differs from other measurable parameters like current and voltage, it presents a unique challenge as it's not readily and directly measurable in most cases. Therefore, accurately estimating the net available energy in the battery necessitates precise understanding of the voltage dynamics concerning battery current and temperature parameters.

B. Prediction models for SOC

The aim of optimization-based (OB) energy management systems (EMS) is to identify the most efficient control sequence, typically referred to as the reference power demand. This optimal sequence is determined by minimizing a cost function while ensuring compliance with dynamic state constraints. These constraints include both global state constraints, such as the state of charge (SoC) of the battery, as well as local state constraints like power limit, speed limit, and torque limit. The OB EMS seeks to strike a balance between minimizing energy consumption and adhering to operational limitations to enhance overall system performance.

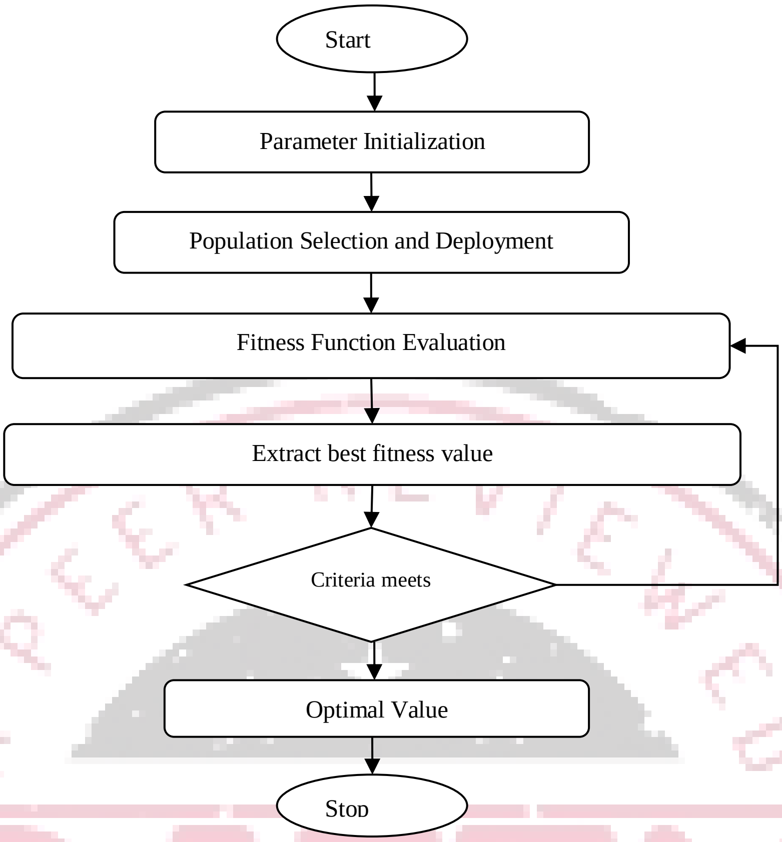

Figure 7 General Flowchart of Bio-inspired Optimization Algorithms

Optimizing parameters for hybrid electric vehicles (HEVs) is a complex and multidisciplinary research area. When designing an HEV, the primary objective is to minimize fuel consumption and emissions while ensuring optimal sizing of internal combustion engines (ICEs), electric motors (EMs), and energy storage systems (ESSs), all while tuning control strategy (CS) parameters. Additionally, it's essential to meet various vehicle performance constraints to ensure safe and efficient operation. The typical multi-objective optimization problem for HEVs involves defining objectives, design variables, and performance constraints. These elements are crucial for achieving the desired balance between reducing fuel consumption, minimizing emissions, and meeting vehicle performance requirements. Here are the key components of the HEV optimization problem.

V. RESULTS AND DISCUSSION

SOC prediction generates valuable data that can be analyzed to understand driving patterns, battery performance, and vehicle efficiency. This information can be leveraged for further improvements in EV technology and infrastructure planning. Precise anticipation of battery State of Charge (SOC) is crucial for optimizing the efficiency, performance, and lifespan of electric vehicles, ensuring a smooth driving experience for users. For businesses operating fleets of electric vehicles, predicting SOC enables efficient route planning and dispatching. It ensures that vehicles are deployed optimally, minimizing downtime due to charging and maximizing productivity.

The Root Mean Square Error (RMSE) is a commonly used metric to measure the accuracy of predictions, including the prediction of State of Charge (SOC) in a Hybrid Electric Vehicle (HEV). To calculate the RMSE, the predicted SOC values and the corresponding actual SOC values are required. The formula for RMSE is as follows:

$$RMSE = \sqrt{\sum (Predicted - Actual)^2 / n} \qquad (5.1)$$

Where:

- "predicted" represents the predicted SOC values.
- "actual" represents the actual SOC values.
- "^2" denotes squaring the difference between predicted and actual values.
- "n" is the number of data points or observations.

The analysis focusses on designing an algorithm for prediction the charging states of the hybrid electric vehicle. The vehicle is subjected to various running conditions as input speed reference and the battery response towards these is recorded. An

AI based artificial intelligence algorithm is used toe extract the data and learn the trends in the change of battery SOC, the algorithm then predicts the SOC% at different driving conditions. The error evaluation is done to study the effectiveness of the algorithm. Monitoring SOC helps in managing the health of the battery. Avoiding overcharging or deep discharging extends battery life, reducing the need for premature replacements and lowering ownership costs. The algorithm used is Hybrid Gradient Tree swarm Optimization (HGTSO) for battery soc prediction.

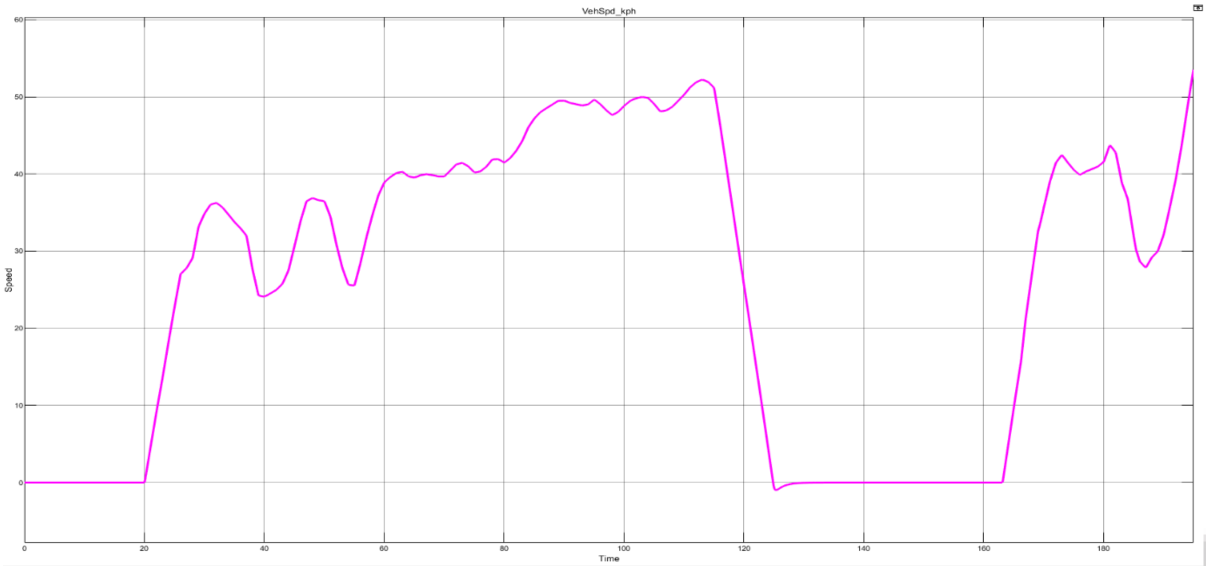

Figure 8 Vehicle speed reference

The speed reference model provides a depiction of the acceleration mode commencing at 20 seconds into the simulation of the Hybrid Electric Vehicle (HEV) model. Throughout the acceleration phase until the 25-second mark, the vehicle speed undergoes non-uniform fluctuations. Subsequent to this, at 115 seconds, the vehicle decelerates and eventually halts for a duration. Similarly, an emulation of the speed reference profile is incorporated into the simulation mode after 10 seconds, showcasing non-linear variations in speed at different time intervals along the axis, as illustrated in Figure 8. These representations offer valuable insights into the dynamic behavior of the vehicle under various operating conditions, aiding in the assessment and optimization of its performance.

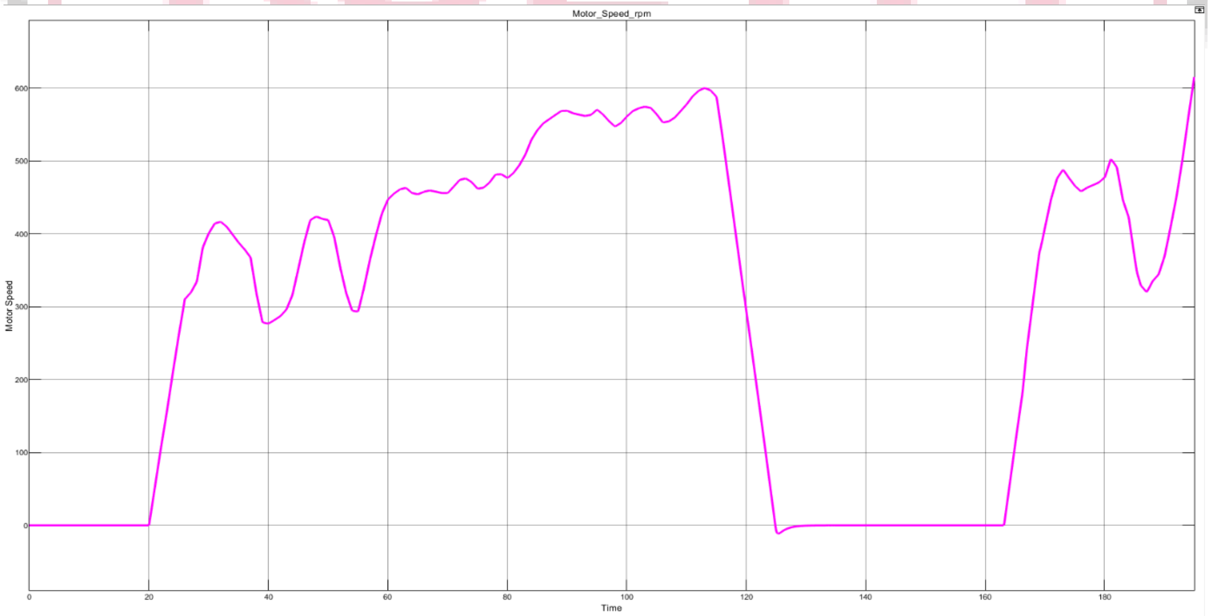

Figure 9 Motor running rpm

The response of motor in driving condition in a Hybrid Electric Vehicle (HEV) is directly related to the vehicle speed during running conditions as it will be directly associated with the drive train mechanism as shown in Figure 9.

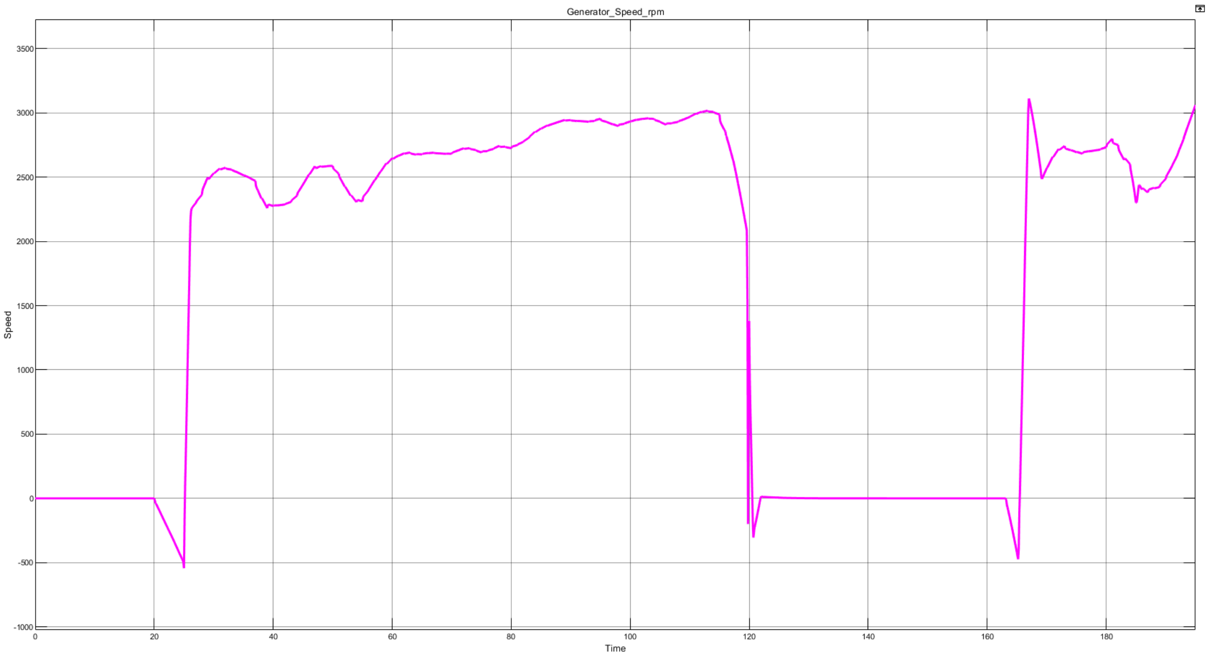

Figure 10 Generator Speed Response under the provided running condition in Hybrid Electric Vehicle

The speed response of the generator for the driving condition is shown in Figure 10. The vehicle speed influences the generator rpm as well. It can be seen that the variation in rpm is at regular time intervals depending upon the speed which is highly non uniform.

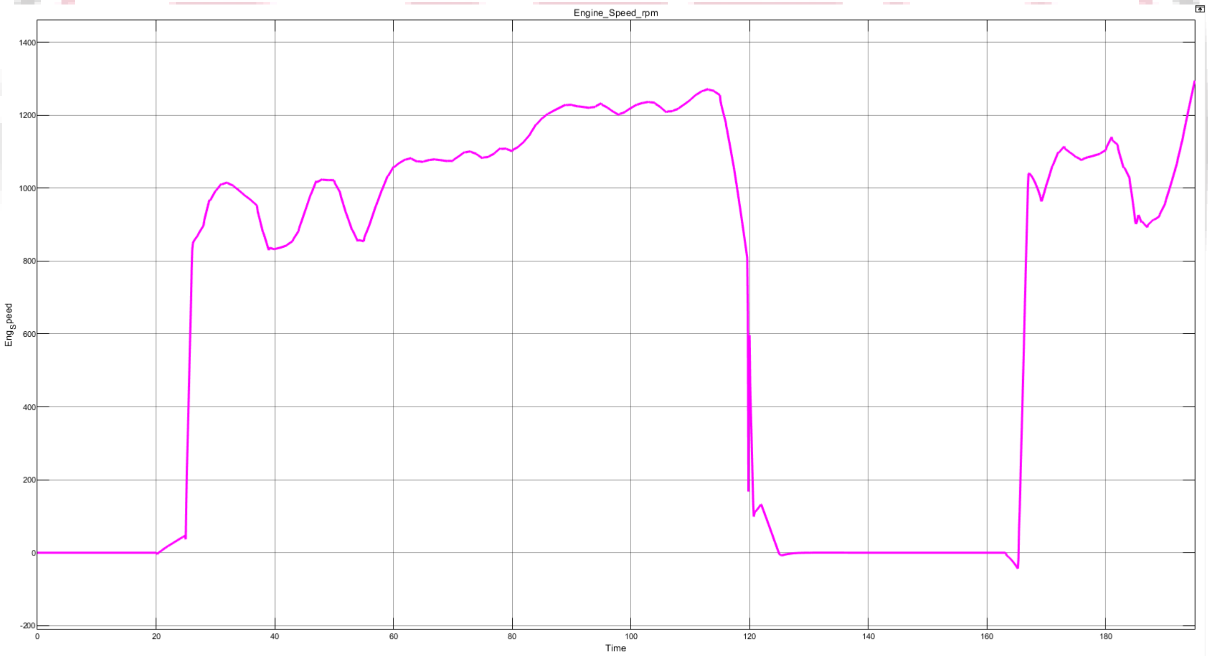

Figure 11 For driving condition the engine speed response

The engine speed in an HEV is influenced by the power demand required to propel the vehicle which is shown in figure 5.4 for driving cycle. At lower speeds or during light load conditions, the engine speed may be lower to match the power needed for efficient operation. As the power demand increases with higher vehicle speeds or when additional power is required for acceleration or climbing inclines, the engine speed will typically increase shown in figure 11.

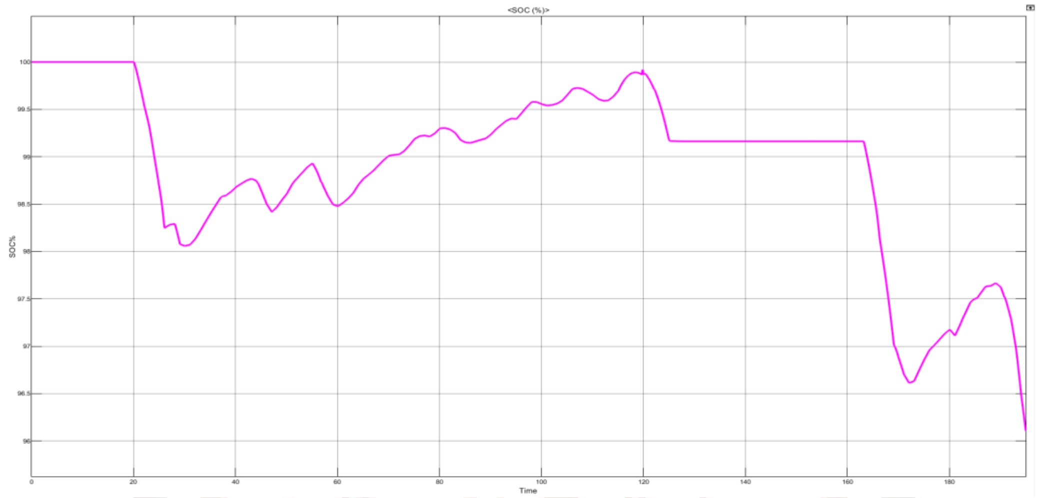

Figure 12 The variation in battery state of charge % as per the driving condition

As the motor rpm reaches zero, it is observed that the battery State of Charge (SOC%) remains constant. Analysis across different speed conditions within the speed reference frame reveals several key observations, as depicted in the graphs presented in Figure 12. These observations provide valuable insights into the behavior of the hybrid electric vehicle system under varying speed conditions, aiding in the refinement and optimization of system performance for enhanced efficiency and reliability.

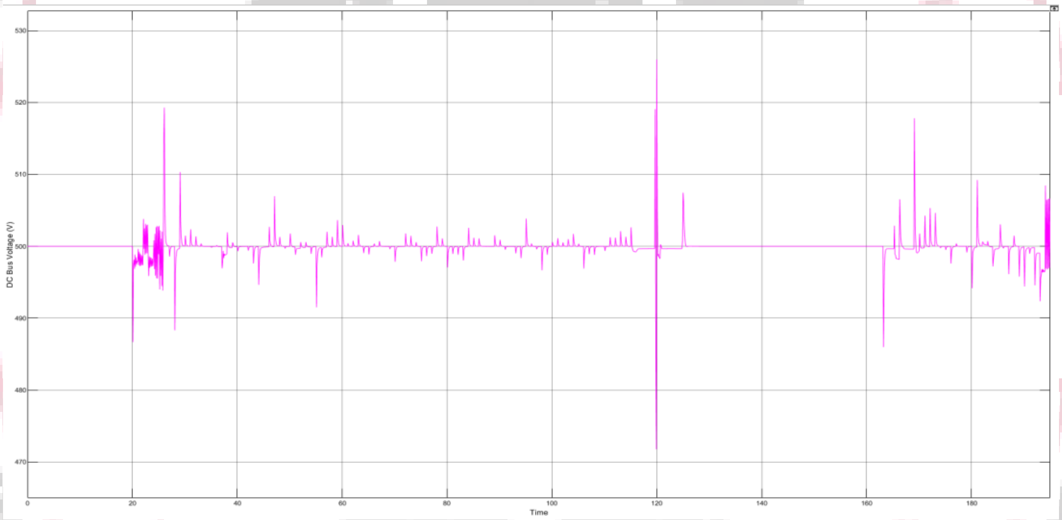

Figure 13 DC bus voltage in the controller of the modelled EV

During the control of the EV model for various running conditions the variation in the DC bus voltage has been shown in figure 13.

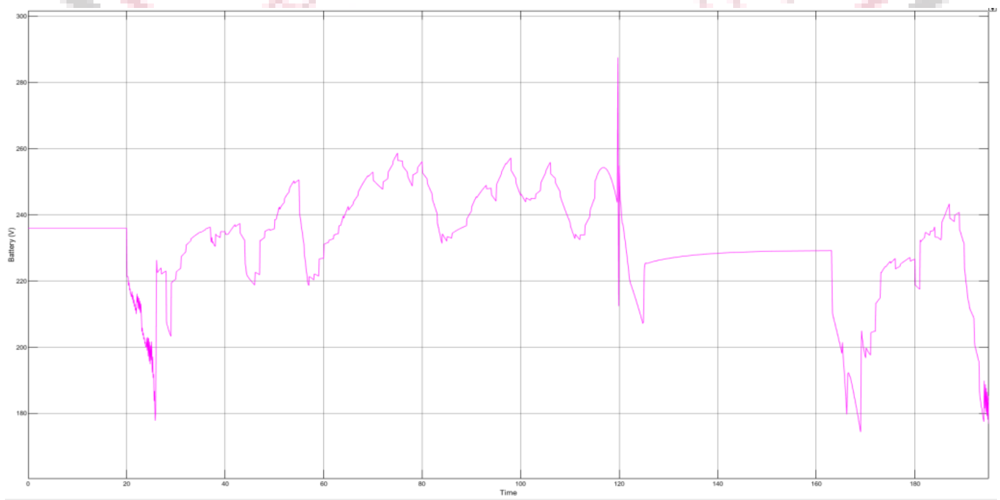

Figure 14 The battery voltage in the EV for the provided non uniform driving condition

The Figure 14 shows the battery voltage condition in hybrid electric vehicle where there is non-uniform driving condition. The voltage highly non uniform under this driving condition of the hybrid electric vehicle.

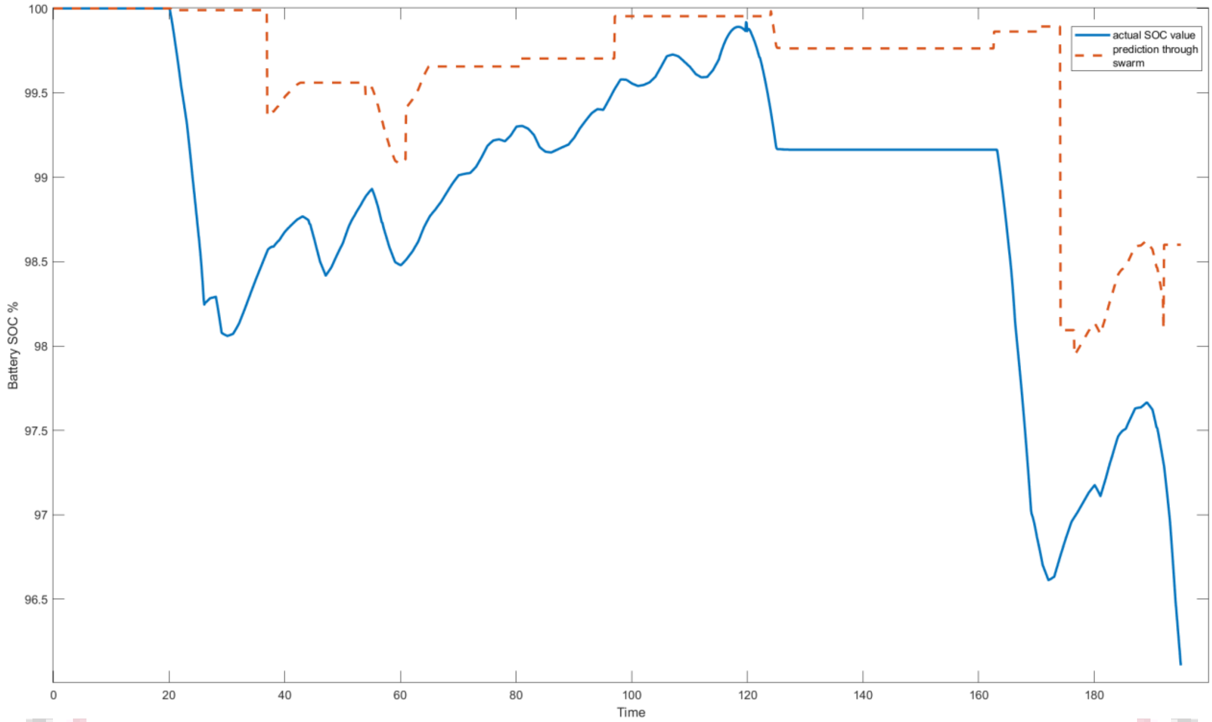

Figure 15 Comparison of the battery SOC % and predicted SOC in the driving condition using prediction model 1

The figure 15 represents the actual battery SOC % by the blue graph under the non-uniform driving condition. The prediction performed by the swarm Optimization technique is represented by the red graph and then the error between these two states is evaluated which is found to be 0.9606.

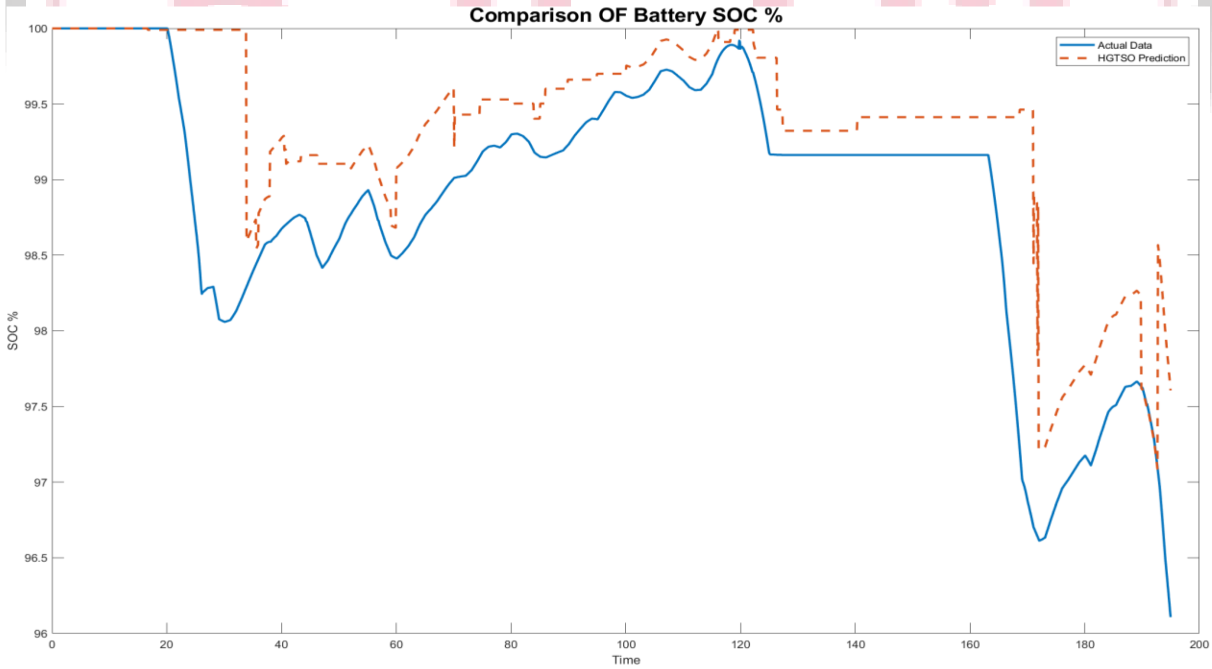

Figure 16 Comparison of the battery SOC % and predicted SOC in the driving condition using prediction model 2

The figure 16 represents the actual battery SOC % by the blue graph under the non-uniform driving condition. The prediction performed by the hybrid Gradient Tree swarm Optimization (HGTSO) algorithm technique is represented by the red graph and then the error between these two states is evaluated which is found to be 0.6605.

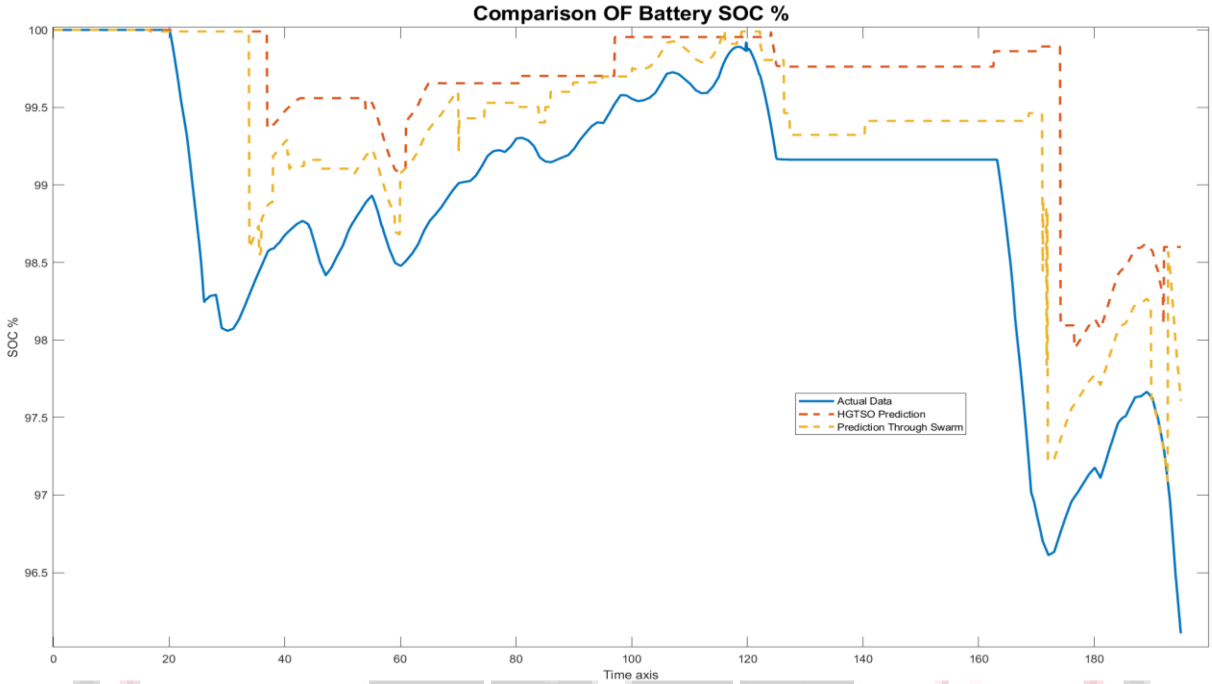

Figure 17 Comparison of the battery SOC % and predicted SOC in the driving condition using two different prediction models

Figure 17 illustrates the simulation results comparing the predicted values generated by the Battery State of Charge (SOC) prediction system. The error evaluation of the swarm-based prediction technique for SOC% during the vehicle's drive mode is depicted by the red graph. This graph highlights a discrepancy of 0.9606 in comparison to the actual SOC% of the vehicle's battery, represented by the blue graph. These findings provide valuable insights into the accuracy and reliability of the swarm-based prediction method, offering guidance for further refinement and optimization of battery SOC prediction systems in hybrid electric vehicles. Utilizing the proposed hybrid Gradient Tree Swarm Optimization (HGTSO) algorithm for battery charge condition prediction, illustrated by the yellow graph, yields a reduced prediction error of 0.6605, closely approaching the actual value of battery 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

We can infer that the HGTSO model achieved a prediction error of 0.6605, as indicated in the table. This suggests that, on average, the predictions produced by the HGTSO model deviated from the actual values by approximately 0.6605 units. A lower prediction error indicates better predictive accuracy and suggests that the model's predictions closely align with the observed data. In summary, both the swarm-based prediction model and the HGTSO model are approaches to making predictions, with the associated prediction errors providing insights into their respective accuracy level with the table 1 which provides numerical values for these errors

V. CONCLUSION

Electric vehicles (EVs) are gaining traction globally as a sustainable alternative in the transportation sector. Policy efforts aimed at bolstering EV adoption, coupled with advancements in battery technology and charging infrastructure, are driving significant progress. However, challenges persist in the EV battery supply chain, necessitating innovative solutions to meet future demand. The development of robust regulatory frameworks and investment in infrastructure are crucial for fostering EV adoption and addressing environmental concerns.

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