OPTIMIZED CONTROL STRATEGIES FOR HYBRID ENERGY STORAGE AND ANN-BASED DRIVING PREDICTION TECHNIQUES FOR ENERGY MANAGEMENT SYSTEMS IN ELECTRIC VEHICLES

A thesis submitted to the

UPES

For the award of
Doctor of Philosophy

In

Electrical and Electronics Engineering

BY

Shanmukha Naga Raju Vonteddu

April 2025

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DECLARATION

I declare that the thesis entitled "Optimized Control Strategies for Hybrid Energy Storage and ANN-Based Driving Prediction Techniques for Energy Management System in Electric Vehicles" has been prepared by me under the guidance of Dr. Prasanthi Kumari Nunna, Senior Associate Professor, Department of Electrical and Electronics Engineering, School of Engineering, UPES and Dr. Ravindra Kollu, Professor, Department of Electrical and Electronics Engineering, University College of Engineering Kakinada, JNTUK.

No part of this thesis has been formed on the basis for the award of any degree or fellowship earlier.

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CERTIFICATE

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ABSTRACT

Electric vehicles (EVs) are a sustainable solution to environmental pollution and energy shortages, offering high efficiency and reduced emissions. Their adoption supports cleaner, quieter, and greener transportation systems. This thesis focuses on the Driver's behavior .depending on various terrain conditions and uses an energy management system in an effective way for utilization of hybrid energy storage with appropriate power splitting.

Initially, this study focuses on improving vehicle performance and driving behaviour using Artificial Neural Network-based prediction techniques. Initially, mathematical calculations related to vehicle dynamics were performed. Data was then collected through sensors and Wi-Fi devices while travelling through various terrains. Multiple training algorithms were evaluated to optimize the data, highlighting inconsistencies in the results. To address this, an Artificial Neural Network (ANN)-based prediction technique was proposed. The ANN model effectively mitigates inconsistencies and provides optimized results. Experimental outcomes demonstrate a significant improvement in performance by training the datasets. This enhancement positively impacts driving behaviors.

Secondly, the power requirements under varying speed conditions are forecasted based on driving cycles and analyzed using a PI controller. An Ideal PI controller without overshoot is taken as the benchmark, and an Artificial Neural Network (ANN) is designed to emulate it in three modes: accurate, semi-accurate, and inaccurate. The battery power required for vehicle propulsion is determined through datasets, training, searching, and validation, enabling precise prediction and optimization of Hybrid Energy Storage System (HESS) sizing. Subsequently, a HESS combining a battery, supercapacitor, and fuel cell is designed to efficiently distribute energy based on the vehicle's power demands. After the optimal sizing of the Hybrid Energy Storage (HESS), depending on the power required from each driving condition like traffic mode, Urban Mode the simulation work gives various datasets depending on various optimal sizing or the power required from the HESS.

Thirdly, Energy Management Systems (EMS) is used for Motor control, Transmission Control and Hybrid Energy Storage Systems (HESS) which is required. Then it is extended to map their capacities to supply the Permanent Magnet Synchronous Motor (PMSM) according to various loading situations (Vehicle-Road interaction scenarios or Drive cycles). The data from the driving cycles will help to extend the ANN controller for EMS. To optimize these objectives, in the proposed work the following three optimization parameters are considered: - power generation, torque ripple, and current fluctuation. The results were compared with Output Power Optimization (OPO).

The simulation results demonstrate that the proposed strategy enhances driving efficiency while reducing torque ripple, ensuring effective braking and improved EV comfort. Control techniques, including Levenberg-Marquardt Backpropagation Training (LMBT), are successfully applied to the Energy Management System (EMS) and Hybrid Energy Storage System (HESS). This approach optimizes hybrid energy systems, leading to extended range and improved performance.This thesis highlights improved efficiency and performance of electric vehicles (EVs) through optimized hybrid energy storage systems (HESS) and advanced energy management strategies. The system integrates batteries, supercapacitors, and fuel cells, managed with Artificial Neural Networks (ANN) and regenerative braking using the Levenberg-Marquardt Backpropagation Training (LMBT) method. Simulation results reveal enhanced driving efficiency, reduced torque ripple, improved braking performance, and a 12.02% increase in battery life.

These advancements highlight the potential of hybridized energy systems to address current challenges in energy storage and management for EVs. Future work can expand on this by testing different motor types, comparing results with prototypes like a 1 kW motor, and leveraging OPAL-RT tools for real-time performance analysis. Evaluating diverse driving cycles like real driver behaviour can refine the model's accuracy. Integration of technologies such as LIDAR for real-time road assessments, Control Area Network (CAN) for vehicle-to-vehicle (V2V) energy sharing, and Digital Twin concepts for virtual system replication can further enhance monitoring, analysis, and optimization, paving the way for more advanced and collaborative EV energy systems.

ACKNOWLEDGEMENT

This Thesis would not be possible without the support and encouragement of many people. First and foremost, I express my profound gratitude and sincere thanks to my supervisor Dr. Prasanthi Kumari Nunna and Dr. Ravindra Kollu for giving me all their support, advice, inspiration and motivation in carrying out this work. Their technical expertise and approach of tackling problems have been of great help to me. Besides, their constant motivation, encouragement, personal guidance and understanding helped me to carry out this work with great zeal and enthusiasm. I thank them for taking me under their wing and providing numerous inputs in the work.

I convey my special thanks to my Cluster Head Dr. Piyush Kuchhal, and faculty members of the Electrical and Electronics Engineering department for providing an excellent academic environment. I am grateful to Dr. Adesh Kumar, Research Coordinator, School of Engineering, for his constant and continuous encouragement to carry out the work.I am grateful to Dr. Pankaj Kumar, Dean, School of Engineering, for his constant and continuous encouragement to carry out the work. I convey my special thanks to Dr. Devender Kumar Saini, Dr. Abhinav Sharma, and all faculty and staff members of the Electrical and Electronics Engineering department for providing an excellent academic environment.

Ultimately, I would like to convey my perpetual appreciation and acknowledgement to my parents, Sri V. Bala Subramanyam Devara and Smt. V. Subba Lakshmi, my sister, Ms V. Sowjanya, my spouse, Mrs Samyuktha, and my son, Mr V. Keeyansh Shree Ishaan Devara, for their affection and assistance throughout my existence. The unwavering support and steadfast belief in my capabilities have served as a significant source of inspiration. Merely expressing gratitude may not be adequate for the assistance that has been provided to me.

I want to thank God for giving me the opportunity to complete my studies and for all the blessings I have received so far.

Shanmukha Naga Raju Vonteddu

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NOMENCLATURE

Letters	Short Form	Abbreviation
A	ACO	Ant Colony Optimization
	ADVISOR	Advanced Vehicle Simulator
	AIT	Artificial Intelligent Techniques
	ANN	Artificial Neural Network
B	BAT	Battery
	BMS	Battery Management System
	BLDC	Brushless Direct Current Motor
C	CBDC	China Bus Driving Cycle
D	DKDE	Diffusion-Based Kernel Density Estimator
	DL	Deep Learning
	DR	Driving Range
	DRL	Deep Reinforcement Learning
	DP	Dynamic Programming
	DC	Driving Cycles
E	EPA	Ensemble Predicting Algorithm
	ECMS	Equivalent Consumption Minimization Strategy
	EV	Electric Vehicle
	ECU	Engine Control Unit
	EMS	Energy Management Strategy
	ESS	Energy Storage System
F	FLC	Fuzzy Logic Controller
	FCHV	Fuel Cell Hybrid Vehicles
	FTP-72	Federal Test Procedure 72
	FCPV	Fuel Cell Passenger Vehicles
	FC	Fuel Cell

	FCEV	Fuel Cell Electric Vehicle
	FFRLS	Forgetting Factor Recursive Least Square
	FEV	Full Electric Vehicle
G	GA	Genetic Algorithm
	GBDT	Gradient Boosting Decision Tree
	GHDC	Global Harmonized Driving Cycle
H	HIL	Hardware-In-The-Loop
	HEV	Hybrid Electric Vehicle
	HESS	Hybrid Energy Storage System
I	ICE	Internal Combustion Engine
	IM	Induction Motor
	ITS	Intelligent Transportation Systems
J	JSON	JavaScript Object Notation
K	KHO	Krill Herd Optimization
L	LV	Low Voltage
	LPM	Liters Per Minute
M	ML	Machine Learning
	MRNN	Modular Recurrent Neural Network
	MER	Maximum Efficiency Range
	MCU	Motor Control Unit
	MIC	Multiple-Input Converter
N	NEDC	New European Driving Cycle
	NN	Neural Networks
	NTP	Network Time Protocol

O	OOL-PMP	Optimal Operation Line and Pontryagin's Minimum Principle
P	PV	Photovoltaic Cell
	PI	Proportional Controller
	PMSM	Permanent Magnet Synchronous Motor
	PSOA	Particle Swarm Optimization Algorithm
	PWM	Pulse Width Modulation
	PMP	Pontryagin's Minimum Principle
	PHEV	Plug-In Hybrid Electric Vehicle
	PEMFC	Proton Exchange Membrane Fuel Cell
R	RDF	Random Decision Forest
	RDR	Remaining Driving Range
	RTG	Rubber Tire Gantry
S	SML	Standard Meta Language
	SoC	State Of Charge
	SDP	Stochastic Dynamic Programming
	SQP	Sequential Quadratic Programming
	SCAP	Security Content Automation Protocol
	SC	Super Capacitor
	SMPC	Stochastic Model Predictive Controller
	SQP	Sequential Quadratic Programming
	SVR	Support Vector Regression
T	TCU	Transmission Control Unit
U	UC	Ultra Capacitor
W	WLTP	Worldwide Harmonized Light Vehicle Test Procedure

CHAPTER 1

INTRODUCTION

1.1. Background:

The global push towards sustainable transportation has spurred rapid advancements in Electric Vehicles (EVs) as a viable alternative to traditional internal combustion engine vehicles. Electric vehicles are increasingly recognized for their potential to reduce greenhouse gas emissions, dependence on fossil fuels, and overall environmental impact[1]. As the adoption of EVs grows, so does the need to optimize their Energy Management Systems (EMS) to enhance efficiency, extend driving range, and ensure the longevity of energy storage systems[3].

Modern EVs incorporate advanced energy storage systems and control strategies to manage power demands efficiently[2]. Among these, Hybrid Energy Storage Systems (HESS), which combine batteries and supercapacitors, have emerged as a promising solution. HESS capitalizes on the complementary characteristics of these storage technologies: the high energy density of batteries and the rapid charge-discharge capabilities of supercapacitors. However, optimizing the control strategies for HESS is critical to balancing energy flow, minimizing losses, and meeting real-time power demands effectively[8].

In parallel, the integration of Artificial Intelligence (AI) techniques in EMS design has introduced new possibilities for predictive energy management. Artificial Neural Networks (ANNs) are particularly well-suited for driving pattern recognition and prediction due to their ability to learn and adapt from large datasets[13]. By predicting driving cycles and energy demands, ANN-based strategies enable more informed decisions for energy allocation, regenerative braking, and power distribution, further improving vehicle performance and efficiency[9].

This thesis focuses on exploring and developing optimized control strategies for HESS and ANN-based driving prediction techniques for energy management systems in electric vehicles[10]. The research delves into the principles of EV types, their energy requirements, and the challenges of efficient energy management. It presents novel approaches to harmonize HESS operations and leverage ANN-driven insights to enhance overall energy utilisation, reduce energy losses, and maximize regenerative braking potential[8].

The findings of this study contribute to the broader goal of creating smarter, more efficient EVs capable of meeting the dynamic demands of modern transportation[12]. By combining advanced hybrid energy storage solutions with intelligent predictive algorithms, this research paves the way for more sustainable and practical implementations of electric vehicle technologies[15].

1.1.1 Classification of Electric Vehicles:

Electric Vehicles are classified based on their propulsion systems, energy storage configurations, and the extent to which they rely on electric power for motion. The primary types of EVs are:

- **Battery Electric Vehicles (BEVs):** Fully electric vehicles powered exclusively by a battery pack and electric motor(s), without any Internal Combustion Engine (ICE). Powered by large-capacity rechargeable batteries[14]. Rely solely on electricity for propulsion. Zero tailpipe emissions. Examples: Tesla Model 3, Nissan Leaf, Chevrolet Bolt. Advantages: Environmentally friendly with no direct emissions. Lower running and maintenance costs compared to ICE vehicles. Challenges: Limited driving range compared to ICE vehicles. Long charging times and reliance on charging infrastructure[20].

- **Hybrid Electric Vehicles (HEVs):** Vehicles that combine an ICE with an electric motor and a battery pack to enhance fuel efficiency and reduce emissions. Features: Use regenerative braking to recharge the battery. The electric motor assists the ICE, especially during acceleration[16]. Cannot be plugged in for charging; relies on the ICE and regenerative braking to recharge. Examples: Toyota Prius, Honda Insight. Advantages: Improved fuel efficiency compared to conventional ICE vehicles. Reduced emissions in urban driving conditions[34]. Challenges: Higher upfront cost due to the dual propulsion systems. Limited reliance on electric power.

- **Plug-in Hybrid Electric Vehicles (PHEVs):** Vehicles that feature both an ICE and an electric motor, with the ability to recharge the battery externally via a plug-in charger. Features**:** Can operate in all-electric mode for a limited range[17]. Use ICE as a backup when the battery is depleted. Larger battery capacity compared to HEVs. Examples: Mitsubishi Outlander PHEV, Toyota RAV4 Prime. Advantages**:** Ability to drive short distances on electric power alone, reducing fuel consumption. Flexibility of using ICE for longer trips. Challenges: Heavier and more complex systems than BEVs or HEVs. Limited all-electric range[24].

- **Fuel Cell Electric Vehicles (FCEVs):** Vehicles that use hydrogen fuel cells to generate electricity, which willpower an electric motor.Features**:** Produce electricity through a chemical reaction between hydrogen and oxygen[34]. Emit only water vapour as a byproduct. Examples**:** Toyota Mirai, Hyundai Nexo.Advantages**:** Zero tailpipe emissions with fast refuelling times compared to BEVS.Longer driving range than most BEVS.Challenges**:** Limited hydrogen refueling infrastructure. High production and storage costs for hydrogen[28].

- **Extended Range Electric Vehicles (EREVs):** Vehicles that operate primarily as BEVs but use a small ICE as a generator to recharge the battery when the charge is low[36].Features**:** The ICE does not directly drive the wheels but extends the driving range by charging the battery. Operate mostly in electric mode under normal conditions.Examples**:** Chevrolet Volt (1st generation).Advantages**:** Eliminates range anxiety asSoCiated with BEVs.Highly efficient due to the predominant use of electric power. Challenges**:** Complex systems and higher costs compared to standard BEVs. Emissions from ICE operation during extended range mode[29].

- **Solar Electric Vehicles (SEVs):** Vehicles equipped with solar panels to generate electricity for propulsion or to supplement battery charging.Features**:** Use photovoltaic cells to convert sunlight into electricity. It can operate as BEVs or hybrids, depending on design. Examples**:** Lightyear 0, Aptera SEV.Advantages**:** Potential for self-charging during daylight, reducing reliance on external charging.Zero emissions.Challenges**:**Limited energy generation capacity of solar panels.Higher initial costs due to solar panel integration[[126].

- **Mild Hybrid Electric Vehicles (MHEVs):** Vehicles that use a small battery and electric motor to assist the ICE, but cannot operate on electric power alone.Features**:**Assist ICE during start-stop conditions and acceleration[37].Use regenerative braking to charge the small battery. Examples: Suzuki Swift Hybrid, Audi A6 TFSI Mild Hybrid.Advantages**:** Improved fuel efficiency without significant changes to the ICE

- design.Lower cost compared to full hybrids[42].Challenges**:**Limited energy savings compared to HEVs or PHEVs.Still heavily reliant on ICE for propulsion

Table 1 Comparison of Key EV Types

Features	**BEV**	**HEV**	**PHEV**	**FCEV**	**EREV**	**MHEV**
Primary Energy Source	Battery	ICE + Battery	Battery + ICE	Hydrogen	Battery + ICE	ICE + Small Battery
Emissions	Zero	Low	Low	Zero	Low	Moderate
Charging Capability	Yes	No	Yes	No	Yes	No
Range	Moderate to High	High	High	High	High	High
Cost	High	Moderate	High	Very High	High	Moderate

The classification of electric vehicles highlights their diversity in propulsion technologies and energy management strategies. Each type caters to specific use cases, environmental goals, and market segments. With advancements in energy storage, hydrogen production, and charging infrastructure, these categories continue to evolve, paving the way for more efficient and sustainable transportation solutions.

1.1.2 Energy Storages:

Energy storage systems (ESS) are a critical component of EVs, providing the energy required for propulsion, auxiliary functions, and regenerative braking. The performance, range, and efficiency of an EV are significantly influenced by the type and configuration of its energy storage system. Below are the primary energy storage solutions used in EVs:

- **Lithium-Ion Batteries (Li-ion):** The most commonly used energy storage technology in modern EVs. Employs lithium ions to store and release energy during charging and discharging cycles[14]. Features: High Energy Density: Enables longer driving ranges with compact size. Lightweight: Suitable for EVs where weight is a critical factor. Rechargeable: Long cycle life with efficient charge-discharge characteristics.Advantages: High energy and power density. Low self-discharge rates. Wide operational temperature range[20]. Supports fast charging Challenges: High cost due to rare materials like lithium and cobalt. Limited recyclability and environmental concerns. Safety risks such as thermal runaway and fire hazards[28] Applications:Used in Battery Electric Vehicles (BEVs) and Plug-in Hybrid Electric Vehicles (PHEVs), e.g., Tesla Model 3, Nissan Leaf.

- **Nickel-Metal Hydride Batteries (NiMH):**A mature battery technology often used in Hybrid Electric Vehicles (HEVs).Features:High energy density compared to older technologies like lead-acid batteries.Excellent durability and long lifespanAdvantages:Environmentally friendlier than lead-acid batteries.High tolerance to overcharging.Proven reliability and safety.Challenges:Higher cost than lead-acid batteries but lower than Li-ion.Lower energy density and higher self-discharge rates compared to Li-ion batteries.Susceptible to overheatingApplications:Commonly used in HEVs, e.g., Toyota Prius.

- **Solid-State Batteries:**An emerging technology that uses a solid electrolyte instead of a liquid or gel electrolyte.Features:Promises higher energy density and enhanced safety compared to Li-ion batteries.Advantages:Improved safety due to the absence of flammable liquid electrolytes[42].Potentially longer lifespan and higher energy capacity. Challenges:Currently expensive and challenging to scale for mass production.Limited availability in commercial vehicles.Applications:Future EVs; currently in the research and development phase[46].

- **Lead-Acid Batteries:**Among the oldest and most reliable battery technologies, primarily used for auxiliary functions rather than propulsion.Features:Simple design and low cost.Suitable for short-range applications and vehicles requiring high reliability.[55]Advantages:Low cost and ease of recycling.Proven track record in automotive applications.Challenges:Low energy density and heavyweight.Shorter lifespan compared to modern batteries.Inefficient for high-energy demands of EV propulsion.Applications:Used in small EVs, forklifts, and for auxiliary power (12V systems)[56].

- **Supercapacitors:**Store energy in an electric field instead of through electrochemical reactions[53].Features:Known for their rapid charge and discharge capabilities.Have very high power density but lower energy density compared to batteries.Advantages:Exceptional performance in regenerative braking systems.Long lifespan with virtually unlimited charge-discharge cycles[55].Highly efficient in short-duration, high-power applications.Challenges:Low energy density makes them unsuitable as the primary energy storage for long-range EVs.Higher costs for large-scale applications.Applications:Commonly used in combination with batteries in Hybrid Energy Storage Systems (HESS).

- **Hydrogen Fuel Cells (HFCs):**Used in Fuel Cell Electric Vehicles (FCEVs) to generate electricity from hydrogen gas.Features:Hydrogen is stored in pressurized tanks and used in a fuel cell to produce electricity[34].Advantages:Zero emissions with water vapour as the only byproduct.Quick refuelling times compared to battery charging. Long driving range. Challenges:High costs of hydrogen production and storage[49].Limited hydrogen refuelling infrastructure. Safety concerns with hydrogen storage and handling. Applications:Used in FCEVs such as Toyota Mirai and Hyundai Nexo.

- **Hybrid Energy Storage Systems (HESS):**Combine two or more energy storage technologies, such as batteries and supercapacitors, to exploit their complementary characteristics[56].Features: Batteries provide long-term energy storage, while supercapacitors handle peak power demands and regenerative braking.Advantages:Enhanced performance and efficiency by leveraging the strengths of different technologies[67].Prolonged battery lifespan by reducing stress during high-power events. Optimized energy management for dynamic driving conditions.Challenges:Increased complexity in design and control strategies.Higher initial costs due to multiple storage systems. Applications:Used in high-performance EVs and research prototypes to maximize energy efficiency[80].

Table II Comparison of Various Energy Storage Technologies

Features	Li-ion	NiMH	Lead Acid	Super Capacitor	HFCs	HESS
Energy Density	High	Moderate	Low	Low	High	Varies
Power Density	High	Moderate	Low	Very High	Moderate	High
Life Span	Long	Long	Short	Very Long	Long	Enhanced
Cost	High	Moderate	Low	High	Very High	High
Charging Time	Moderate to Fast	Moderate	Slow	Very Fast	Fast	Moderate to Fast
Applications	BECVs, PHEVs	HEVs	Auxillary Systems	HESS, Regenerati ve	FCEVs	High Performance EVs

The choice of energy storage technology in EVs depends on various factors such as range, cost, weight, and application requirements. Lithium-ion batteries dominate the EV market due to their superior performance, while emerging technologies like solid-state batteries and hybrid systems offer promising alternatives. The ongoing evolution of energy storage technologies aims to address challenges such as cost, energy density, and environmental impact, driving the future of electric mobility.

1.1.3 Energy Management Systems:

Energy Management Systems (EMS) in electric vehicles are critical for optimizing energy utilization, enhancing vehicle efficiency, and ensuring the longevity of energy storage systems[7]. An EMS oversees the flow of energy among components such as the battery, electric motor, regenerative braking system, and auxiliary systems. Effective energy management minimizes energy losses, extends driving range, and improves overall vehicle performance.[19]

Purpose of Energy Management Systems:

1. Optimize Energy Utilization: Efficiently allocate energy to propulsion and auxiliary systems while minimizing waste[19].
2. Maximize Range: Ensure optimal energy consumption to extend the vehicle's driving range[44].
3. Enhance Component Longevity: Prevent overloading and optimize the lifespan of batteries, motors, and power electronics.
4. Regenerative Braking Efficiency: Maximize energy recovery during deceleration[26].
5. Ensure Stability and Safety: Maintain consistent power delivery and protect components from overcharging, overheating, or deep discharging.

Components of an EMS:

1. **Energy Storage System (ESS)**: Manages charging, discharging, and state-of-charge (SoC) control[14].
2. **Powertrain**: Coordinates between the electric motor and power electronics to meet torque demands[51].
3. **Regenerative Braking System**: Captures kinetic energy and stores it in the ESS.
4. **Auxiliary Systems**: Distributes energy to non-propulsion functions such as lighting, HVAC, and infotainment[24].
5. **Control Algorithms**: Execute real-time decisions for energy distribution, regeneration, and optimization[27].

Control Strategies in Energy Management Systems:

1. **Rule-Based Control Strategies:** Use predefined rules or logic to govern energy flow based on operating conditions. Approach: Operates based on real-time SoC, speed, and power demand[16]. Simple if-then rules determine when to charge, discharge, or activate regenerative braking. Advantages: Simple to implement and computationally efficient. Reliable and robust for known driving conditions. Challenges: Limited adaptability to dynamic driving conditions. Suboptimal for highly variable or complex scenarios. Examples: HEVs: Switching between ICE and electric motor based on load[17].

2. **Optimization-Based Control Strategies:** Aim to optimize a performance metric such as energy efficiency, cost, or emissions. Approach**:** Use mathematical models to predict future conditions and optimize energy allocation. Examples include Dynamic Programming (DP) and Model Predictive Control (MPC)[22]. Advantages**:** Delivers near-optimal energy management decisions. Adapts to complex and dynamic scenarios[15]. Challenges**:** High computational complexity. Requires accurate models and real-time data. Examples**:** MPC predicts energy demands and optimizes battery and motor operation[22].

3. **Heuristic-Based Control Strategies:** Incorporate heuristics or rules derived from human experience or simulations[29]. Approach**:** Combines simple rule-based systems with optimization for better adaptability. Relies on historical data and simulations to define energy management rules. Advantages: Provides a balance between simplicity and adaptability[50]. Performs well in a wide range of scenarios. Challenges**:** Limited adaptability to unforeseen conditions. Examples**:** Control strategies for regenerative braking in city versus highway driving.

4. **Fuzzy Logic Control:** Uses fuzzy logic to handle uncertainties and imprecise inputs in energy management[16]. Approach**:** Converts linguistic rules into numerical decisions. Handles nonlinear systems and variable inputs effectively. Advantages: Robust under uncertain or variable conditions[45]. Flexible and easy to integrate into existing systems. Challenges: Requires careful design and tuning of membership functions. Examples**:** Adaptive control of regenerative braking based on speed and deceleration rates.

5. **Artificial Intelligence-Based Strategies:** Employs machine learning (ML) and neural networks (ANNs) to predict and optimize energy management[18]. Approach**:** Use historical driving data to train AI models for real-time predictions. Predict driving cycles, power demands, and regeneration opportunities[29]. Advantages**:** Highly adaptive and efficient in dynamic scenarios. Capable of self-learning and improving performance over time. Challenges**:** Computationally intensive and data-dependent. Requires robust datasets for training[31]. Examples**:** ANN-based prediction of driving patterns for optimal battery utilization.

6. **Hybrid Energy Management Strategies:** Combine multiple strategies to exploit their respective strengths[39]Approach: Integrate rule-based control for baseline operations and optimization-based strategies for dynamic adjustments. Advantages**:** Offers high efficiency and adaptability[49]. Combines robustness with flexibility. Challenges**:** Increased complexity in system design and control logic. Examples**:** Combining fuzzy logic with MPC for real-time energy distribution[74].

Applications of EMS Control Strategies

- **Regenerative Braking Control**:: Maximizes energy recovery during braking. Prioritizes energy recovery over mechanical braking in low-demand conditions[128].
- **Hybrid Energy Storage Systems (HESS)**:Optimizes the coordination between batteries and supercapacitors for power and energy distribution[67].
- **Torque Split Control**: Distributes torque between the electric motor and ICE in hybrid vehicles to optimize efficiency[24][30].
- **Thermal Management**: Manages temperature to ensure optimal battery and motor performance.[46][38]
- **Driving Prediction-Based Control**: Predicts energy demands based on historical and real-time data to improve energy allocation.[111][78]

Energy Management Systems are indispensable for enhancing the efficiency, reliability, and sustainability of electric vehicles. Control strategies range from simple rule-based systems to advanced AI-driven approaches, each tailored to specific vehicle architectures and operational scenarios. The evolution of EMS, driven by advancements in AI and hybrid storage technologies, continues to improve EV performance, making them a cornerstone of modern transportation innovation[113].

1.2 Motivation:

The growing global emphasis on sustainable transportation has accelerated the adoption of electric vehicles (EVs), which rely heavily on efficient energy management systems (EMS) to maximize performance and reliability[11]. However, challenges such as range anxiety, dynamic driving conditions, battery degradation, and the need for improved energy recovery highlight the necessity for advanced solutions. Hybrid Energy Storage Systems (HESS), combining batteries and supercapacitors, present an opportunity to enhance energy efficiency and longevity by leveraging the strengths of each storage type. Optimized control strategies for HESS are essential to achieve seamless energy distribution and maximize system performance[19].

Artificial Neural Networks (ANN)-based driving prediction techniques offer a transformative approach to EMS by enabling real-time adaptation to driving patterns and energy demands[25]. These methods can optimize regenerative braking, extend vehicle range, and reduce operational costs. This research is motivated by the need to address gaps in existing EMS, improve EV performance, and contribute to the global push for decarbonization[24]. By integrating optimized HESS control and ANN-driven predictions, the study aims to develop intelligent, efficient, and adaptable solutions for next-generation EVs[31].

1.3 Objectives:

Present research work aims to propose the following objectives:

- To identify the power dynamics of the Electric Vehicle for driving conditions & driving cycles, and to predict the control strategy through ANN.
- Design an appropriate Hybrid Energy Storage System with a better trade-off between power density and energy density.
- Optimization of Energy Management System during regenerative braking and acceleration phase of Electric Vehicle’s for better performance.

1.4 Organization of the Thesis

This thesis is structured into six chapters, with each chapter focusing on a specific aspect of the research. The following provides a brief overview of the content of each chapter.

Chapter - 1: Provides the introduction to the Electric vehicles, Energy Management Systems, and Hybrid Energy Storage

Chapter - 2: Presents the literature survey on electric vehicles

Chapter - 3: Provides the detailed Mathematical Analysis and Training using different Driving mode Datasets.

Chapter -4: Discuss the topology of the proposed Hybrid Energy Storage and Simulation Results of Power Splitting Strategy

Chapter -5: Discuss the proposed Energy Management Strategy and validation of the results

Chapter -6: Presents conclusions and proposes future scope.

1.5 Summary

This chapter discusses the background of Hybrid Energy Storage (HES) and Energy Management Systems (EMS) in Electric Vehicles (EVs), highlighting the challenges and motivations of the research and formulating the objectives that will be accomplished in the following chapters.

CHAPTER 2

LITERATURE SURVEY

A comprehensive literature survey on electric vehicles has been carried out over the last 10 years, several researchers presented their works on numerous problems related to i) Mechanical aspects of EVs, ii) Elements of HESS (batteries, fuel cells, ultracapacitors) along with different control strategies using ANN.

Electric vehicles (EVs) have emerged as a sustainable alternative to conventional internal combustion engine (ICE) vehicles, to minimize pollution. This section highlights the distinctions between EVs and conventional vehicles, focusing on key aspects such as driving cycles, terrains, energy storage systems, energy management strategies, regenerative braking, and control mechanisms.

The Driving cycles play a critical role in assessing the performance of EVs, influencing energy consumption, range estimation, battery life, and overall efficiency. These cycles are standardized or custom-designed test protocols that simulate various driving conditions. Understanding how driving conditions impact EV performance is vital for designing efficient powertrains and enhancing battery technologies. Driving cycles are sequences of speed versus time profiles used to replicate real-world driving conditions. They provide a standardized way to evaluate vehicle performance, fuel economy, and emissions.

2.1Standardized Driving Cycles:

2.1.1 Various Types of SDC: Worldwide Harmonised Light Vehicles Test Procedure (WLTP): Offers a globally unified framework to assess energy consumption and emissions. New European Driving Cycle (NEDC): Previously widely used but criticized for its lack of real-world accuracy. Federal Test Procedure (FTP-75): Commonly used in the U.S. for emissions and fuel economy testing.

2.1.2 Custom Driving Cycles: Developed for specific regions, terrains, or operational conditions to better reflect local driving behaviour. Examples include urban driving cycles, highway cycles, and off-road cycles tailored for specific vehicle use cases.

2.2 Impact of Driving Conditions on EV Performance

2.2.1 Energy Consumption: Variations in speed, acceleration, and deceleration significantly influence the energy usage of EVs. Studies reveal that aggressive driving patterns lead to higher energy consumption.External factors like temperature and road gradient also impact energy efficiency, with colder temperatures requiring additional energy for battery heating.[13]

2.2.2 Range Estimation: Accurate range prediction depends on the relevance of the driving cycle to real-world conditions[11]. Standardized cycles often overestimate range due to their simplified profiles, emphasizing the need for realistic testing conditions.

2.2.3 Battery Health and Longevity: Repeated cycles of rapid acceleration and braking can accelerate battery degradation[14][20]. Thermal management systems must account for heat generated during intensive driving conditions[43].

2.3 Recent Developments in Driving Cycle Research

2.3.1 Machine Learning and Data Analytics: Advanced algorithms analyze real-world driving data to create more accurate and representative driving cycles[29]. Tools like clustering and principal component analysis (PCA) are used to group similar driving patterns[111].

2.3.2 Real-World Driving Data: The proliferation of connected vehicles and telematics provides extensive datasets for analyzing driving conditions[25]. Real-time data enables adaptive driving cycles for personalized EV performance evaluations[73].

2.3.3 Region-Specific Driving Cycles: Emerging markets and diverse geographic areas necessitate localized driving cycles. For instance, cycles for regions with high traffic density differ significantly from those for rural or mountainous areas[16].

2.3.4 Training Driving Sets for Driving Cycles

The necessity of Driving cycles are for standardized representations of vehicle speed versus time, used for assessing fuel consumption and emissions. ML Role: Data Analysis: Use clustering algorithms to classify real-world driving data into patterns or cycles. Driving Cycle Synthesis: ML models (e.g., Generative Adversarial Networks, Recurrent Neural Networks) can create synthetic driving cycles that reflect real-world conditions more accurately than conventional methods. Prediction and Customization:

Predict future driving cycles based on current conditions or customize cycles for specific regions.

The Levenberg–Marquardt optimization algorithm is employed to fine-tune the parameters of the fuzzy controller[117]. The proposed type-2 fuzzy control method shows significant improvements in frequency stability and response time compared to conventional LFC techniques. The results indicate enhanced performance in managing load disturbances and system dynamics. By utilizing multilayer neural networks to model the state of the system, aiming for accurate and reliable performance in safety-critical environments.Levenberg-Marquardtalgorithm is employed for training the neural networks. It combines gradient descent and the Gauss-Newton method, providing efficient and effective training for nonlinear least-squares problems.[108] The study demonstrates that the proposed training method significantly enhances the accuracy of state estimation compared to traditional methods. It shows that the neural network can effectively learn and adapt to the system dynamics.

The study highlights the synergy between batteries and supercapacitors, leveraging their energy and power density to handle power fluctuations effectively, especially during braking. Dynamic programming optimizes the use of storage systems and fuel cells, ensuring efficiency without compromising system longevity. The research explores the predictive modelling of driving range using machine learning[80]. The study applies a gradient-boosting decision tree algorithm to overcome the limitations of conventional regression methods, accommodating numerous influencing factors. The results demonstrate significant improvements in prediction accuracy, with a maximum error of ±1.58 km compared to larger errors in traditional methods[54]. The enhanced prediction capability ensures more reliable range estimation for electric vehicles in real-world conditions.Focused on cyber-physical systems (CPS), this study employs multilayer neural networks trained using the Levenberg-Marquardt algorithm to enhance state estimation. The methodology combines gradient descent with the Gauss-Newton method for efficient nonlinear problem-solving[29]. Results show significant accuracy improvements, enabling reliable performance in safety-critical applications such as automotive and industrial systems. The findings suggest that advanced neural network training can substantially improve the adaptability and robustness of CPS frameworks[88].This work develops a type-2 fuzzy logic controller for managing frequency variations in interconnected power systems. By integrating the

Levenberg-Marquardt optimization algorithm, the controller effectively handles uncertainties and variabilities associated with fluctuating loads. Simulation results highlight improved frequency stability and response times compared to conventional load frequency control methods[116]. This innovation enhances system resilience and adaptability, particularly crucial for power systems incorporating renewable energy sources.

2.4 Hybrid Energy Storage Systems (HESS)

Hybrid Energy Storage Systems (HESS) combine complementary energy storage technologies, such as batteries and supercapacitors, to leverage their respective advantages. Batteries, with high energy density, are ideal for sustained energy demands, while supercapacitors, with superior power density, handle rapid energy fluctuations efficiently. This synergy addresses the limitations of using a single storage system, improving energy efficiency, lifespan, and cost-effectiveness. HESS has proven particularly advantageous in EVs for optimizing performance under varied driving conditions, including regenerative braking and dynamic driving patterns.

Electric vehicles demand energy storage systems capable of balancing high energy and power requirements. A single storage solution, like a battery, may face challenges such as reduced lifespan or limited responsiveness to rapid energy demands[67]. Hybrid Energy Storage Systems (HESS) offer a versatile solution by integrating batteries for long-term energy supply with supercapacitors for high-power needs[30].

The implementation of HESS allows:

- **Improved Energy Management:** Efficient energy distribution between storage components reduces stress on the battery, prolonging its life[27][55].
- **Enhanced Performance in Dynamic Conditions:** Supercapacitors respond swiftly to energy spikes during acceleration or regenerative braking[26].
- **Cost Optimization:** Reduced battery wear and energy losses contribute to lower lifecycle costs[33].

Dynamic programming and advanced control strategies, such as krill herd optimization and random decision forests, optimize HESS operations[80]. These systems are being increasingly adopted in EVs, demonstrating significant improvements in efficiency, durability, and sustainability. Dynamic programming (DP) is used to optimize configuration and energy-split strategies for a hybrid energy storage system (HESS) in electric city buses[71]. The integration of batteries and supercapacitors achieves significant cost savings, reducing the energy storage system's lifecycle costs by 47% and 60% under the China Bus Driving Cycle and Urban Dynamometer Driving Schedule, respectively. Rule-based strategies derived from DP results effectively balance energy demands, improving efficiency and extending the lifespan of the system components.

Stochastic Dynamic Programming (SDP) to optimize fuel cell usage in low-speed campus vehicles, enhancing fuel cell lifespan by 14% with minimal fuel consumption increase. Daming Zhou compares various energy management strategies (EMS) for fuel cell hybrid electric vehicles (FCHEVs) using an extremum-seeking controller[45]. Experimental results validate the controller's efficiency in maintaining fuel cell operation within optimal regions, reducing hydrogen consumption and ensuring system durability[31]. The band-pass filter-based controller is highlighted for its balance of performance and fuel cell protection.

A high-performance FC/supercapacitor hybrid power source for FCHEVs, achieving 96.2% power efficiency, high-speed performance (158 km/h), and extended driving range (435 km). Meanwhile, Ponnupandian introduces a KHO–RDF[12]-based control scheme to optimize HESS operation by dynamically adjusting supercapacitor voltage based on load conditions. Simulation results confirm improved power distribution and system responsiveness under real-world driving scenarios[73].

A nonlinear optimization approach for energy management in FCHEVs, dynamically allocating energy among batteries, supercapacitors, and fuel cells to improve efficiency and extend system lifespan[117]. The optimal sizing strategies for hybrid energy storage systems, demonstrating enhanced energy efficiency, cost-effectiveness, and vehicle performance through tailored storage configurations[91]. Both studies highlight advanced optimization techniques as critical for sustainable and efficient energy management in future electric vehicle designs.

The optimization of hybrid energy storage systems, particularly batteries and supercapacitors, for electric vehicles (EVs)[90][88]. The study introduces a systematic framework that aligns energy storage capacity and power ratings with vehicle-specific requirements, driving conditions, and operational profiles. By integrating these parameters, the proposed approach achieves tailored energy management strategies that significantly enhance energy efficiency and system performance[104].

Key metrics evaluated include energy efficiency, cost-effectiveness, and impacts on vehicle range and lifespan[118]. The optimized sizing strategy outperforms conventional methods, demonstrating marked improvements in operational efficiency and durability. The research underscores the importance of customized energy storage designs to maximize EV performance, promoting sustainable energy management practices[105].

2.5 Integration of Hybrid Energy Storage Systems (HESS) in EVs

Recent advancements in hybrid energy storage systems (HESS), combining batteries and supercapacitors, have shown promising improvements in EV performance.

2.5.1 Power Splitting: Optimally distribute power between various energy sources (e.g., battery and fuel cell) to maximize efficiency[83]. The role of Reinforcement Learning (RL) can be used to dynamically determine optimal power split decisions based on real-time driving conditions.Pattern Recognition: NNs identify power demand patterns and predict energy requirements. The Adaptive NN models can fine-tune power-splitting strategies based on driver behaviour, road conditions, and vehicle states[77].

2.5.2 Energy Splitting in Hybrid Energy Storage Systems (HESS): Manage energy flow between different storage components, like batteries and supercapacitors, to enhance lifespan and efficiency[59]. Control Strategy Design: ML-based controllers optimize the charge/discharge cycles of HESS components. State Prediction: Predict state of charge (SoC) and health (SoH) for individual components to make informed energy management decisions[89]. Load Balancing: RL models dynamically adjust energy flows to handle transient load conditions efficiently.

2.5.3 Dynamic Programming for Optimization: Dynamic programming (DP) approaches help determine the optimal configuration and energy split strategies in HESS, particularly for applications like electric city buses.[80] HESS candidates in the transition area are regarded as optimal solutions. Using rule-based strategies derived from DP results[93], studies demonstrate reductions in ESS life cycle costs by 47% and 60% under the China Bus Driving Cycle and Urban Dynamometer Driving Schedule, respectively.[74]

2.5.4 Fuel Cell/Supercapacitor Hybrid Power Sources:A novel fuel cell (FC)/supercapacitor (SC) hybrid power source, integrating a 90 kW proton exchange membrane fuel cell (PEMFC) stack and a 600 F SC bank, has shown exceptional performance for fuel cell hybrid electric vehicles (FCHEVs). Experimental results indicate a power efficiency of 96.2% around rated power, robust DC-link voltage regulation, and optimized stator current delivery via PWM techniques.[34] Performance highlights include a maximum speed of 158 km/h, acceleration from 0-100 km/h in 12.2 seconds, and a cruising range of 435 km for a vehicle weighing 1880 kg. Comparative analyses confirm superior efficiency, speed, and acceleration relative to state-of-the-art alternatives[31].

2.5.5 Optimized Component Sizing: Optimal sizing methodologies for hybrid systems focus on minimizing total costs while fulfilling speed profile requirements[50]. For urban buses meeting the Buenos Aires and Manhattan Driving Cycles, hybrid configurations combining batteries and supercapacitors address rapid power demand changes effectively. The integration ensures high energy density from batteries and high power density from supercapacitors, enhancing braking energy recovery and system efficiency[55]. Dynamic programming facilitates the analysis and optimization of storage systems and fuel cells for such setups.

2.6 Machine Learning in Driving Range Prediction

2.6.1Predictive Modeling:A conventional multiple linear regression model was developed to predict driving range. However, its residual errors between -3.6975 km and 3.3865 km were insufficiently accurate for real-world applications[12]. To address these limitations, the gradient-boosting decision tree algorithm was applied. This machine-learning method accounts for numerous factors beyond the scope of conventional regression, achieving a maximum prediction error of 1.58 km, a minimum error of -1.41 km, and an average error of 0.7 km[29].Comparisons confirm that the gradient-boosting decision tree outperforms traditional approaches in predictive accuracy.

2.6.2 Energy Management in FCEVs:A comparative study evaluated various extremum-seeking control (ESC) schemes for online energy management in fuel-cell hybrid electric vehicles (FCEVs). Using the ESC, fuel cell system operating points were maintained in high-efficiency regions, reducing hydrogen consumption. Evaluation criteria included lithium-ion battery utilization, fuel cell system output power fluctuations, efficiency, and hydrogen consumption.[26] Hardware-in-the-loop (HIL) experimental validation showed all ESC controllers closely matched offline benchmark dynamic programming performance[48]. The band-pass filter-based ESC controller demonstrated superior capability in limiting fuel cell power dynamics, improving both performance and ESS durability[66].

2.6.3 Optimized Component Sizing: Optimal sizing methodologies for hybrid systems focus on minimizing total costs while fulfilling speed profile requirements[25]. For urban buses meeting the Buenos Aires and Manhattan Driving Cycles, hybrid configurations combining batteries and supercapacitors address rapid power demand changes effectively. The integration ensures high energy density from batteries and high power density from supercapacitors, enhancing braking energy recovery and system efficiency. Dynamic programming facilitates the analysis and optimization of storage systems and fuel cells for such setups. [33]

2.6.4 Game Theory in Energy Management:A game theory-based energy management strategy for fuel cell/battery hybrid energy storage systems has been initiated This strategy ensures optimal energy distribution between components, improving system efficiency and lifespan. The game-theoretic approach enables adaptive responses to varying load demands, enhancing overall system performance.[45]

2.7 Energy Management Systems:

Energy Management Systems (EMS) in electric vehicles (EVs) and hybrid electric vehicles (HEVs) are designed to optimize energy utilization across all vehicle components[67]. The overarching goal is to enhance vehicle performance, maximize driving range, ensure component longevity, and achieve energy efficiency. EMS integrates and manages energy flow for various subsystems, including transmission, braking, motor control, power distribution, energy control, and hybrid energy storage systems (HESS)[54]. The EMS employs sensors, actuators, control algorithms, and advanced computational techniques to monitor and control energy flow. Here's how it functions across various subsystems:

2.7.1 Transmission Management: Ensure optimal energy transfer from the electric motor to the wheels. Enhance vehicle efficiency and performance.It works with Load Analysis where EMS determines the required torque and speed based on driver inputs and road conditions.[75] Gear Ratio Adjustment: For EVs with multi-speed transmissions, the EMS selects the optimal gear ratio to minimize motor strain and energy losses. Adaptive Controls: Uses real-time data (speed, load, terrain) to dynamically adjust torque and energy flow.

2.7.2 Braking Management: Enable energy-efficient deceleration and maximize regenerative braking. Enhance vehicle safety by blending regenerative and mechanical braking. Here the Regenerative Braking Converts kinetic energy during deceleration into electrical energy. Stores recovered energy in the battery or hybrid storage system. Brake Force Distribution: Balances braking force between regenerative and traditional friction brakes. Ensures smooth deceleration and prevents wheel locking. Adaptive Regeneration: Adjusts regenerative braking intensity based on battery state of charge (SoC), speed, and road conditions[79].

Effective Energy Management with Regenerative Braking:To Maximize the recovery of kinetic energy during braking and manage its storage efficiently[54].NN/ML Role:Optimization: RL algorithms and predictive NN models determine the optimal braking force distribution between mechanical brakes and regenerative systems[25].Energy Recovery Prediction: ML models predict potential energy recovery based on vehicle speed, mass, and road gradient.Driver Behaviour Adaptation: Customize regenerative braking levels based on individual driving habits to enhance comfort and efficiency.[110]

2.7.3 Motor Control: Efficiently manage the conversion of electrical energy into mechanical energy to drive the wheels. Torque and Speed Control: EMS employs algorithms like Field-Oriented Control (FOC) or Direct Torque Control (DTC) for precise motor operation. Thermal Management: Monitors motor temperature and limits power output to prevent overheating. Fault Detection: Identifies issues such as winding failures or rotor misalignment to maintain motor reliability. Dynamic Efficiency: Adjusts motor performance dynamically to optimize efficiency under varying loads.

PMSM stands out for its high efficiency and high torque density, making it the motor of choice for high-performance EVs where efficiency and compactness are critical[126]. However, the high cost of permanent magnets remains a downside. Induction motors are cost-effective and durable, making them suitable for mass-market EVs, though they tend to be less efficient and heavier than PMSMs. BLDC motors offer good efficiency and low maintenance but require complex controllers for commutation. SRMs and RMs are simpler and cheaper in terms of construction, but both face challenges like lower torque density and complex control systems[127].

Table I Merits and Demerits of Various Motors Used in Electric Vehicles

Features	**Permanent Magnet Synchronous Motor (PMSM)**	**Induction Motor (IM)**	**Switched Reluctance Motor (SRM)**	**Brushless DC Motor (BLDC)**	**Synchronous Reluctance Motor (SynRM)**
Torque Density	High	Moderate	Low	Moderate to High	Moderate
Cost	High due to PM	Low as it doesn’t has a Permanent Magnets (PM)	Low as it consists of simple rotor construction	Moderate due to PM	Moderate
Complexity	High as it requires precise control	Moderate simple in control	High as it requires complex control	High as it requires precise commutation control	Moderate
Durability	Moderate as it requires cooling	Hight as it is simple in construction	Very High as its don't has brushes or PM	High as it doesn’t has brushes and low wear	High as it doesn’t require PM
Regenerative Braking	Efficient	Moderate	Less Efficient	Efficient	Efficient

2.7.4 Power Control: Allocate electrical power efficiently across all vehicle subsystems.Load Balancing: Distributes power among the traction motor, auxiliary systems (HVAC, lighting), and HESS.[102] Demand Prediction: Forecasts power needs based on driving conditions, terrain, and driver behavior. Dual Power Management (for

HEVs): Balances power delivery between the internal combustion engine (ICE) and electric motor for maximum efficiency[100]. Voltage Regulation: Ensures stable voltage supply across all components to prevent power surges or drops[82].

2.7.5 Energy Control: Coordinate the generation, storage, and consumption of energy within the vehicle. State Monitoring: Tracks the state of charge (SoC), state of health (SoH), and temperature of energy storage systems. Energy Flow Optimization: Implements advanced algorithms (e.g., dynamic programming, reinforcement learning) to minimize energy losses[110]. Route-Based Prediction: Uses GPS and route data to anticipate energy needs for uphill/downhill terrains or urban/highway driving[111].

2.7.6 Hybrid Energy Storage System (HESS) Management: Efficiently manage energy flow between multiple storage devices, such as batteries and supercapacitors. Extend battery life and improve energy delivery for transient loads. Energy Splitting: Supercapacitors handle high-power, short-duration tasks (e.g., acceleration, regenerative braking). Batteries provide steady power for long-duration tasks. State Prediction: Predicts SoC and SoH for both storage devices to optimize usage[94]. Load Balancing: Dynamically adjusts energy flow between battery and supercapacitors to meet load requirements. Thermal Management: Monitors and controls the temperature of both systems to prevent overheating and degradation[91].

Integrated Energy Management Framework: The combination of these areas leads to a comprehensive energy management system:Holistic Optimization: Leverage deep learning to integrate power and energy splitting, driving cycle adaptation, and regenerative braking.[112]Predictive Control: Utilize predictive algorithms to anticipate energy needs and optimize distribution across the EV system.Continuous Learning: Implement online learning models that adapt to evolving conditions, such as battery degradation, driving patterns, and road conditions[114].

Technologies and Algorithms Used in EMS

1. **Machine Learning and AI**:
    - Predictive energy demand models.
    - Adaptive driving behavior analysis for customized energy strategies[113].
2. **Reinforcement Learning**:
    - Optimizes real-time decision-making for energy flow and storage utilization.

3. **Model Predictive Control (MPC)**:
   - Implements predictive strategies to maintain energy efficiency while considering future states[74][82].
4. **IoT and Vehicle-to-Grid (V2G)**:
   - Enables bi-directional communication for smart charging and grid energy management[97].

   Present research focus on

Benefits of EMS in EVs and HEVs

1. **Improved Efficiency**: Optimizes energy usage across all systems, extending driving range.
2. **Cost Savings**: Reduces energy wastage and prolongs battery life, lowering maintenance costs[106].
3. **Sustainability**: Enhances energy recovery and minimizes environmental impact.
4. **Enhanced Safety**: Monitors system health and ensures safe operation of all components.
5. **Real-Time Adaptability**: Adjusts to changing driving conditions, ensuring optimal performance at all times[88].

Challenges and Future Directions

While standardised cycles provide consistency, they often fail to replicate the variability of real-world conditions. Future approaches must balance standardisation with representativeness. Integration of Advanced Technologies: Autonomous vehicles and intelligent transportation systems introduce new dynamics that traditional driving cycles may not capture. Environmental and Policy Impacts: Stricter emission norms and renewable energy integration will influence the evolution of driving cycles and testing protocols. Driving cycles are indispensable tools for evaluating and optimising the performance of electric vehicles. Advances in data analytics, hybrid energy storage systems, and regional customisation offer promising avenues to make these cycles more representative of real-world conditions. Addressing current challenges will pave the way for more efficient and sustainable EV designs.

Table 2.1: Summarized Literature Review.

Ref. No	Objective	Contribution	Methodology	Conclusion
1	To design HESS using battery &supercapacitor targeting at a commercialized EV model and a driving condition-adaptive rule-based energy management strategy (EMS)	Superior power & energy management of each ESS and also the protection to each ESS. A dynamic degradation model for the battery is adopted to evaluate the life cycle cost of the HESS.	A driving condition-based Rule base is formed and for each scenario, an optimal amount of energy is supplied by battery &supercapacitor.	In this research, a HESS is designed and a driving condition-adaptive rule-based energy management strategy (EMS) is proposed for the HESS.
2	Minimize the difference between actual and reference power in the battery and Super Capacitor (SCAP)	Power management of optimal control scheme for a hybrid energy storage system (HESS) like super capacitor and (SCAP) battery in electric vehicles.	New EMS scheme for Battery and SCAP	In this work, the EM is to build the vehicle autonomy by recovering the stages of decelerations energy and increment the lifespan of batteries by the SCAP reconciliation. the proposed EMS grants to the SCAP to have high SoC, considering better energy management and giving an extended range of EV.
3	An optimized energy management strategy (EMS) based on maximum efficiency range (MER) identification for a fuel cell/battery hybrid sightseeing car	An optimized strategy for PEMFC/battery hybrid system is proposed in this paper. The FFRLS technique is proposed to improve the estimation accuracy. SQP algorithm is used to solve the optimization problem of the proposed strategy.	By using a forgetting factor recursive least square (FFRLS) online identification approach. Then the sequential quadratic programming (SQP) algorithm is used to solve the majorization problem of equivalent consumption minimum strategy (ECMS)	PEMFC system has the MER and MEP, and controlling the PEMFC system operation in MER could improve system performance and efficiency.The proposed strategy also can maintain a stable output power of PEMFC systems.
4	Optimal Driving Range for Battery Electric Vehicles Based on Modeling Users Driving and Charging Behavior using their Daily Trip Chain for BEV Users, Correlation between Behavioral Variables with Monte Carlo Simulation	The main contribution of this paper is to construct a daily trip chain to analyze the optimal driving ranges of various heterogeneous users.	To meet the goal of the fitness of driving range, a stochastic simulation framework is established by the Monte Carlo method.	The Monte Carlo simulation is adopted to reconstruct BEV users' daily trip chains and quantify the fitness of the driving range. Increasing both the charging opportunity and charging power is more beneficial to drivers with large daily vehicle kilometers traveled.
5	In this paper, an energy management strategy using equivalent consumption minimization strategy is proposed for improving fuel cell efficiency and extending fuel cell lifespan.	In this paper, an energy management strategy for electric vehicles equipped with fuel cell (FC), battery (BAT), and a supercapacitor (SC) is considered, aiming at improving the whole performance under a framework of the vehicle to a network application.	The proposed EMS separated the required power into two components by WT (Wavelet Transform). A supercapacitor is used to supply the high component of the required power to reduce the impact of load fluctuation on the fuel cell and battery.	Simulation results show that the proposed EMS can effectively reduce fuel cell power fluctuation and limit it within ± 250 W/s, which is supposed to significantly extendthefuel cell lifespan. Meanwhile, with the proposed

6	This work proposes a Bi-level multi-objective design and control framework with the nondominated sorting genetic algorithm-II and fuzzy logic control as key components, to obtain an optimal sized hybrid energy storage system and the corresponding optimal real-time power management system based on fuzzy logic control simultaneously.	1) A systematic Bilevel multi-objective optimal sizing and control framework incorporating the battery dynamic model, supercapacitor model, evaluation model, and adaptive parametric real-time EMS is proposed. 2) Pareto optimal solutions of a HESS for an electric race car are obtained using NSGA-II under the proposed framework.	The proposed Bi-level optimal sizing and control framework in this work makes it possible to obtain the solutions with enhanced optimality since it enables the optimization algorithm to search both the design and control parameters simultaneously.	The results of the multi-objective optimal sizing and control of the HESS are presented and analyzed taking the total mass of the HESS is limited to 320 kg and the average current is used to evaluate the capacity loss. All of the solutions demonstrated in are asSoCiated with corresponding design and control parameters.
8	In this journal, a machine learning method of gradient boosting decision tree (GBDT) algorithm is implemented for accurate driving range prediction.	It improves the driving range prediction accuracy to provide battery electric vehicle users with reliable Information. Different variables that affect the driving range & speed of the vehicle are also studied and their correlation is also found using Pearson's simple correlation coefficient.	In this study, a prediction model for the BEV driving range based on machine learning has been established. . Moreover, the study is novel in its accuracy and reliability of a prediction model for the BEV driving range.	The result of the machine learning method shows that the maximum prediction error is 1.58 km, the minimum prediction error is -1.41 km, and the average prediction error is about 0.7 km. The predictive accuracy of the gradient boosting decision tree is compared against that of the conventional approaches.
10	Improving fuel economy and performance of a fuel-cell hybrid electric vehicle (fuel-cell, battery, and ultra-capacitor) using optimized energy management strategy based on Fuzzy Logic Control (FLC).	1) The commanded power is fully provided. 2) Equivalent fuel economy is improved entirely. 3) The vehicle's dynamic performance is boosted.	The energy management strategy (EMS) is achieved by presenting a novel power-sharing method and by implementing an intelligent control technique constructed based on Fuzzy Logic Control (FLC).	It is seen that the EMS makes sure that FC is running at optimum operating points and in some cases, depending on the driving cycle, uses the battery in its high-efficient operation points, by regular charging/discharging cycles, contributes to the extension of battery life, decreasing its maintenance cost, and keeping it as a potential range extenderoption in case of hydrogen fuel limitation.
11	This paper emphasizes on review of various energy management systems (EMSs) based on fuel cell hybrid electric vehicles (FCHEV) in combination with two secondary energy storage systems like batteries and ultracapacitors to provide a high-performance energy storage system	1) For different sizes of HESS, this paper compares different control strategies like: PWM control, PI control, Fuzzy logic control, Wavelet Transform with FLC 2) Cost prediction analysis with reducing technology prices and the introduction of newer technologies need to be performed more frequently for accurate cost estimations.	This working paper is to emphasize the state of the art of power conversion configurations, comparison of different energy sources, recovery of braking energy, and different energy management strategies like PI control, Fuzzy logic control, Wavelet Transform with FLC.	Energy execution is a vital factor in driving efficiency. . By pairing the high power density of ultracapacitors with a high energy density of batteries leads to reduce in FC stack size and total cost of a hybrid powertrain. The dual-energy storage can assist the FC for different driving conditions. The power-sharing between the three power sources should be properly analyzed and unified to arrange a stable hybrid powertrain.

Table – 2.2: Various Control Strategies Used in EV's

S.No.	Type of Algorithm Used	Control Strategies Considered	Merits	Research gap or Challenges	Reference No.
1.	Learning based	Neural Networks	Adaptive capability and learning	Uncertain behaviour out of the training space. Quantity and quality of training data needed to be qualified.	[110]
		Reinforcement	Model Free control	Time consuming for database	[44]
2.	Online Optimization Based	ECMS	Engineering interpretation of one cost function	Local optima	[61] [35]
			Online implementation	Driving cycle sensitivity for equivalence factor	[39][29]
		MPC	Adaptive and predictive capability	Requirement of preview driving pattern, terrain	[58]
			Solutions close to global optima with less computational effort online	Prediction horizon sensitivity	[74]
		Robust Control	Robustness with parametric uncertainties and sensor noises	Mathematical complexity due to a nonlinear time invariant system	[111]
		Sliding Mode	Robustness with parametric uncertainties and sensor noises	Complex mathematical formulation	[60]
3.	Offline Optimization Based	Derivative Free	Capability of getting rid of local optima by stochastic solution search	Optimality not guranteed in limited number of iterations	[86]
		DP	Benchmark for other EMS	Curse of dimensionality	[77]
			Global optimality	Driving cycle information needed in advance High computational cost	[19]
		Game Theory	Comprehensive trade of conducting objectives	Curse of dimensionality	[22]
			Consider driver behaviour in EMS	Burden of computation	[51]
		Gradient	Fast computation	Strong model simplification Derivative information of objective function needed Complex mathematics	[47]
		PMP	Global trajectory optimal control	Complex mathematics Required approximation of modelling to reduce computation effort	[74]
4.	Rule Based	Deterministic	If-Then rules	Low fuel economy	[62]
		Fuzzy Logic	Adaptiveness, Predictive capabilities and robustness	Need calibration for control parameters regarding various driving cycles.	[70]

Table – 2.3: Parameters used in Hybrid Energy Storages

Parameters Considered	Battery – Ultra Capacitor	Fuel Cell – Battery	Fuel Cell - Ultra Capacitor	Fuel Cell – Battery – Ultra Capacitor
System Configuration	Primary Source: Battery Auxiliary Source: UC	Primary Source: FC Auxiliary Source: Battery	Primary Source: FC Auxiliary Source: UC	Primary Source: FC Auxiliary Source: Battery and UC
Initial Load Demand	Battery	Battery	Fuel Cell	Battery or Fuel Cell
Transient Load Demand	Ultra Capacitor	Fuel Cell	Ultra Capacitor	Ultra Capacitor
Implementation Process	Easy	Easy	Easy	Sometimes gets complex
Equivalent Fuel Consumption	---	Moderate	Low	Lowest
Energy Conversion Efficiency	Higher	High	High	Highest
SoC Estimation	When UC State of Charge is below the required level, the battery will charge the UC via UC will charge the battery.	FC will charge the battery, when the battery State of Charge is below the required level	FC will charge the UC, when the UC State of Charge is below the required level	When State of Charge for battery and UC is below the required level, the FC will charge the battery and UC.
Dynamic Performance	Good	Good	Good	Better
Stress on Battery	Reduced by UC	Lessened by FC	Reduced by UC	Reduced by FC and UC
Robustness	Pleasant	Pleasant	Pleasant	Pleasant
Battery Lifetime	Long	---	Long	Longest
Emissions	No Emission	Low	Low	Low
Availability	Commercially	Commercially	Commercially	Commercially
Relability and Flexibility	Good	Good	Good	Excellent
Frequency Management	▪ UC manages the high frequency components. ▪ The battery controls the low frequency components	▪ FC controls the high frequency components. ▪ The battery holds the low frequency components	▪ UC handles the high frequency components. ▪ FC handles the low frequency components.	▪ UC manages the high frequency components. ▪ FC and battery hold the low frequency components.
Performance on Different Driving Cycle	Satisfactory	Satisfactory	Satisfactory	Satisfactory
Simulation Probability on Suitable Software	Exists	Exists	Exists	Exists

2.8 Research Gaps

Limited Real-World Testing & Deployment: Most studies are simulation-based or use synthetic driving cycles. Real-world validation using actual EV platforms under varying environmental and driving conditions is scarce. Integrating of real-time road and user data into EMS design and validate using field trials can be addressed.

Lack of User-Centric EMS: Few papers (e.g., Ref. 4 and 8) consider user behavior, trip patterns, and charging habits. Most EMS focus on energy efficiency rather than user satisfaction or behavioral adaptation. Development of personalized EMS that adapt in real-time based on user driving patterns, mood, range anxiety, or calendar schedule is needed.

Limited Integration of AI/ML for Real-Time EMS: Although ML is used in driving range prediction (Ref. 8), most EMS frameworks rely on rule-based, fuzzy logic, or optimization algorithms. Explore reinforcement learning, deep learning, or online adaptive models to make real-time decisions under uncertainty, including traffic, weather, or sudden demand changes.

Limited Focus on Degradation-Aware Real-Time Control: Only Ref. 1 and 6 consider battery degradation models. Most strategies ignore real-time health estimation of battery or super capacitor. Include health-aware control systems that actively adapt power distribution based on remaining useful life (RUL) or degradation rate of BESS.

Inadequate Cost-Benefit Analysis: Few papers (like Ref. 11) touch on cost forecasting, but a detailed total cost of ownership (TCO) including EMS algorithm complexity, computational cost, and HESS sizing is lacking. Integrate techno-economic models with EMS to support decision-making for real-world deployment.

Limited Use of Vehicle-to-Grid (V2G) and Grid Interaction: Most EMS are vehicle-focused. Integration of HESS-based EVs into smart grids, considering V2G, bidirectional flow, and energy market participation, is rarely addressed.

2.9 Summary

The literature survey provides a detailed overview of existing methods and technologies, identifying gaps and opportunities for further research. It sets the foundation for the thesis by formulating objectives focused on enhancing energy management systems, optimizing hybrid energy storage, and leveraging ANN-based algorithms for real-time and efficient control in EV applications.

CHAPTER3

DRIVING CYCLES

This chapter focuses on the driving cycle, which represents the vehicle’s speed and acceleration patterns over time and plays a crucial role in determining energy consumption, and battery life for overall system efficiency. In this context, mathematical analysis is employed to analyze and predict the vehicle's energy needs under urban, rural, highway and semi-urban terrains. This leads to developing algorithms that accurately model the relationship between the driving cycle and power demand.

3.1 Power Dynamics & Driving Cycles

Power dynamics in electric and hybrid vehicles are heavily influenced by driving cycles, which define the vehicle's speed, acceleration, and deceleration patterns over time. These cycles simulate real-world driving conditions, such as urban, highway, or mixed driving, and help assess the vehicle's energy consumption and efficiency. Understanding the power dynamics allows for better energy management by optimizing the use of the battery and powertrain. Accurate modelling of driving cycles is crucial for predicting fuel consumption, battery life, and overall system performance. This section explores how different driving cycles impact power distribution and energy requirements in hybrid energy storage systems (HESS).Due to its efficiency, cost-effective, compact size, and limited weight PMSM with high mechanical strength are the best match for electrical vehicles. The details of the parameters considered for the study are given in tables 3.1,3.2and 3.3.

Table– 3.1: Electric Vehicle Main Parameters

S.No	Main Parameters:
1	Vehicle mass(kgs)
2	Vehicle frontal area(sq.mts)
3	Wheel radius(mts)
4	Gearbox ratio
5	Inverter efficiency

Table – 3.2: Electric Vehicle Auxiliary Inputs

S.No.	Auxiliary Inputs (if more precision is required):
1	Air density(kg/m^3)
2	Rolling coefficient
3	Aerodynamic drag coefficient
4	Grade angle

Table –3.3: Electric Vehicle Output Parameters

S.No	Output Parameters:
1	Speed vehicle (Kmph)
2	Electric power (Kw)
3	State-of-charge
4	Torque (N-M)

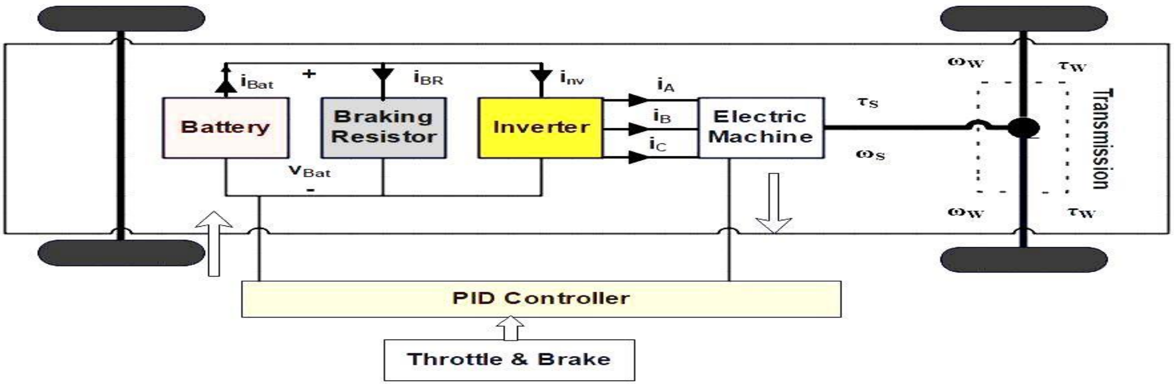


Fig:3.1Basic Structure of Electric Vehicle

3.2 Drive Resistance Calculations

The four resistances which contributed to the drive resistance are given below:

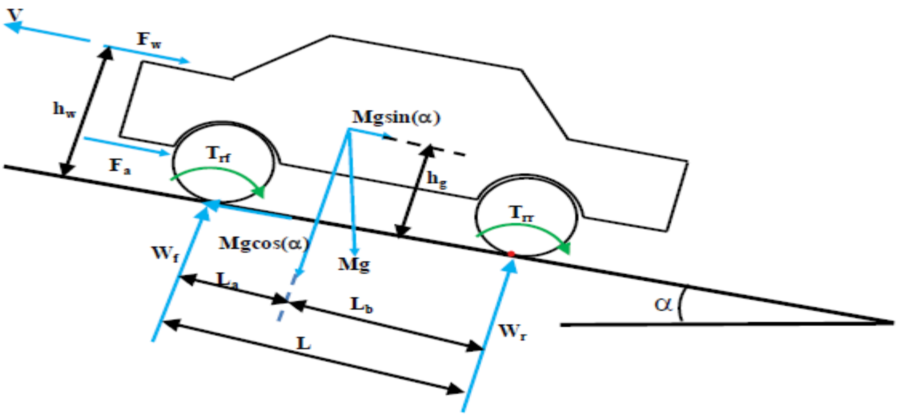


Figure.3.2: Forces acting on a vehicle going uphill

3.2.1 Rolling Resistance

Rolling resistance is the resisting force that opposes the rolling of tyre on road pavement[37].

$$R_{(r)} = M \times g \times \mu \times \cos\theta \quad (3.1)$$

Where

–M - Gross vehicle weight

–g - Acceleration due gravity (9.81 m/ s^2)

–μ = .01(Coefficient of rolling friction for asphalt surface)[38]

3.2.2 Gradient Resistance

When vehicle negotiates a slope, one component of its weight acts against the direction of motion of vehicle, this component is called gradient resistance[37].

$$G_{(r)} = M \times g \times \sin\theta \text{ or } M \times g \times S\% \quad (3.2)$$

$$G_{(r)} = 850 \times 9.81 \times .1$$

$$G_{(r)} = 833.85 \text{ N}$$

where

– θ<1:25 (1/25) highways, < (1/8) local roads, 1:5 (1/5) maximum grade[39]

– G = gradient ratio [1: n = 1/n]

– θ = gradient angle < 2.3o (highways), 5.70 to 6.9o(local roads),≈ 11.5o (max.)

– S = gradient percentage [%]

– S< 4% (highways), <10% to12% (local roads), ≈ 20% (maximum gradient)

3.2.3 Air Drag

The resisting force on an object that opposes its motion through fluid is called drag. When the fluid is gas like air then it is known as aerodynamic drag or air drag[37].

$$A_r = (1/2)\times\rho\times C\_d\times A\_f\times v\text{^}2 \quad (3.3)$$

Where

–ρ=1.205 kg⁄m^3 (Density of air at NTP)

–C_d=0.43(Coefficient of drag) [39]

–A_f=2.85 m^2(Frontal area of vehicle)

–v= 30 km⁄h or 8.3 m⁄s(Instantaneous velocity of vehicle)

–A_r= (1/2)×1.205×.43×2.85×(8.3)^2

–A_r=51.2 N

3.2.4 Inertial Drag

When a vehicle starts from zero velocity and accelerates, the inertia of the vehicle poses a resistance to its motion which is known as inertial drag.

$$Ir = M\times a \quad (3.4)$$

Where

– M – Mass of vehicle

–a – Acceleration

$$v=u+at \quad (3.5)$$

$$a=(v-u)/t$$

Where

–u=0 km⁄hr (Initial velocity)

– v=27.7 km⁄hr or 7.7 m⁄s (Final Velocity)

–t=10 sec (Time)

a=(7.7-0)/10

a=0.77 m⁄s^2

Ir=850×0.77

Ir=654.5 N

3.2.5 Total Drive Resistance

In order to calculate the total drive resistance(T_r) there were four cases which were taken into consideration:

1. Tr = Rr + Ar (The vehicle is steady on level road)
2. Tr = Rr + Ar + Gr (The vehicle is steady on a gradient)
3. Tr = R_r + Ar + Ir (The vehicle is accelerating on level road)
4. Tr = Rr + Ar + Gr + Ir (The vehicle is accelerating on gradient)[39]

3.2.6 Steady State Motion on Level Road

When a vehicle run at constant speed on a level road i.e. there is no acceleration component and no gradient,only rolling resistance and drag contribute to the drive resistance.

$$Tr = Rr + Ar \tag{3.6}$$

Tr =83.38 + 51.2

Tr = 134.58 N

3.2.7 Steady State Motion on Gradient

When vehicle run on constant speed on inclined road i.e. there is no acceleration component, only rolling resistance, air drag and Gradient resistance are contributing to the drive resistance.

$$Tr = Rr + Ar + Gr \tag{3.7}$$

$$Tr = 83.38 + 51.2 + 833.85$$

$$Tr = 968.43 \text{ N}$$

3.2.8 Accelerating on Level Road

When vehicle run on level road and accelerating i.e. there is no gradient only rolling resistance, air drag and inertial force are contributing to the drive resistance.

$$Tr = Rr + Ar + Ir \tag{3.8}$$

$$Tr = 83.38 + 51.2 + 654.5$$

$$Tr = 789.08 \text{ N}$$

3.2.9 Accelerating on Gradient

When a vehicle run on an inclined road and accelerates i.e. all four rolling resistances, air drag, gradient resistance and inertial force contribute to the drive resistance.

$$T_r = R_r + A_r + G_r + I_r \tag{3.9}$$

T_r = 83.38 + 51.2 + 833.85 + 654.5

T_r = 1622.93 N

3.2.10 Torque Calculations

•Torque required at axle(τ_a) = $T_r \times R_t$ (3.10)

•Motor torque required(τ_m)=$\tau_a \times I_g \times \eta_g$ (3.11)

$=\tau_r \times R_t \times I_g \times \eta_g$

The peak motor torque required during acceleration or on a gradient, and the rated torque required for steady-state motion on level ground, are illustrated in the table 3.4. The next step is designing an optimal Hybrid Energy Storage System (HESS) to efficiently manage energy distribution based on the vehicle's power demands. The HESS is composed of a combination of components: 1) Battery, 2) Super-Capacitor, and 3) Fuel Cell. This combination enhances the reliability of the energy storage system for pure electric vehicles while balancing power density and energy density. The goal is to ensure efficient power distribution to various vehicle components, optimizing performance and energy use.

Table – 3.4: Parameters Considered in Mathematical Modeling

Parameters Considered	**Values**
Mv-Vehicle mass (kg)	1500
d-Rotational inertia factor	1.013
CD -Aerodynamic drag coefficient	0.32
Af-Vehicle front area (m2)	2
r Radius of the wheel (m)	0.3
r-Air density (kg/m2)	1.202
a-Slope angle	0^0
Vmax -Maximum vehicle speed (km/h)	120

3.3 Various types of Electric Motors used in Electric Vehicles

1. DC Series Motor
2. Brushless DC Motor
3. Three-Phase AC Induction Motors
4. Switched Reluctance Motors (SRM)
5. Permanent Magnet Synchronous Motor (PMSM)
6. Permanent Magnet Brushless Motor (PM-BLM)

Permanent Magnet Synchronous Motor (PMSM)

The PMSM is an exact resemblance to that of the BLDC motor which has permanent magnets placed on the rotor. These motors also have characteristics like high efficiency, high power ratings,and high power density. The basic difference between the BLDC and PMSM is the BLDC consists of trapezoidal back EMF whereas PMSM consists of sinusoidal back EMF. These motors are generally used for applications like buses, cars, and other automobile vehicles. Apart from the cost factor, this PMSM is providing tight competition with Induction Motors in the aspect of increased efficiency. So the present automotive companies like Toyota Prius, Nissan Leaf, BMW i3 are using PMSM motors in their electric vehicles.

Table – 3.5: Various Motors Used in EV's.

Type of Motor	**Advantages**	**Disadvantages**	**Key Points**
Induction Motor (IM)	The most mature commutator with minimal motor drive system	Problematic during regenerative braking	Used in two wheelers and four wheelers
Brushed DC Motor	Maximum torque at low speed	Bulky in structure. Low efficiency. Heat generation at brushes.	Used in small cars, scooters and bikes
Brushless DC Motor (BLDC)	No rotor copper loss. More efficiency than induction motors. Lighter, smaller with better heat dissipation. More reliability. More torque density and specific power.	Short constant power range. Decreased with increase in speed. High cost because of PM.	Used in medium level cars, and maximum for two wheelers available in the market
Permanent Magnet Synchronous Motor (PMSM)	Efficient and compact. High torque even at very low speeds. Suitable for in-wheel applications. Can be operated at different speed ranges with out using the gear system.	Huge Iron loss at high speeds during in – wheel operation. High cost because of PM.	Used in present days SUV Models

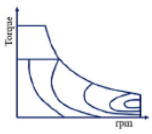
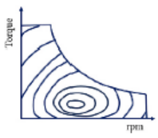
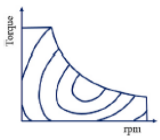
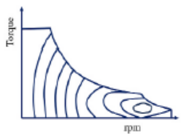
The specifications of the PMSM motor considered in the study are given in Table 3.6.These are the specifications of the model of RTML-032.The detailed specifications are given in A1 of the appendix.

Table – 3.6: EV Motor Parameters Considered

Motor Maximum Power	(kW)	100
Motor Maximum Speed	(rpm)	12500
Motor Average Efficiency	(%)	90
No. of phases	--	3
Back EMF waveform	--	Sinusoidal
Rotor Type	--	Salient Pole
Mechanical Input	--	Torque Tm

A detailed comparison of the performance of different electric motors is presented and their compatibility with EV application is also analyzed. It is observed that the SRM and PMSM has high power density and they are have equal controllability. The PMSM is the most costly motor and SRM is the best and most economical.

Table – 3.7: Comparison of various Motor Parameters

	Brushed DC	IM	PMSM	SRM
Motor efficiency map				
Power density	2.5	3.5	5.0	3.5
Efficiency	2.5	3.5	5.0	3.5
Weight	2.0	4.0	4.5	5.0
Controllability	5.0	5.0	5.0	3.0
Reliability	3.0	5.0	5.0	4.5
Technology maturity	5.0	5.0	5.0	4.0
Cost	4.0	5.0	3.0	4.0
Total	24.0	31.0	32.5	28.0

3.4 Driving Cycles

The driving cycle can be analyzed as a collection of data points that represent the vehicle speed versus time. It can be represented depending on the performance of the vehicle in different ways for example like fuel consumption, electric vehicle autonomy, and emissions from the vehicle. Another advantage of the driving cycles is that they can be used for simulations of the vehicles also they can be used in transmission, electric drive systems, and energy storage systems.

Driving cycles are commonly categorized into two types:

1. Modal Driving Cycles: These cycles consist of periods of steady acceleration and constant speed, without accounting for real driver behavior.
2. Transient Driving Cycles: These cycles involve frequent speed variations, simulating real-world driving conditions with dynamic, real-time changes.

Various driving cycles are used worldwide to reflect different road conditions and driving behaviors, such as the New European Driving Cycle (NEDC), Japanese 10-15 Mode Cycle, Federal Test Procedure (FTP-75), Artemis Cycle, and others like WLTC and SORDS. These cycles differ in distance, duration, and average speed, depending on the region (e.g., Europe, the U.S., India, Japan, Germany). This thesis considers a few of these cycles, with key characteristics outlined in Tables 3.9 and 3.10, to analyze energy consumption and vehicle performance across different driving conditions.

Table – 3.8: Various Driving Cycles

S.No	**Various Driving Cycles**
European Driving Cycles:	
1	New European standard (NEDC)
2	Worldwide Harmonized Light vehicles Test Procedures (WLTP)
3	The Artemis driving cycle
4	Urban
5	Rural
6	Motorway 130
7	Motorway 150
American Driving Cycles:	
1	Federal Test Procedure (FTP-75)
2	Highway fuel economy test (HWFET)
Japanese Driving Cycles:	

1	10-15 mode Japanese Cycle
2	JC08 cycle
Global Harmonized Driving Cycle (GHDC):	
1	Class 3
2	Class 2
3	Class 1
Other Driving Cycles:	
1	Indian Driving Cycle (IDE)
2	Australian Driving Cycle (ADC)
3	Chinese Driving Cycle (CDC)

3.4.1 Data collection:

It is the collection of test road or road conditions like (Example: Highways, Urban, Hill Area, Rural area) where the measured data are the inputs for the driving cycle preparation. The process comprises of the instrumentation of the vehicles to be tested which has to collect the information while driving on the test road conditions or real-time driving conditions. Here there are two important types of data to be gathered first one is the Driver behavior data which is used to prepare the Driver Model and the second one the vehicle versus road data which is used to prepare the road driving cycle.

3.4.2 Driving Cycle Design:

These driving cycles are used to cut down the expense of on-road tests, the time of the test, and the responsibility of the test engineer. The main idea is to analyze the road to the test lab or the simulation work. Two kinds of driving cycles can be developed. The first one is Distance Dependent which is related to (Speed versus Distance Versus Altitude) and the second one is Time-Dependent which is related to (Speed versus Time Versus Gear Shift).

Table – 3.9: Transient Cycle

Characteristics	**Units**	**Artemis**				**FTP-75**
		Urban	**Rural**	**Motorway 150**	**Motor way 130**	
Distance	Miles (km)	4870	17272	29545	28735	17.77
Duration	Sec (s)	993	1082	1068	1068	1874
Average Speed	Mph (km/h)	17.6	57.5	99.6	96.9	34.1

3.4.3 Driving Cycle Prediction:

Driving Cycle Prediction is designed to predict future driving cycles and patterns for various vehicle applications. Combining available measured data with traffic models for light vehicles and traffic simulators, it enables the visualization of future driving cycles. Specifically, traffic simulation models are automatically generated and used to collect predictive cycles, offering a more accurate forecast of driving behaviour and road conditions for enhanced vehicle performance and energy management.

3.4.4 Driving Cycle Recognition:

This is dependent on the type of application, where the driving cycles vary from passenger cars to commercial vehicles.

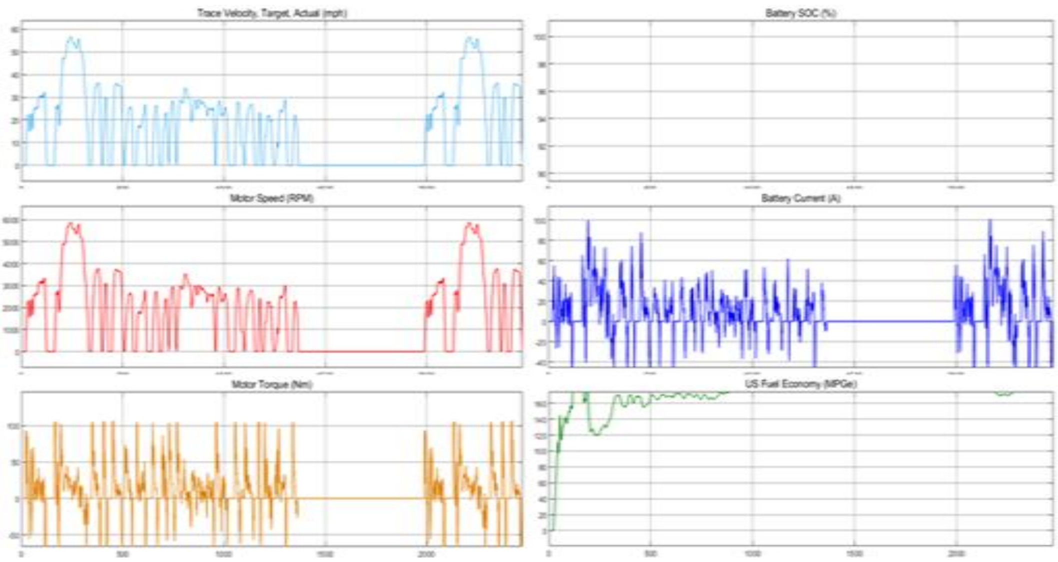


Fig.3.3: General Layout of a Driving Cycles.

The above Figure 3.3 represents the general driving cycle condition with respective trace velocity (mph) meters per kilometer, motor speed of the vehicle in rpm, motor torque (Nm), Battery SoC(%), Battery Current (A) and US Fuel Economy.

3.4.5 Steps for Generating Driving Cycle:

I. How to create a driving cycle?

Creating a region-specific driving cycle is crucial due to the significant variation in traffic and road conditions across different areas. While standardized cycles are useful for vehicle testing, they often fail to reflect real-world driving patterns, impacting the accuracy of performance assessments for factors like fuel consumption, emissions, and battery health. Tailored driving cycles help optimize vehicle components, such as motors and energy storage systems, to align with local conditions, improving efficiency and reliability. For instance, driving patterns in European cities differ greatly from those in Indian cities, influencing acceleration, braking, and energy demand. Designing such cycles provides valuable insights into vehicle behavior under specific conditions, enabling better predictions of performance. This process supports vehicle designs that are more suited to the unique characteristics of local environments, enhancing overall functionality.

II. Route choice: Step - 1

The selection of a driving cycle route is critical and depends on the intended use of the cycle and the performance parameters being evaluated. For instance, transient driving cycles are suitable for assessing vehicle performance in city traffic, using real-world data. The route should reflect the region where the vehicle will primarily operate. For a vehicle intended for a European city, the driving cycle must capture its unique traffic patterns, road conditions, and driving behaviours. A region-specific cycle provides more accurate and relevant data compared to generic cycles, ensuring realistic performance assessment. Accurate route selection minimizes bias, making the driving cycle reflective of real-world conditions. This enables effective simulation of the target market's driving environment, leading to better vehicle optimization and performance tuning for its intended use.

III. Data gathering, Step - 2

Creating a generalized driving cycle for a region requires extensive speed vs. time data, as a single trip cannot represent typical driving patterns. Common data collection methods include vehicle chasing and onboard instrumentation. In vehicle chasing, a data-collecting car follows another vehicle to record parameters like speed, though some variation occurs as the actions of the leading vehicle are not perfectly replicated. Modern vehicles with connected instruments allow for more accurate and autonomous data collection. Drivers navigate predetermined routes while real-time speed and other metrics are recorded, capturing regional traffic patterns.

Variables such as weather, driver demographics, emotional state, and time of day must also be considered. Comprehensive data collection may span several years, often exceeding five years, to ensure the driving cycle accurately reflects regional driving behaviors.

IV Classifying the data: Step - 3

The collected data will be organized into smaller units called **micro-trips** for easier analysis. These micro-trips are created by dividing the overall journey into segments based on criteria such as start-stop phases, equal time intervals, or specific speed ranges. This segmentation helps in analyzing specific driving behaviors and patterns more effectively, leading to a more accurate driving cycle representation.

V Drive cycle construction, Step - 4

Using the collected data, multiple micro-trips are created and refined by removing irrelevant or outlier data. Relevant data points are selected based on trends that best represent the driving behavior within each micro-trip. Key reference parameters such as minimum, maximum, and average speed, acceleration, and their probability and frequency distributions (SAPD and SAFD) are analyzed. These parameters guide the selection and combination of the most representative micro-trips to construct the driving cycle. The final driving cycle is formed by aligning key parameters of the selected micro-trips with those of the original dataset. The cycle with parameters closest to the collected data is considered the most accurate and is chosen as the ideal driving cycle for the region.
The parameters for the standard driving cycles considered in the study are presented in **Table 3.10**.

Table – 3.10: Modal Cycles

Characteristics	**Units**	**NEDA**	**HWFET**	**Japanese 10-15**	**JC08**	**GHDC**		
						Class - 3	**Class - 2**	**Class - 1**
Distance	Miles (km)	11.23	16.45	4.16	8.17	23.262	14.664	8.91
Duration	Sec (s)	1180	765	660	1204	1800	1477	1022
Average Speed	mph km/h	33.6	48.3	22.7	24.4	46.5	35.7	28.5

3.5 Practical Implementation:

Fig 3.4.Practical Implementation of Driving Sets

For the collection of real time data a module having the NEO-6M GPS Module with the Arduino is connected as shown in Fig 3.4 and installed in a vehicle. The data is collected for 6 months in different terrains and traffic condition. The velocity is predicted based on the data collated.

3.5.1 NEO-6M GPS Module with Arduino:

This section explains interfacing the NEO-6M GPS module with Arduino to retrieve GPS parameters like latitude, longitude, altitude, date, time, speed, and satellite count. GPS is a satellite-based navigation system comprising 24 satellites orbiting Earth, transmitting data such as identification, position, and transmission time. The GPS receiver calculates its distance from satellites and triangulates its position (latitude and longitude) using signals from three or more satellites, or 3D positioning (latitude, longitude, and elevation) using four or more satellites.

A GPS receiver also provides speed and direction, making the system versatile and globally accessible. GPS applications include GIS data collection, surveying, and real-time navigation. The NEO-6M GPS module can track up to 22 satellites and locate any point on Earth. It features a high-performance u-blox 6 positioning engine, compact dimensions (16 x 12.2 x 2.4 mm), and low power consumption, making it ideal for IoT projects and a cost-effective GPS solution.

3.5.2 NodeMCU:

NodeMCU, a low-cost microcontroller with Wi-Fi, can be used to collect driving cycle data by integrating sensors like GPS and accelerometers to monitor vehicle speed, acceleration, and location. The data is processed and transmitted wirelessly to cloud platforms such as Google Firebase or AWS for real-time analysis. This setup allows continuous monitoring and analysis of driving patterns. NodeMCU is cost-effective, scalable, and provides real-time insights for optimizing vehicle performance. By using this system, accurate, region-specific driving cycles can be created and analyzed.

.3.5.3 ACS712 Current Sensor:

The ACS712 Current Sensor is a Hall effect-based linear sensor designed to measure current without affecting system performance. It provides 2.1kV RMS voltage isolation and uses a low resistance current conductor. The sensor detects current in a conductor and outputs a proportional signal as either analog voltage or digital data. Current sensing can be done directly by measuring voltage drop using Ohm's law or indirectly by detecting the magnetic field generated by the current. Indirect sensing relies on principles like Faraday’s or Ampere’s law, utilizing devices such as transformers, Hall effect sensors, or fiber optic sensors to measure the magnetic field effectively.

3.5.4 Collection of Data sets:

The NEO-6M GPS Module, Arduino, Nodeb MCU, and ACS712 Current Sensor are connected on a breadboard placed in a vehicle, along with a laptop and mobile phone, for data collection. As the vehicle moves, the devices record parameters such as point, time, duration, speed, distance, altitude, latitude, and longitude, forming datasets. GPS data is uploaded online using Thing Speak software and can be retrieved in CSV, JSON, or XML formats.

The Arduino software loaded onto the laptop includes a program to identify the vehicle's location via GPS. A blinking LED on the breadboard indicates that the system is active and recording. Data was collected during trips from Kakinada to Annavaram, Visakhapatnam, and Guntur using a conventional vehicle. These datasets are utilized to train driving cycles for Energy Management Systems (EMS). Figure 3.5 demonstrates latitude data over time and includes the date and other recorded parameters like longitude, altitude, and speed logged in the Thing Speak app.

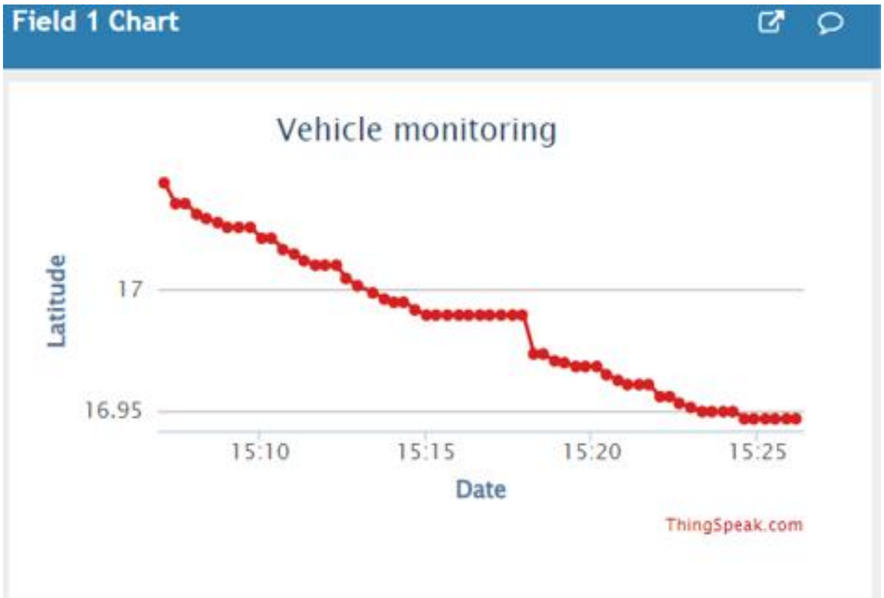


Fig.3.5 : Latitude of the vehicle

Figure 3.5 gives the real time variation of the latitude in the driving cycle of the vehicle

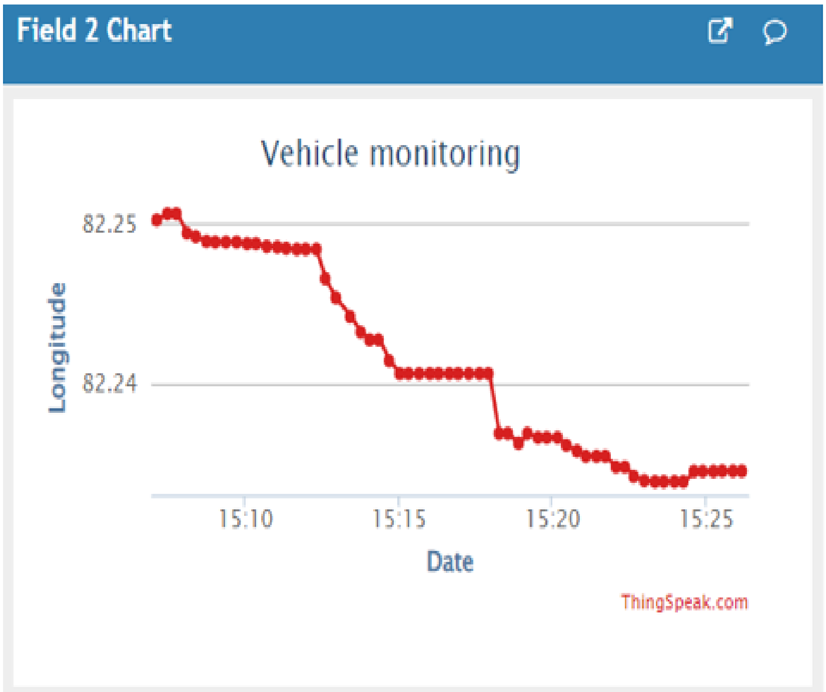


Fig.3.6: Longitude of the vehicle

The Figure 3.6 give the real time variation of the latitude in the driving cycle of the vehicle

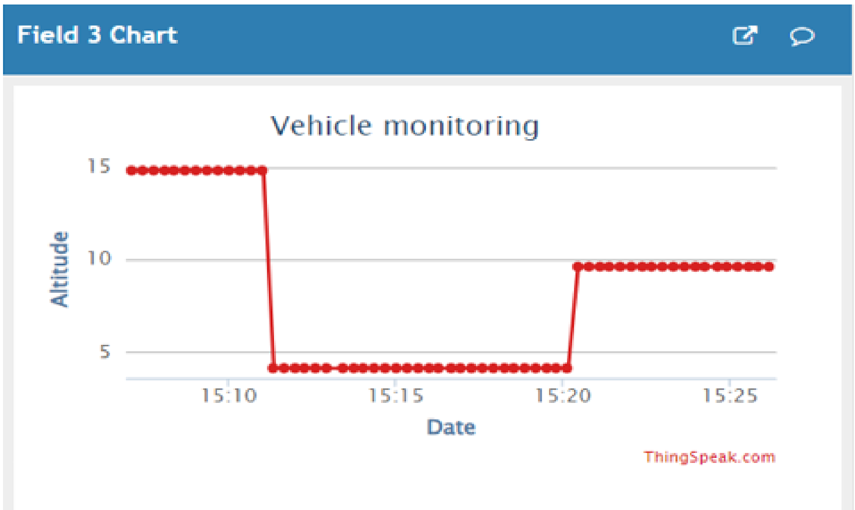


Fig 3.7: Altitude of the vehicle

The Figure 3.7 give the real time variation of the terrain in the driving cycle of the vehicle

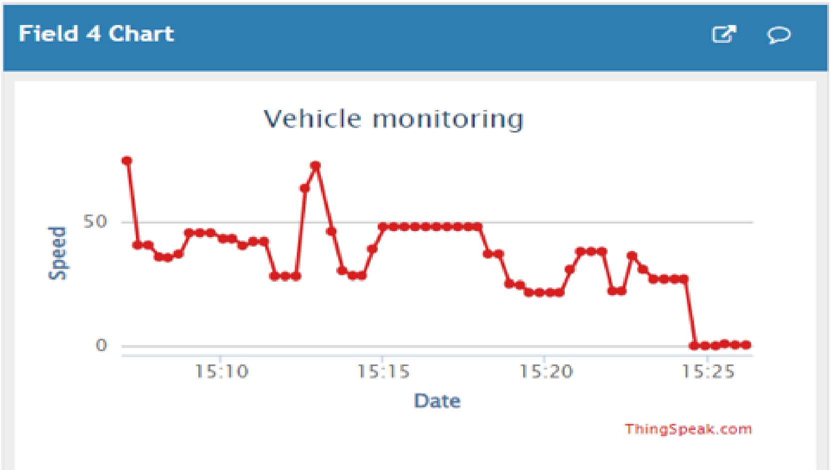


Fig. 3.8: Speed of the vehicle

Figure 3.8 gives the real time variation of the velocity in the driving cycle of the vehicle. From the Figure the map represents the source and destination points where it travelled along with positions of longitude, latitude, speed and time. For each sec it can be clearly seen the speed of the vehicle travelled. It also shows the elevation grade profile of the distance and speed travelled by the vehicle.

In this work, the data is considered in five different terrain conditions. After travelling in various driving conditions, the data set points are taken from the Arduino application on the laptop. The overall data can be retrieved using this application as represented in Fig 3.9. Once it is terminated or the signals are lost then data can be saved automatically. The data can be converted into excel format and the data can be extracted from it. The data sets are created practically from five different driving conditions highway, Urban, Rural, Hilly Area and Semi Urban areas. The speed, duration and times vary with respective to distances for various modes.Depending on the road conditions and driving conditions these data sets are recorded and used in this work.

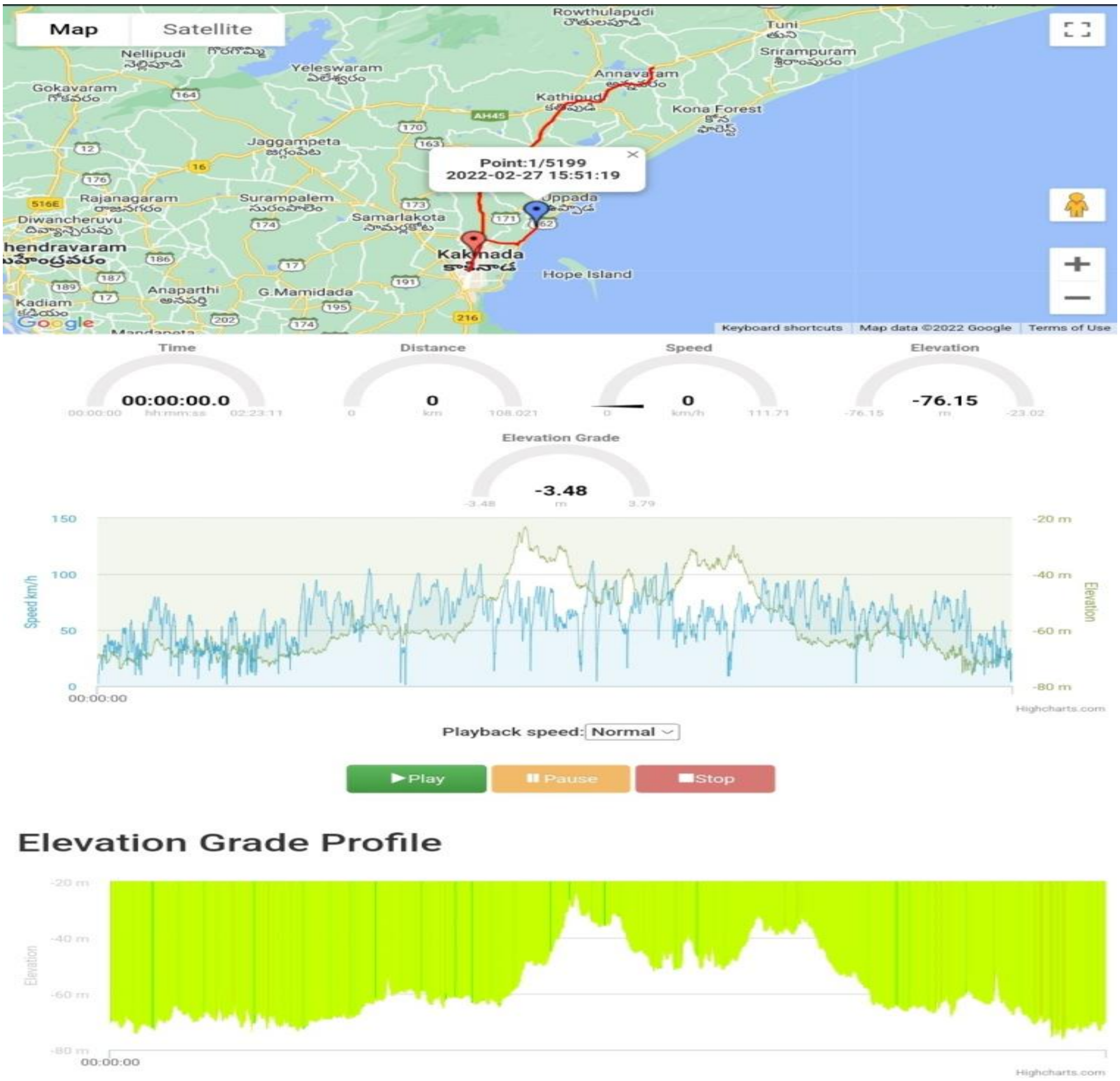


Fig.3.9: Snap short of the Speedometer Application used from mobile to retrieve data sets.

In this work, the data is considered in five different terrain conditions. After travelling in various driving conditions, the data set points are taken from the Arduino application on the laptop. The overall capture of the data can be retrieved using this application as represented in Fig 3.9. Once it is terminated or the signals are lost then data can be saved automatically. The data can be converted into excel format and the data can be extracted from it. The data sets are created practically from five different driving conditions highway, Urban,Rural, Hilly Area and Semi Urban areas. The speed, duration and times varies with respective to distances for various modes.Depending on the road conditions and driving conditions these data sets are recorded and used in this work.

3.6 Artificial Intelligence Based Prediction Methods:

3.6.1 Recognition Based Prediction Technique:

Artificial Intelligence-Based Methods: AI-based methods such as Artificial Neural Networks (ANNs), Machine Learning (ML), Decision Tree Algorithm (DTA), and Support Vector Machine (SVM) are capable of establishing complex relationships between inputs and outputs through the "learning" process. They can also be divided into two sub-categories. The first sub-part is known as "recognition-based" prediction, and the main procedure of this approach is depicted in Fig. 3.10.

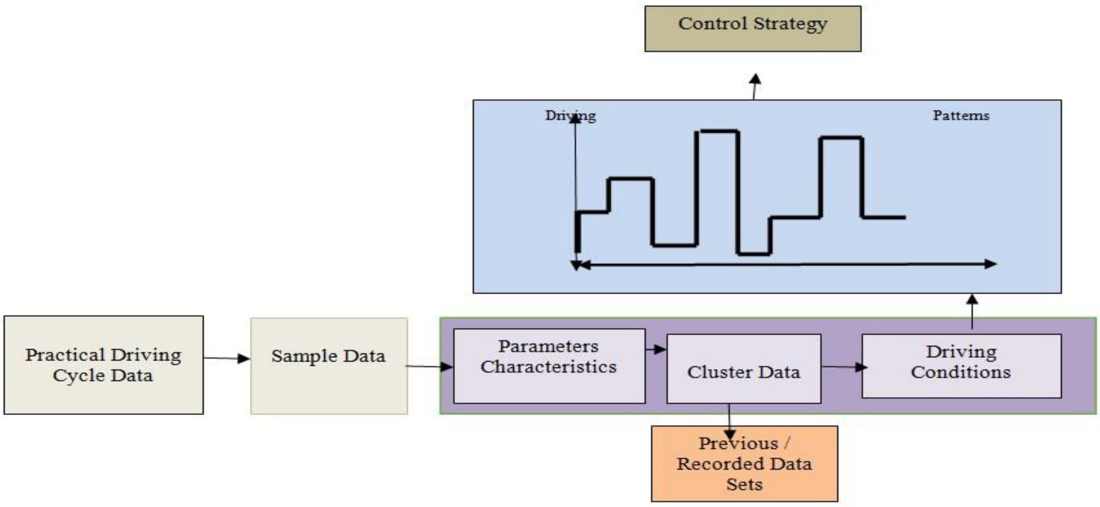


Fig 3.10. Block diagram of identification-based prediction

To begin, various clustering methods (e.g., k-means approach, etc.) are used to divide historical data into several groups, where driving cycle segments with similar characteristic parameters (e.g., average acceleration, maximum velocity, and average positive power demand, etc.) are classified into the same groups. Each group represented a different type of pre-planned driving pattern (for example, urban congested, urban normal, suburban, highway.., denoted as IV-I, etc.). Second, real driving data of sufficient duration (e.g., 100-150s) were sampled and stored to calculate corresponding driving characteristic parameters. These calculated parameters were fed into well-trained classifiers (e.g., SVM, NN, etc.) to generate driving patterns for the current segment. Finally, corresponding control strategies (e.g., PEMS IV-I) designed for various driving patterns are implemented based on the recognition results.

Many attempts have been made in recent years to use recognition-based prediction. This approach's primary research focus is the tradeoff between recognition accuracy and computation burden. The reduced number of classification characteristic parameters can reduce computation time, making the algorithms more suitable for online applications. 62 [83], 40 [82], 17 [81], and 14 [86] characteristic parameters are used to characterize a specific driving cycle in these studies. This number is reduced to 3 or 2 in [91], respectively. In particular, in [66], six original characteristic parameters were composed of three new parameters using a linear mapping approach, and the newly composed parameters contained more than 90% of the variance information in the original data.

As a result, a hierarchical cluster is built based on composed parameters to extract the characteristic parameters from real driving cycles, and SVM is used to generate the driving patterns.

3.6.2 Levenberg-Marquardt Algorithm

Like the quasi-Newton methods, the Levenberg-Marquardt algorithm was designed to approach second-order training speed without having to compute the Hessian matrix. When the performance function has the form of a sum of squares (as is typical in training feed forward networks), then the Hessian matrix can be approximated as

$$H = J^T J \tag{3.12}$$

and the gradient can be computed as

$$g = J^T e \tag{3.13}$$

where **J** is the Jacobian matrix that contains first derivatives of the network errors with respect to the weights and biases, and **e** is a vector of network errors. The Jacobian matrix can be computed through a standard backpropagation technique (see [HaMe94]) that is much less complex than computing the Hessian matrix.

The Levenberg-Marquardt algorithm uses this approximation to the Hessian matrix in the following Newton-like update:

$$x_{k+1} = x_k - [J^T J + \mu I]^{-1} J^T e \tag{3.14}$$

When the scalar μ is zero, this is just Newton's method, using the approximate Hessian matrix. When μ is large, this becomes gradient descent with a small step size. Newton's method is faster and more accurate near an error minimum, so the aim is to shift toward Newton's method as quickly as possible. Thus, μ is decreased after each successful step (reduction in performance function) and is increased only when a tentative step would increase the performance function. In this way, the performance function is always reduced at each iteration of the algorithm.

The original description of the Levenberg-Marquardt algorithm is given in [Marq63]. The application of Levenberg-Marquardt to neural network training is described in [HaMe94] and starts on pages 12-19 of [HDB96]. This algorithm appears to be the fastest method for training moderate-sized feedforward neural networks (up to several hundredweights). It also has an efficient implementation in MATLAB® software, because the solution of the matrix equation is a built-in function, so its attributes become even more pronounced in a MATLAB environment.

Try the *Neural Network Design* demonstration nnd12m [HDB96] for an illustration of the performance of the batch Levenberg-Marquardt algorithm is shown in Fig 3.11.

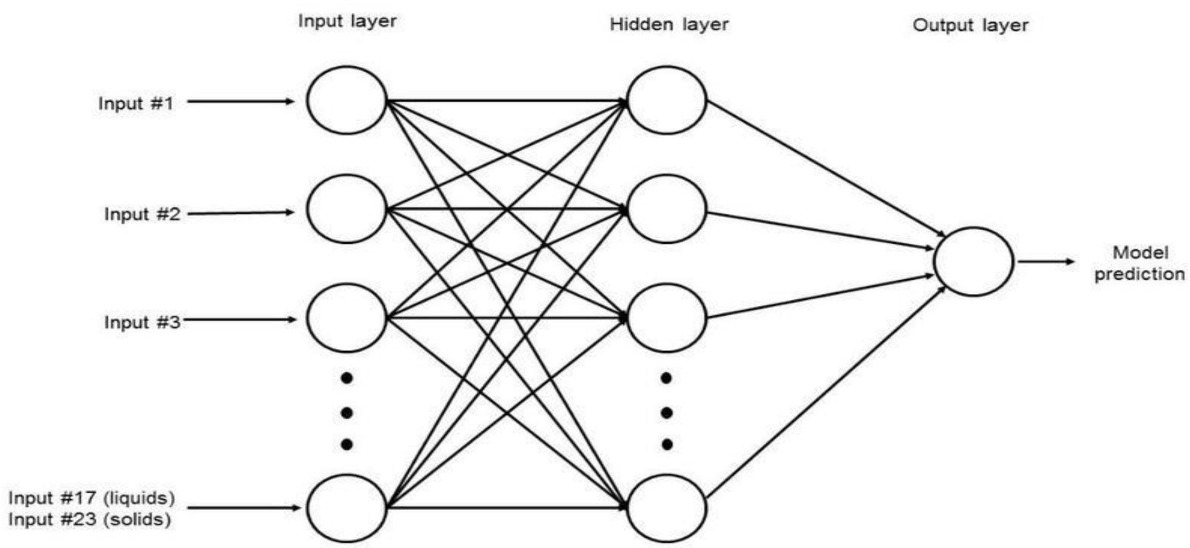


Fig.3.11 Basic Structure of LMBT.

3.6.3 Training of Levenberg-Marquardt backpropagation

The detailed algorithm used for of LBMT is given in Appendix A4.The Levenberg-Marquardt algorithm is a popular optimization technique used to train neural networks, particularly when employing the backpropagation method. It's designed to optimize non-linear functions, and it's often preferred for training neural networks due to its efficiency and effectiveness. Validation vectors are used to stop training early if the network performance on the validation vectors fails to improve or remains the same for max_fail epochs in a row. Test vectors are used as a further check that the network is generalizing well, but do not have any effect on training.

[x, t] = bodyfat_dataset;

net = feedforwardnet(10, 'trainlm');

net = train(net, x, t)

Train Neural Network Using trainlm Train Function

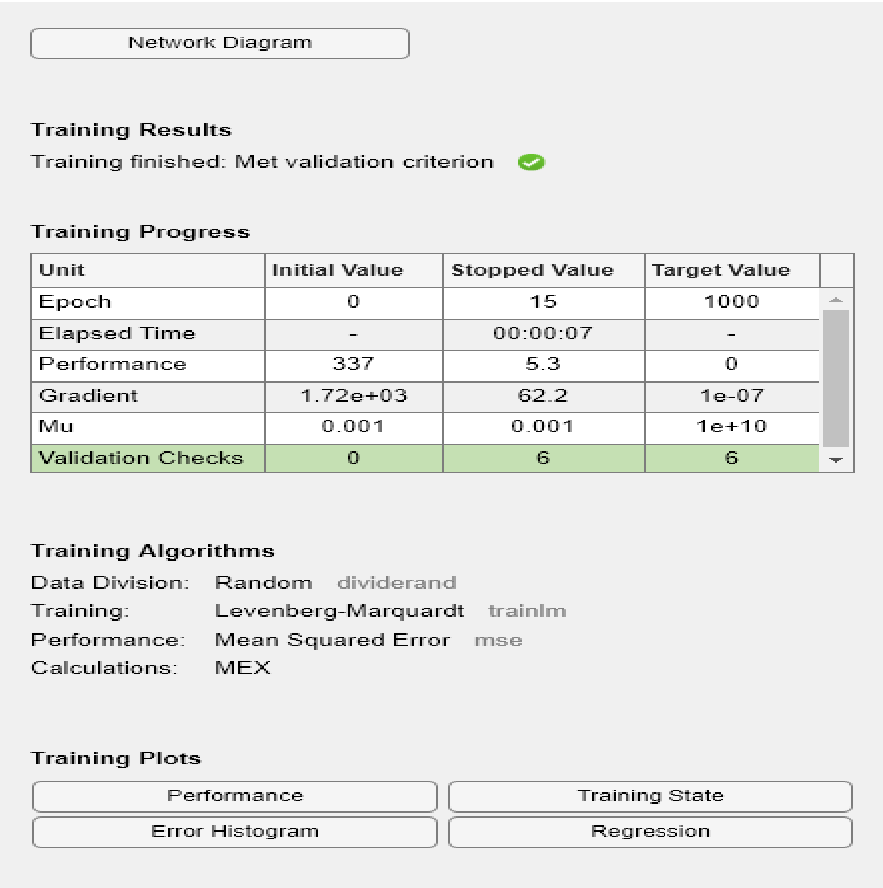


Fig.3.12LMBT Train Neural Network Using trainlm Train Function

y = net(x);

Input Arguments:

Input network, specified as a network object. To create a network object, use for example, feedforwardnet or narxnet. Net- Input network matrix.

Output Arguments:

Trainednet- Trained network.

Tr-Training Record Structure

Training record (epoch and perf), returned as a structure whose fields depend on the network training function (net.NET.trainFcn). It can include fields such as:

- Training, data division, and performance functions and parameters
- Data division indices for training, validation and test sets
- Data division masks for training validation and test sets
- Number of epochs (num_epochs) and the best epoch (best_epoch).
- A list of training state names (states).
- Fields for each state name recording its value throughout training
- Performances of the best network (best_perf, best_vperf, best_tperf)

Limitations:

This function uses the Jacobian for calculations, which assumes that performance is a mean or sum of squared errors. Therefore, networks trained with this function must use either the mse or sse performance function.

3.6.4 Network Use:

You can create a standard network thatses trainlm with feedforwardnet or cascadeforwardnet. To prepare a custom network to be trained with trainlm,

1. Set NET.trainFcn to trainlm. This sets NET.trainParam to trainlm's default parameters.
2. Set NET.trainParam properties to desired values.

In either case, calling train with the resulting network trains the network with trainlm.
See feedforwardnet and cascadeforwardnet for examples.

3.6.5 Algorithm Steps:

trainlm supports training with validation and test vectors if the network's NET.divide Fcn property is set to a data division function. Validation vectors are used to stop training early if the network performance on the validation vectors fails to improve or remains the same for max_fail epochs in a row. Test vectors are used as a further check that the network is generalizing well, but do not have any effect on training .trainlm can train any network as long as its weight, net input, and transfer functions have derivative functions.

Backpropagation is used to calculate the Jacobian jX of performance perf with respect to the weight and bias variables X. Each variable is adjusted according to Levenberg-Marquardt,

jj = jX * jX

je = jX * E

dX = -(jj+I*mu) \ je

where E is all errors and I is the identity matrix.

The adaptive value mu is increased by mu_inc until the change above results in a reduced performance value. The change is then made to the network and mu is decreased by mu_dec.

Training stops when any of these conditions occurs:

- The maximum number of epochs (repetitions) is reached.
- The maximum amount of time is exceeded.
- Performance is minimized to the goal.
- The performance gradient falls below min_grad.
- mu exceeds mu_max.
- Validation performance (validation error) has increased more than max_fail times since the last time it decreased (when using validation)

3.6.6 Flowchart:

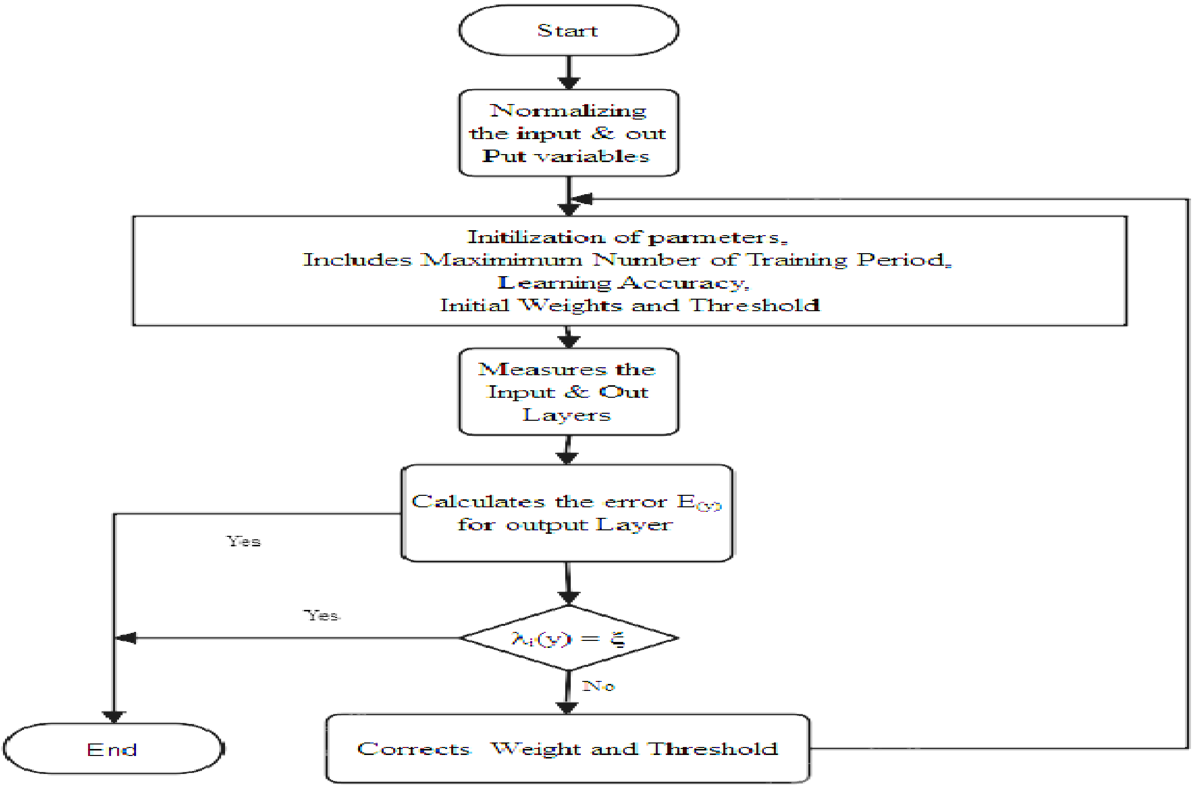
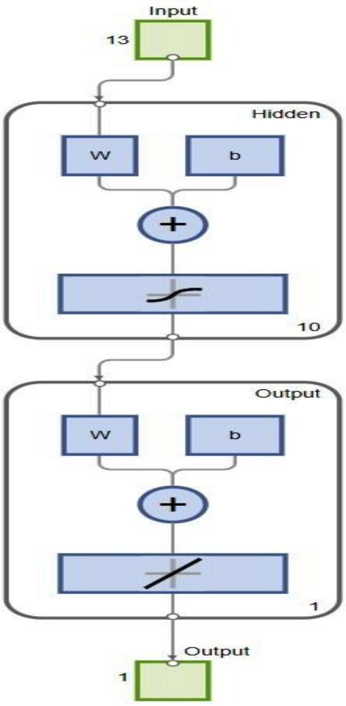


Fig. 3.13LMBT Flow chart

The flow chart for the LMBT is shown in Fig 3.13 .The process to compute the Gradient and Hessian Approximation, Levenberg-Marquardt Update, Convergence Check and parameter finalization are presented in the flow chart.

3.6.7 Trained Datasets Along With Its Simulation Results

From the Figure, it is clearly observed that the Neural Network training with an input layer, output layer and a hidden layer has been considered. And after completion of the training, the results should be validated. In the training process the various units considered are the Epoch, Elapsed Time, Performance, Gradient, MU and Validation checks along with the values of Initial Value, Stopped Value and Target Values.



Input Parameters:
Data Points
Duration
Speed (km)
Time (sec)
Distance (km)
Latitude
Longitude
Altitude
Battery SoC
Temperature of Battery
Average Acceleration
Maximum Velocity
Average Power Demand
Output Parameters:
Reference Velocity
(Driver Behavior)

Fig. 3.14 Network Diagram of LMBT-MNN.

In Fig 3.14 the network diagram proposed LMBT-MNN for training is presented. The performance of the LMBT-MNN can be checked in the process of the training algorithms with respect to the data division, training, performance and calculations. In the training for data division Random is selected, for training here LMBT-MNN is considered for training, for performance Mean squared Error is chosen and for calculation MEX is taken. After the training is completed, the outputs can be observed precisely in the training plots.

In the training plot Fig 3.15, one can observe the performance, training state, error histogram and regression analysis of the training algorithm. In this analysis, an epoch is used frequently. In the training state, the data sets collected will be trained and from the Figure, the testing for the particular network with various classes 1-5is considered. All numeric representations describe dates and times with respect to a point in time called an epoch. Computers typically measure time by the number of seconds or clock ticks since the specified epoch.

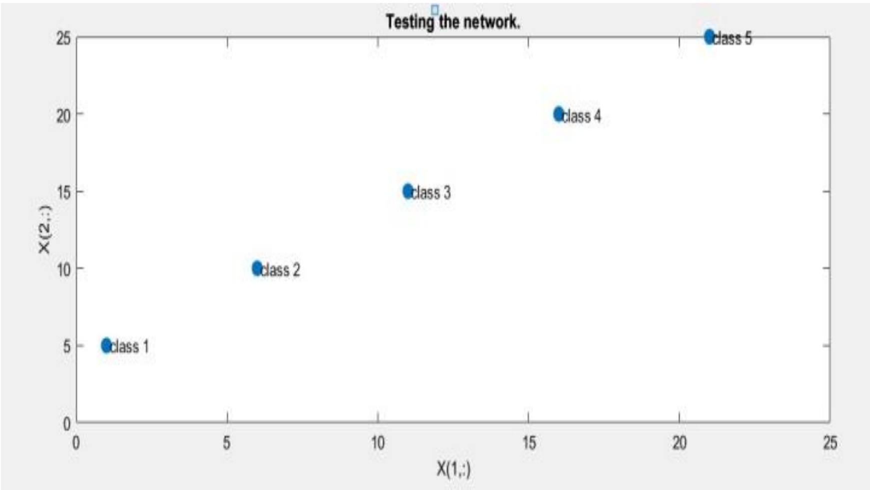


Fig. 3.15 Performance of a training data.

In the Figure-3.16, the performance of the test network can be precisely seen with respective to the gradient = 62.2473 and MU=0.001 at epoch 15. Finally with the validation checks of 6 at epoch 15 has been clearly identified from the graph.

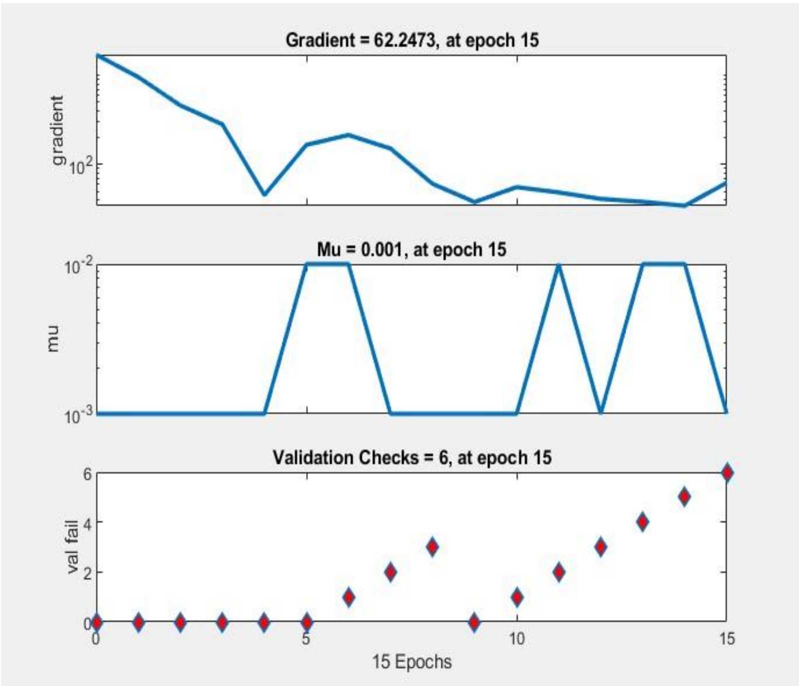


Fig.3.16 Training state for the data sets.

From Figure 3.17, the name is particularly related to the error histogram with nodes of 20 bins taken. The targets are subtracted from the outputs to achieve the errors. The training takes more instances compared with the other parameters and the test and validation are considered once the training is completed, also the zero error is considered with respect to the 20 binds and it can be observed that after 6 stages the zero error is placed and remaining 14 are considered on the other side of the zero error.

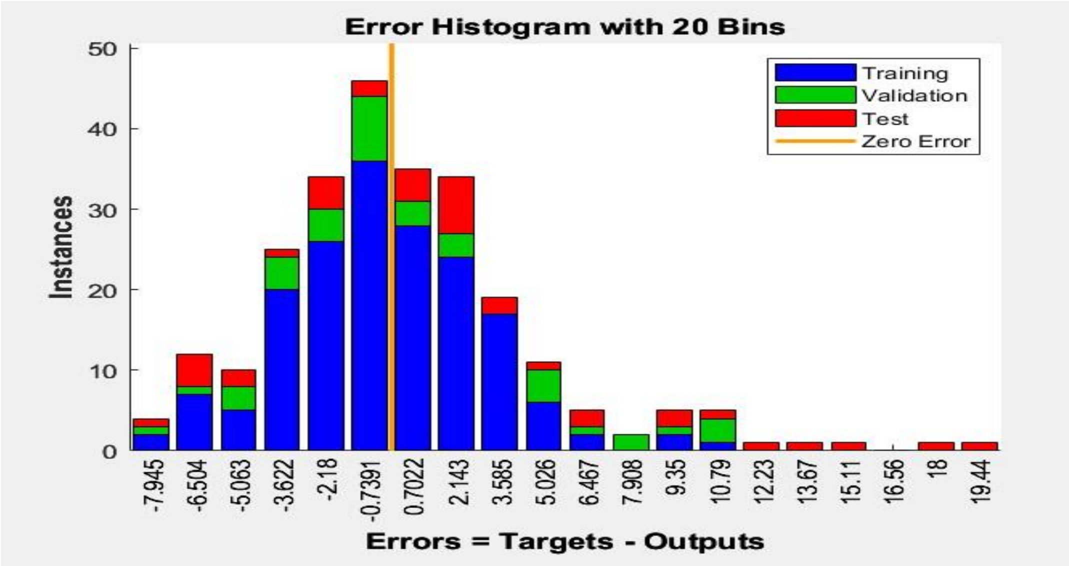


Fig. 3.17 Error Histogram for the training data.

Once the training is completed, the next step is to validate the results. Here 4 cases are considered,

In the first case the training, R =0.91764 and the output=0.85*Target+3, where data values, Fit and the deviation Y+T varies along with the fitness function.

In the second case the validation, R =0.80195 and the output=0.76*Target+3, where data values, Fit and the deviation Y+T vary more and also only a few data sets are present after the training process is completed & are present for validation.

In the third case the test, R =0.70185 and the output=0.62*Target+4.8, where data values, Fit and the deviation Y+T, where the data sets scatter away from the fit function more widely.

In the fourth case the All together, R =0.85426 and the output=0.79*Target+3.7, where data values, Fit and the deviation Y+T, so it can clearly observe the combination of all the above graphs in a single sheet.

In regression analysis, the **R-value** (often referred to as the **correlation coefficient**) is a crucial statistic that quantifies the strength and direction of the linear relationship between the independent and dependent variables. The R-value ranges from -1 to 1. An R-value close to 1 indicates a strong positive linear relationship, while an R-value close to -1 indicates a strong negative linear relationship. An R-value around 0 suggests a weak or no linear relationship.

A higher absolute value of **R** (close to 1 or -1) indicates a strong correlation between the independent variable(s) and the dependent variable. Specifically:

- An **R-value close to 1** suggests a strong positive linear relationship, meaning that as the independent variable(s) increase, the dependent variable also increases.
- An **R-value close to -1** suggests a strong negative linear relationship, meaning that as the independent variable(s) increase, the dependent variable decreases.
-

In either case, the closer **R** is to 1 or -1, the stronger the association between the variables, meaning changes in the independent variables is closely linked to changes in the dependent variable. Conversely, an **R-value near 0** indicates little to no linear relationship between the variables. Conversely, an R-value near 0 implies that the variables do not have a strong linear relationship.

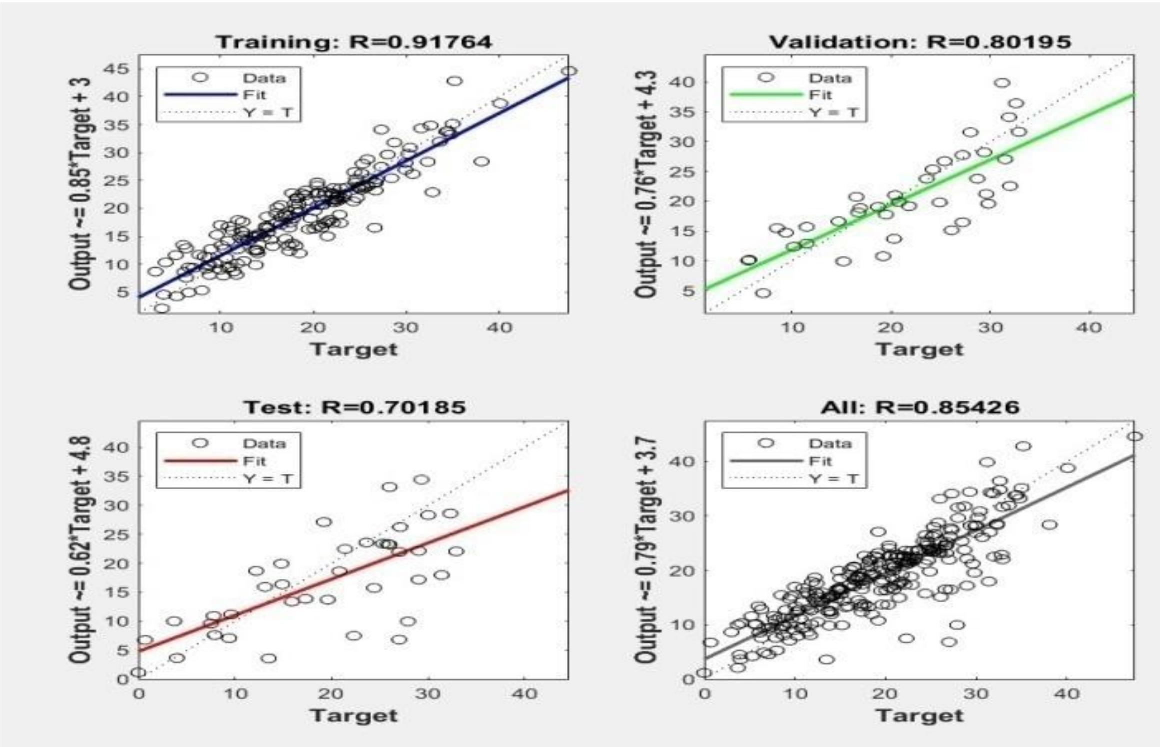


Fig.3.18 Regression Analysis for the training data.

Based on the above-discussed importance of the R-value from Figure 3.18 it is observed that during the case with an output target of (0.85*Target+3) has the highest correlation and impact on the output. As per the calculation, various parameters are considered for the Hybrid energy storages.

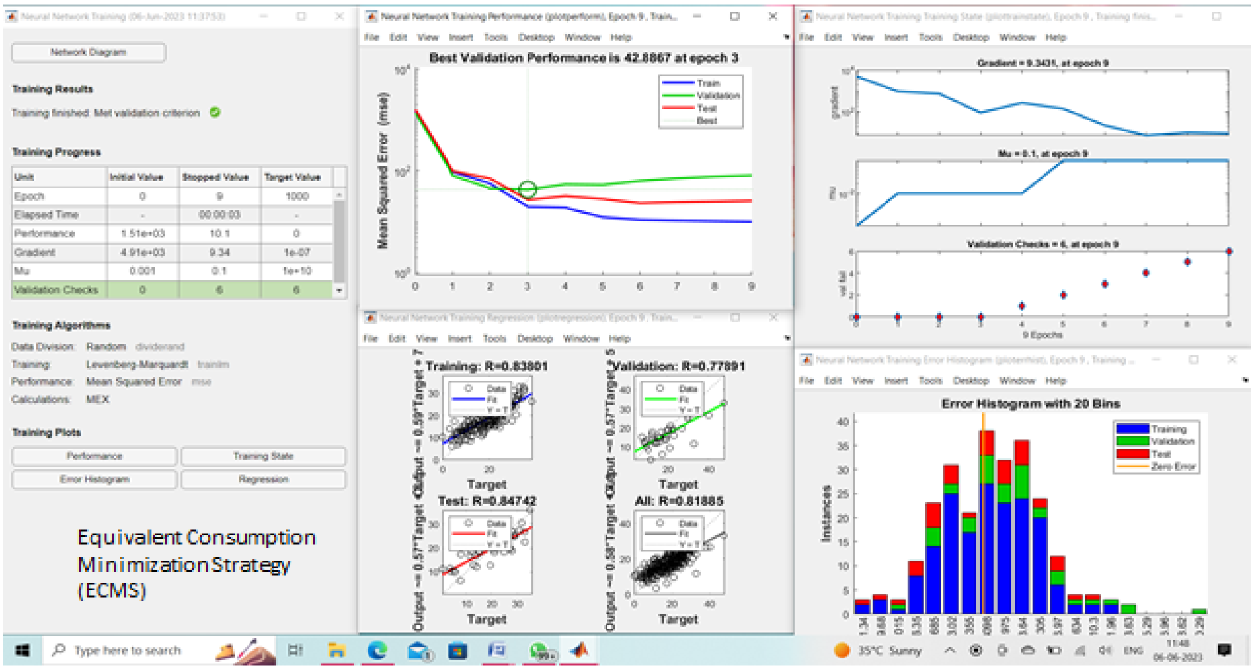


Fig.3.19: Equivalent Consumption Minimization Strategy

The Equivalent Consumption Minimization Strategy focuses on optimizing the use of resources by converting different types of consumption into a common measure and then minimizing this measure to achieve cost savings, efficiency improvements, and sustainability goals. It involves defining objectives, formulating and solving optimisation problems, and continuously adjusting strategies to meet performance and resource constraints effectively.From Fig. 3.19 it is observed the best validation performance is at 42.866.

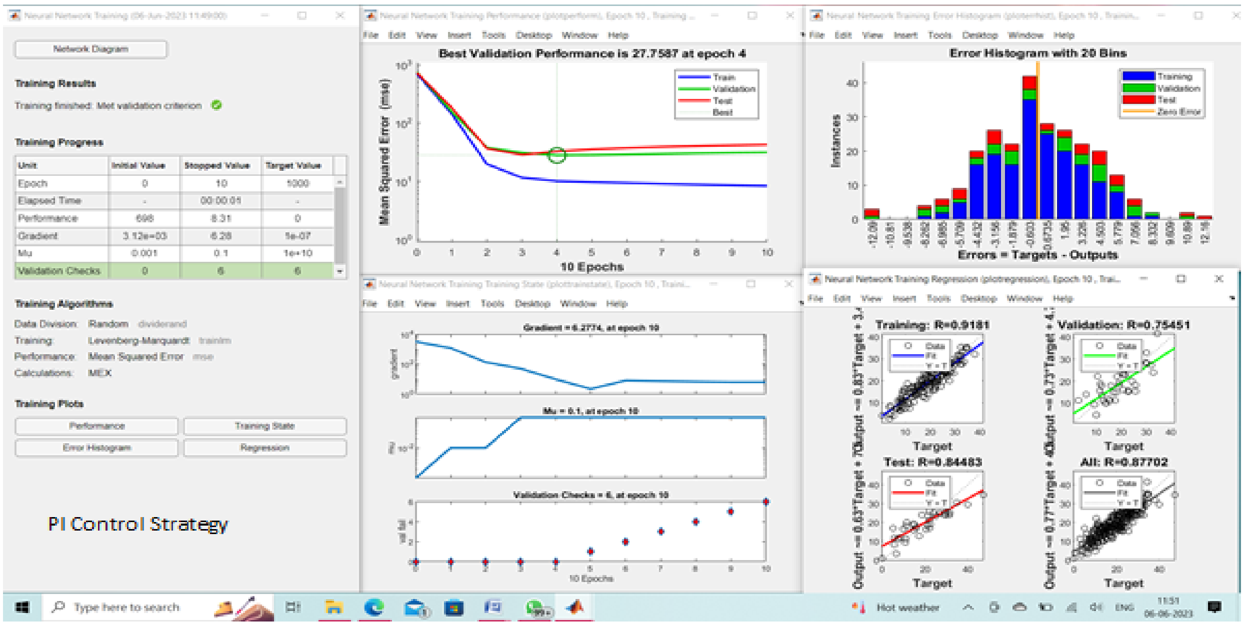


Fig.3.20: PI Control Strategy

The goal of a PI controller is to maintain a desired output or set point by adjusting the control input based on the error signal (the difference between the desired set point and the actual output). From Fig 3.20 it is observed that the PI control strategy has the best validation performance at 27.785.

Frequency decoupling is ideal for managing systems with complex frequency interactions, while state machine control is effective for systems with discrete modes of operation and transitions. From Fig 3.21, it is observed that validation performance is at 27.787.

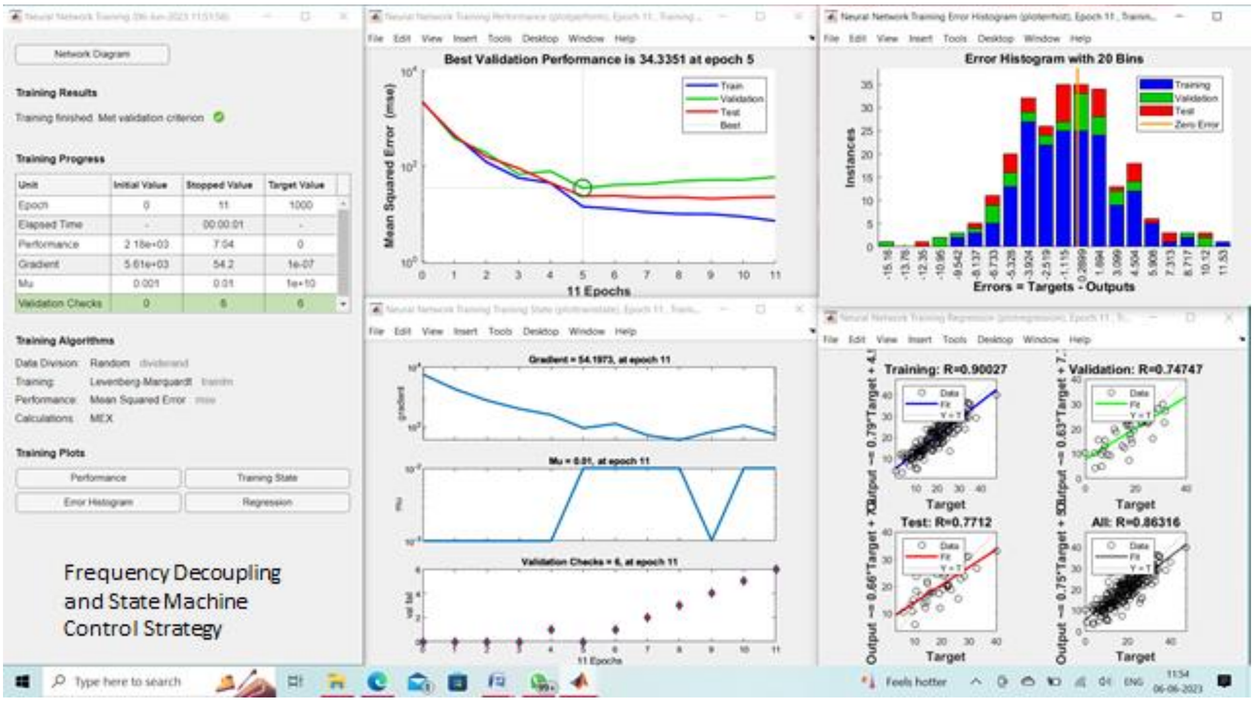


Fig.3.21: Frequency Decoupling and State Machine Control Strategy

The **Broyden-Fletcher-Goldfarb-Shanno (BFGS) Algorithm** is a widely used iterative optimization algorithm for solving unconstrained optimization problems. It is part of the quasi-Newton methods family, which are designed to find the local minimum of a differentiable scalar function.From Fig 3.22 it is observed that the best validation performance is at 16.392.

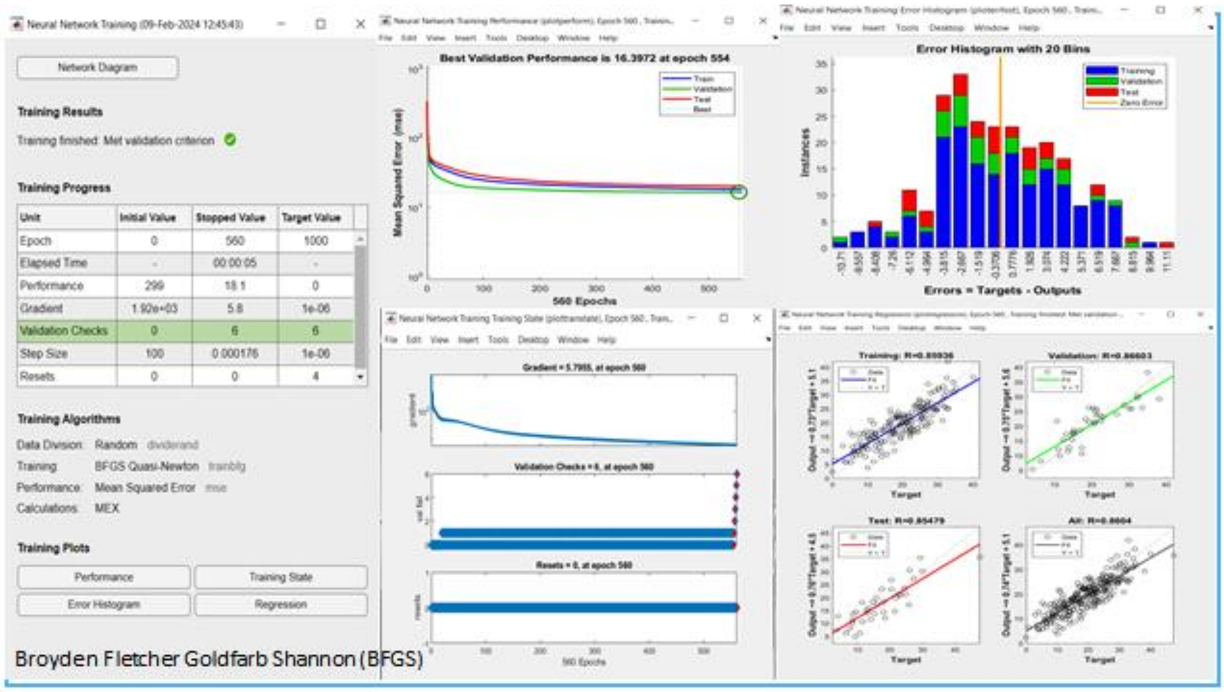


Fig.3.22: Broyden Fletcher Goldfarb Shannon Algorithm

Table.3.11 Comparison of different strategies for preparing training data set with real-time data

Strategy	Best validation performance	R_{value}	E_{pochs}
ECMS	42.8867	0.8188	3
FDSMCS	34.3351	0.86316	5
BFGS	16.3972	0.8604	554
Conventional PI	27.7587	0.87702	4

From Table3.11 it is observed that ECMS takes less number of epochs to converge and BFGS has high epocs but it has a high validation performance. The PI strategy has the better R-value near unity which is 0.87702. It can be conserved that the BFGS generates the best training set for feature correlation. Applying the above test data is fed to the LMBT optimizer the velocity required for the driving cycle is determined and given in Table 3.12.

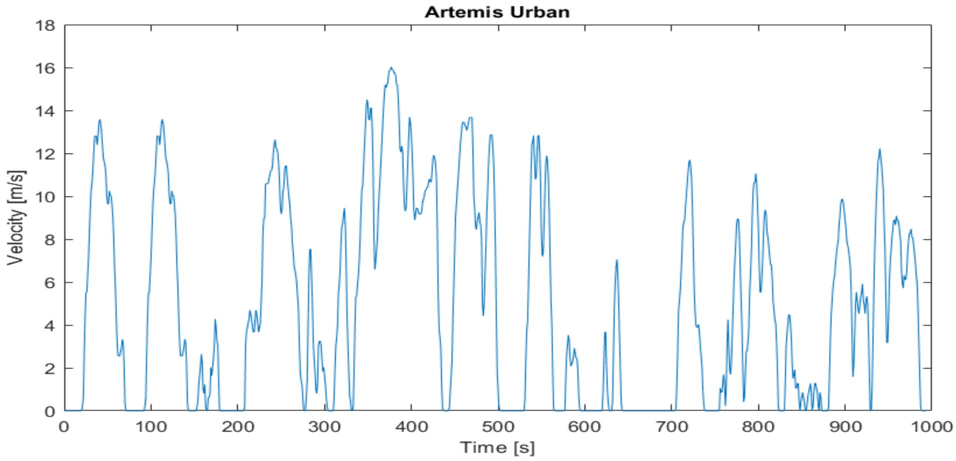


Fig. 3.23 Artemis Urban Driving Cycle Velocity Vs Time

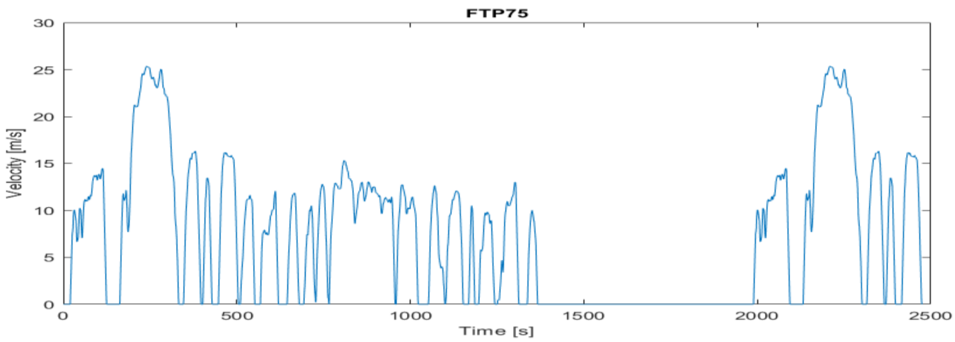


Fig. 3.24 FTP75 Driving Cycle Velocity Vs Time

In below table 3.12,the total driving cycles classified based on the velocity are represented as per the experimental work considered.

Table 3.12: Specified Driving Route Topology

Phases	Event information	Vehicle Speed [km/h]
Phase-1	Urban Flowing	50-70
Phase-2	Urban Congested	20-40
Phase-3	Subway	30-50
Phase-4	High way	80-120
Phase-5	Others	40-60
Phase -6	Acceleration and climbing a slope 10%	60-80

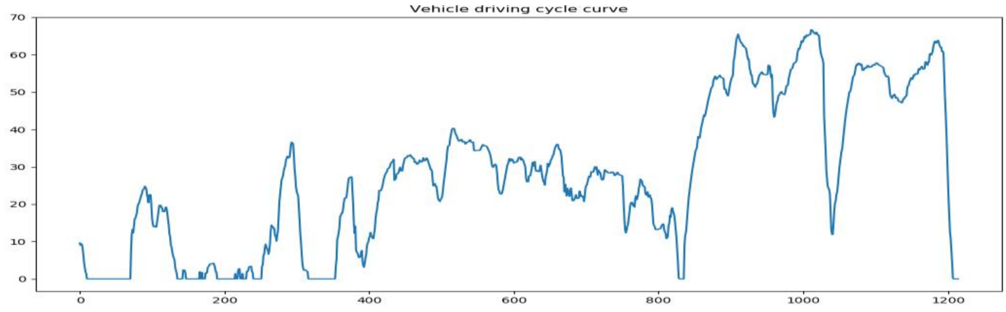


Fig. 3.25 Practical Vehicle Driving Cycle Curve

The final predicted data cycle is represented in Fig 3.25 and they are compared with the standard practical data set Artemis Urban Driving Cycle shown in Fig. 3.23 and FTP75 Driving Cycle shown in Fig 3.24.

3.7 Experienced Based Prediction Technique:

The second sub-part of the AI-based approach is called "experience-based" prediction whose procedure is shown in Fig. 3. In order to simplify the illustration process, an NN-based predictor, which is composed of the input layer, a hidden layer and an output layer, is used here as a representative of AI-based prediction models. In Fig. 3.28, Hm, Hp, tk denote the input horizon, output (prediction) horizon of prediction models and current time instant, respectively. Xi and Yj denote input and output (predicted) variables, respectively, where i = 1,2, ...,m. j = 1,2, ...,p.

In this approach, prediction models (also known as predictors) were defined as one or more specific time-series forecasting functions. By importing current and historical data as input variables into these models, output variables (in time sequences) could be forecasted within prediction horizons. Due to the uncertainty and complexity of realistic driving scenarios, future driving conditions were hard to describe accurately by traditional time-series forecasting models, which had relatively fixed structures, such as linear regression models (LRM) or autoregressive integrated moving average (ARIMA) models.

For that reason, AI-based data-driven prediction models were widely adopted by researchers, which had flexible structures and could obtain necessary characteristics from training datasets automatically as long as specific training rules (e.g. activation functions, maximum training errors etc.) were established. However, it should be noted that there are always differences between training databases and real driving data. Therefore, corresponding prediction errors would dramatically increase when such discrepancies have reached a certain level. In that case, an updating mechanism should be established to introduce novel driving characteristics to prediction models by adding newly-measured data into the training database and then retraining prediction models so that corresponding errors could be compensated.

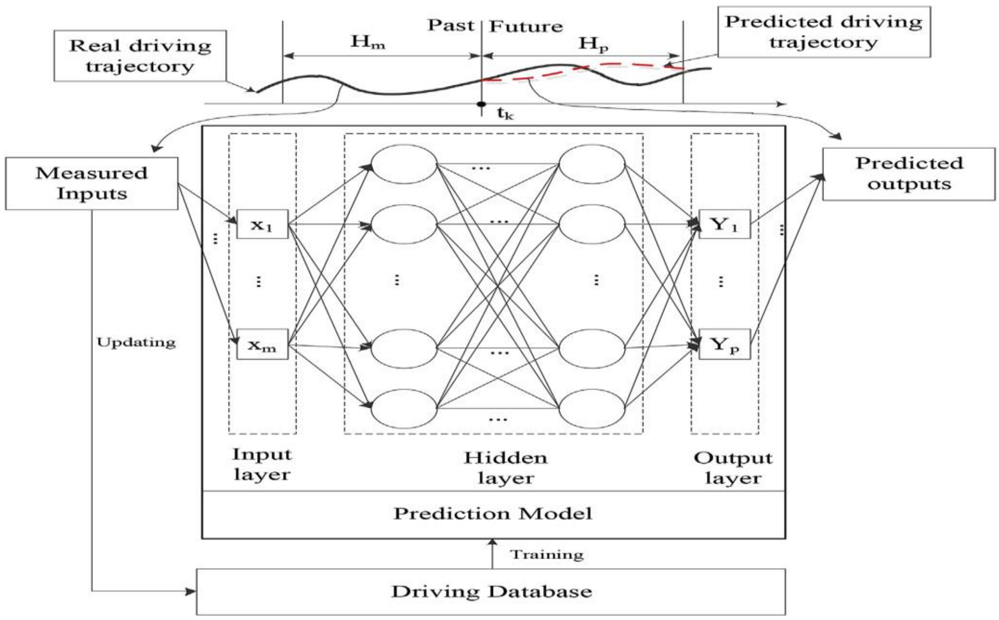


Fig 3.26: Block Diagram of Experienced-Based Prediction Method

Two types of AI-based prediction approaches, “recognition-based” and “experience-based” prediction, shared the same operation framework —“offline training” and “online predicting”. However, there are two major differences between them. In “recognition-based” prediction approaches, the number of input variables is larger than that of “experience-based” prediction approaches (e.g. 100–150 vs. less than 10, respectively). The reason is, in the former approaches, it is necessary to store a larger amount of data to ensure the completeness and recognition accuracy of the current driving segment, while there is no need to calculate characteristic parameters in the latter approaches. Besides, the outputs of the “recognition-based” prediction model are driving patterns which are used as switches to select proper pre-designed PEMSs according to the recognition results.

However, the outputs of the “experience-based prediction model are physical quantities like velocities, accelerations or power demands and these predicted profiles were regarded as the measured disturbances, which were imported into online optimizers to find satisfied solutions within prediction horizons.

3.7.1 Long Short Term Memory (LSTM):

Long Short-Term Memory is an advanced version of recurrent neural network (RNN) architecture that was designed to model chronological sequences and their long-range dependencies more precisely than conventional RNNs.

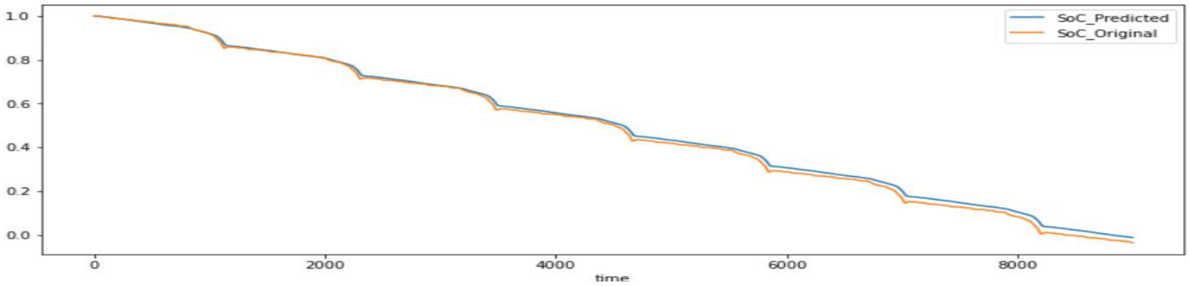


Fig. 3.27 Battery SoC Training Results

From Fig 3.27 it is observed that the SoC is predicted accurately with the provided data and further analysis is done in the sections below.

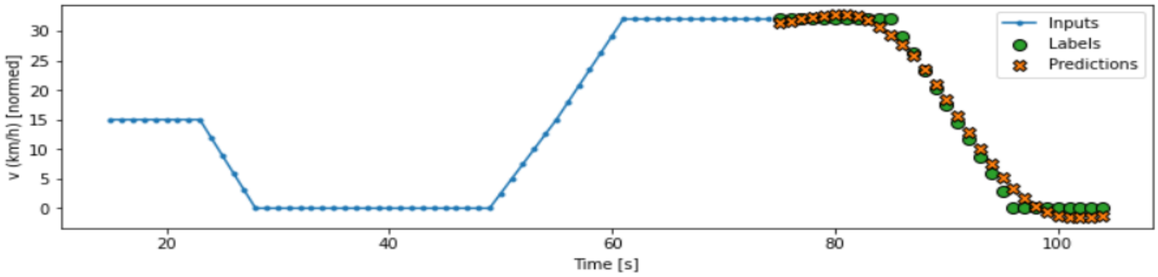
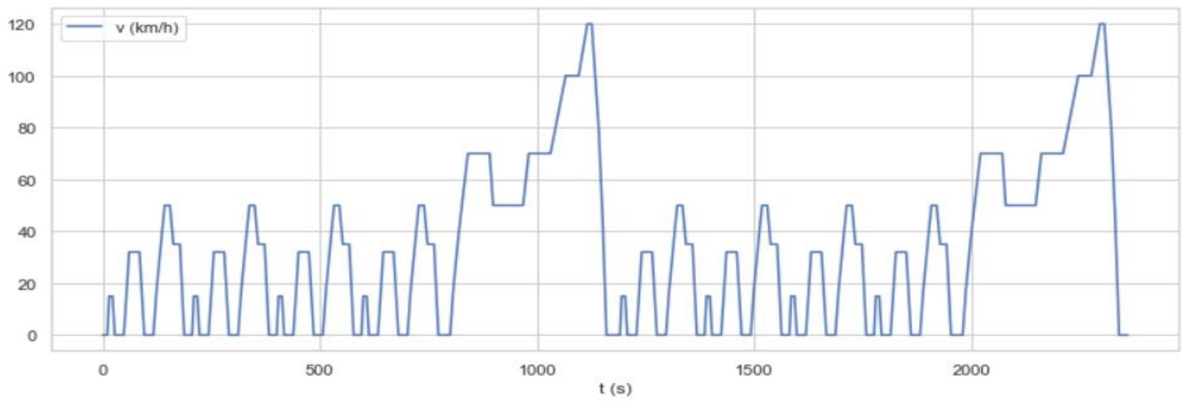
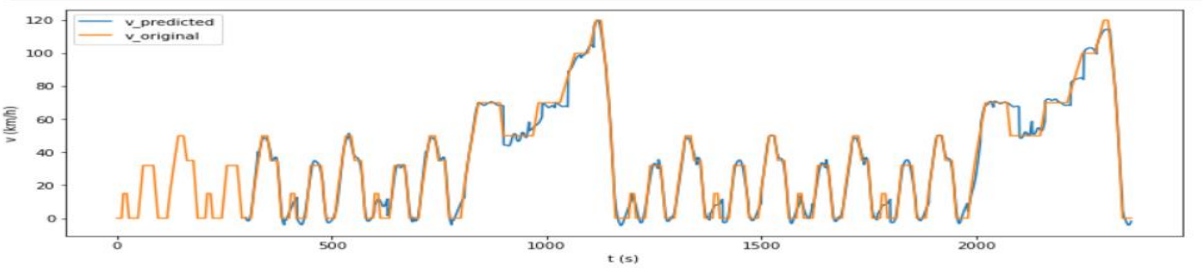


Fig.3.28 Training Results Time vs Velocity

From Fig 3.28 it is observed that by rigorous training the model is able to predict the velocity of the vehicle based on the driving cycle and SoC is maintained by adjusting the participation of the HESS.



a) Original Velocity



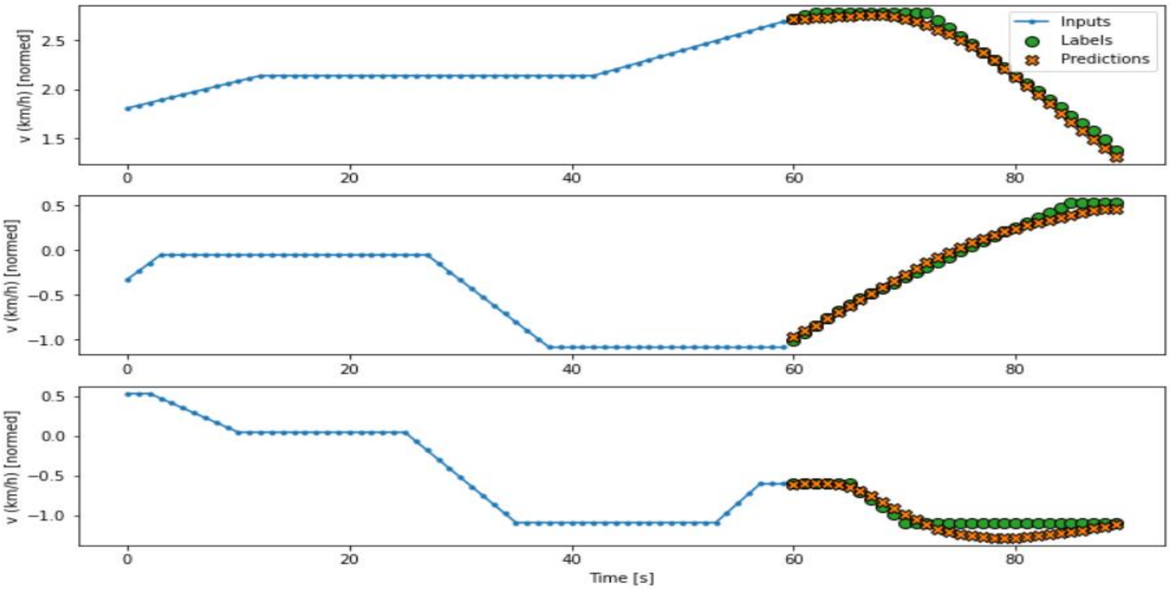
b) Original vs Predicted Velocity

	count	mean	std	min	25%	50%	75%	max
v (km/h)	2361.0	33.612876	30.985363	0.0	2.5	32.0	50.0	120.0

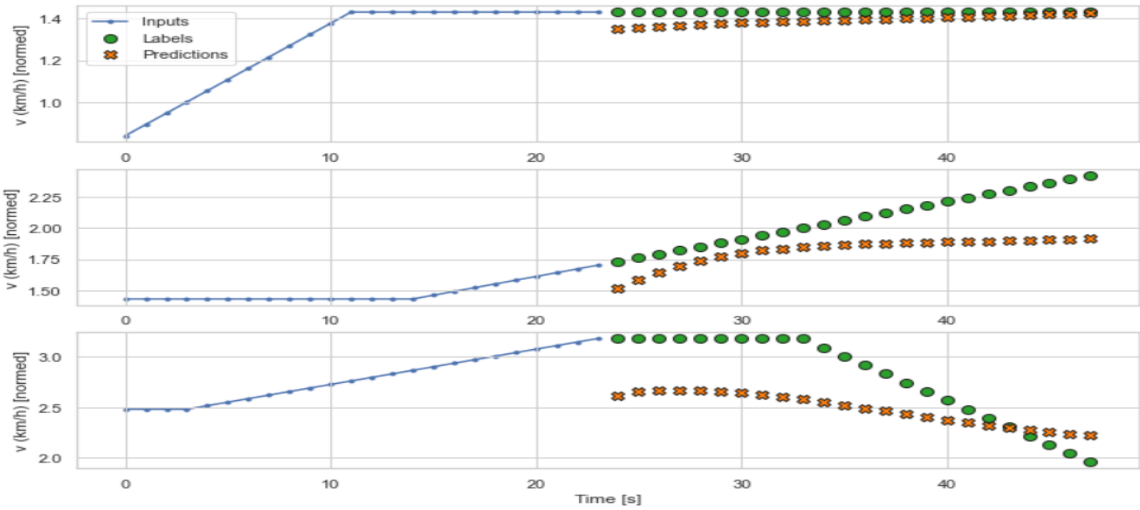
c) Training and Validation

Fig.3.29 Driving Cycles Training Results a) Original, b) Original vs Predicted c) Validation

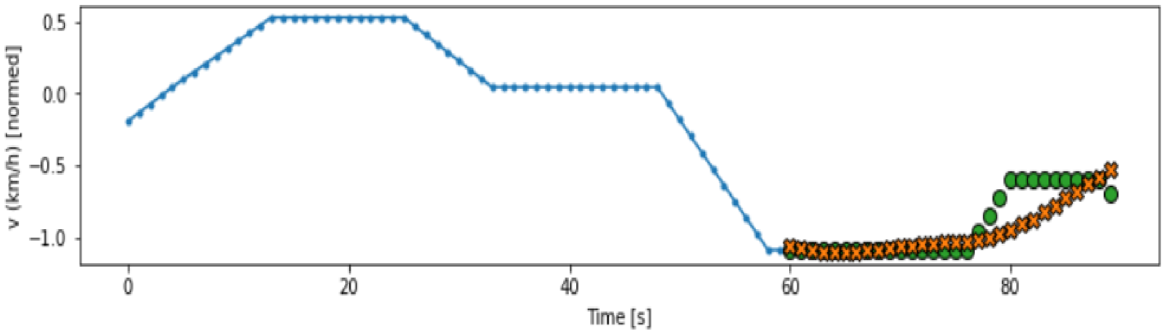
The comparison of predicted and actual velocities along with the validation parameters is represented in Fig 3.29. A practical driving cycle represents real-world driving conditions experienced by vehicles in specific environments, often derived from actual data collected from on-road vehicle operations. These cycles account for various factors such as traffic patterns, road conditions, and driving behaviors (e.g., acceleration, deceleration, idling). For instance, the Worldwide Harmonized Light Vehicles Test Procedure (WLTP) and the Urban Dynamometer Driving Schedule (UDDS) are examples of standardized cycles that aim to replicate typical driving scenarios. Practical driving cycles are essential for evaluating vehicle performance, emissions, and fuel efficiency under conditions that closely resemble everyday use. he key difference between practical and prediction-based driving cycles lies in their data foundation and application. Practical driving cycles are grounded in empirical data, making them more reliable for assessing vehicle performance in real-world scenarios. They help manufacturers and policymakers understand the environmental impact of vehicles more accurately. On the other hand, prediction-based driving cycles offer flexibility and can be tailored for various conditions, making them useful for simulations and early-stage design processes. However, they may lack the precision needed for regulatory compliance or real-world performance validation. Ultimately, both approaches are valuable, with practical cycles providing a benchmark for validation and prediction-based cycles facilitating exploratory analysis and design optimization.



a)



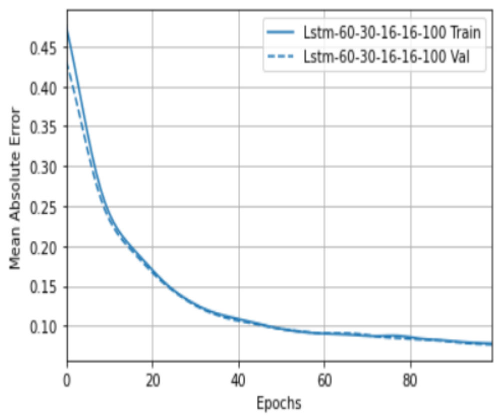
b)

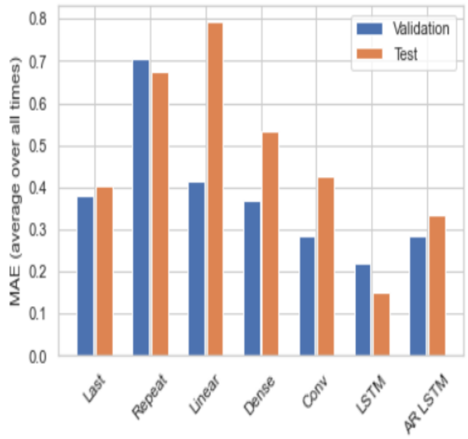


c)

Fig.3.30: Other Training Results a) Original, b) Original vs Predicted c) Validation

The comparison of predicted and actual velocities along with the validation parameters with LSTM is represented in fig 3.30.





a) Training and Validation

b) Comparison Graph

Last	0.4044
Repeat	0.6754
Linear	0.7917
Dense	0.5319
Conv	0.4266
LSTM	0.1508
AR LSTM	0.3339

c)Validation Count

Fig.3.31AR-LSTM Training Results a) Training and Validation, b) Comparison Graph c) Validation Count

The comparison of predicted and actual velocities along with the validation parameters with AR-LSTM are represented in Fig 3.31.Driving cycle prediction using Long Short-Term Memory (LSTM) networks involves utilizing this specialized type of recurrent neural network to model and forecast vehicle behaviour over time. Driving cycles consist of sequences of vehicle parameters, such as speed and acceleration, captured during actual driving conditions. These cycles reflect real-world factors like traffic patterns, road types, and driver behaviour, making accurate predictions crucial for applications in vehicle design and energy management. LSTMs are particularly well-suited for this task due to their ability to learn long-term dependencies in sequential data. The architecture includes memory cells and gates that manage the flow of information, allowing LSTMs to retain relevant past information while filtering out irrelevant data. This capability enables them to effectively capture complex patterns and temporal dynamics inherent in driving cycle data, making them powerful tools for predicting future driving behaviour based on historical sequences.

The prediction process begins with preprocessing the driving cycle data, which may involve normalization and segmentation into sequences. Once the model is trained on historical data, it can predict future cycles by taking the most recent data points as input. By doing so, LSTMs provide valuable insights into expected driving behaviours, supporting applications such as optimizing energy consumption in electric vehicles and enhancing the accuracy of vehicle performance simulations. This predictive capability ultimately contributes to the development of more efficient and intelligent transportation systems. the plot of forecast and observed data of IDC after the training process. The forecast IDC starts after 2487 seconds right after the previous IDC. Figure 3.32a shows the root square mean error (RSME) between the speed and time of the forecast and test data. From the figure, it shows that the RSME is 6.2252%. An RMSE of 6.2252% often denotes very strong predictive performance for the predictive model. Achieving an even lower value implies that the model is making accurate predictions relative to the scale of the target variable. An RMSE of 6.2252% denotes that, on average, the model's predictions are only 6% off from the actual value. For these applications and domains, this level of accuracy may be sufficient. It is frequently very desirable. Real-world driving data may be noisy and inconsistent due to a number of issues, including measurement flaws or erratic traffic circumstances. LSTM networks are able to handle noisy data well and may be trained to identify patterns in the noise. The LSTM's capacity to eliminate unimportant noise and concentrate on crucial aspects aids in better driving cycle prediction. Moreover, depending on the length of the trip or the traffic, driving cycles can vary in length. LSTM networks are adaptable to handling various driving cycle durations without requiring set input sizes since they can process sequences of varying lengths. This versatility is especially useful when working with driving data from the real world, where route lengths can vary greatly.

In AIRA, which stands for Artificial Intelligence for Real-time Analysis, is a powerful tool designed to enhance acceleration prediction in various applications, including electric vehicles and performance training. By leveraging advanced machine learning algorithms and real-time data processing, AIRA can analyze numerous variables influencing acceleration, such as vehicle dynamics, driver behaviour, and environmental conditions. This technology aims to provide accurate forecasts that enable improved decision-making and performance optimization.

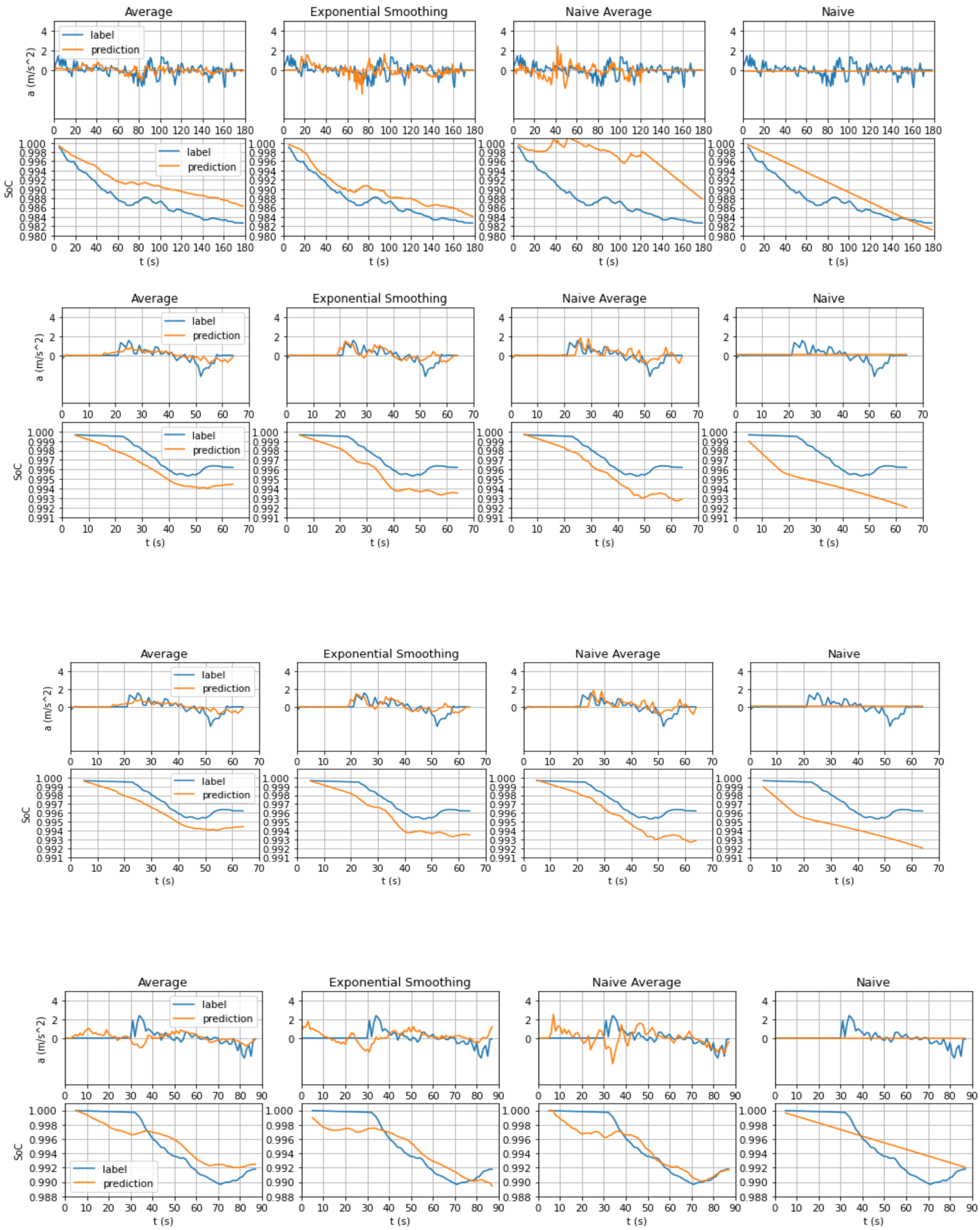


Fig.3.32 Prediction Acceleration Training Results for Urban flowing, Urban Congested, Subway, High way patterns.

From Fig 3.32 it is observed that the acceleration prediction is done for different drivingpatterns and the results show that the accuracy of prediction improved with LSTM

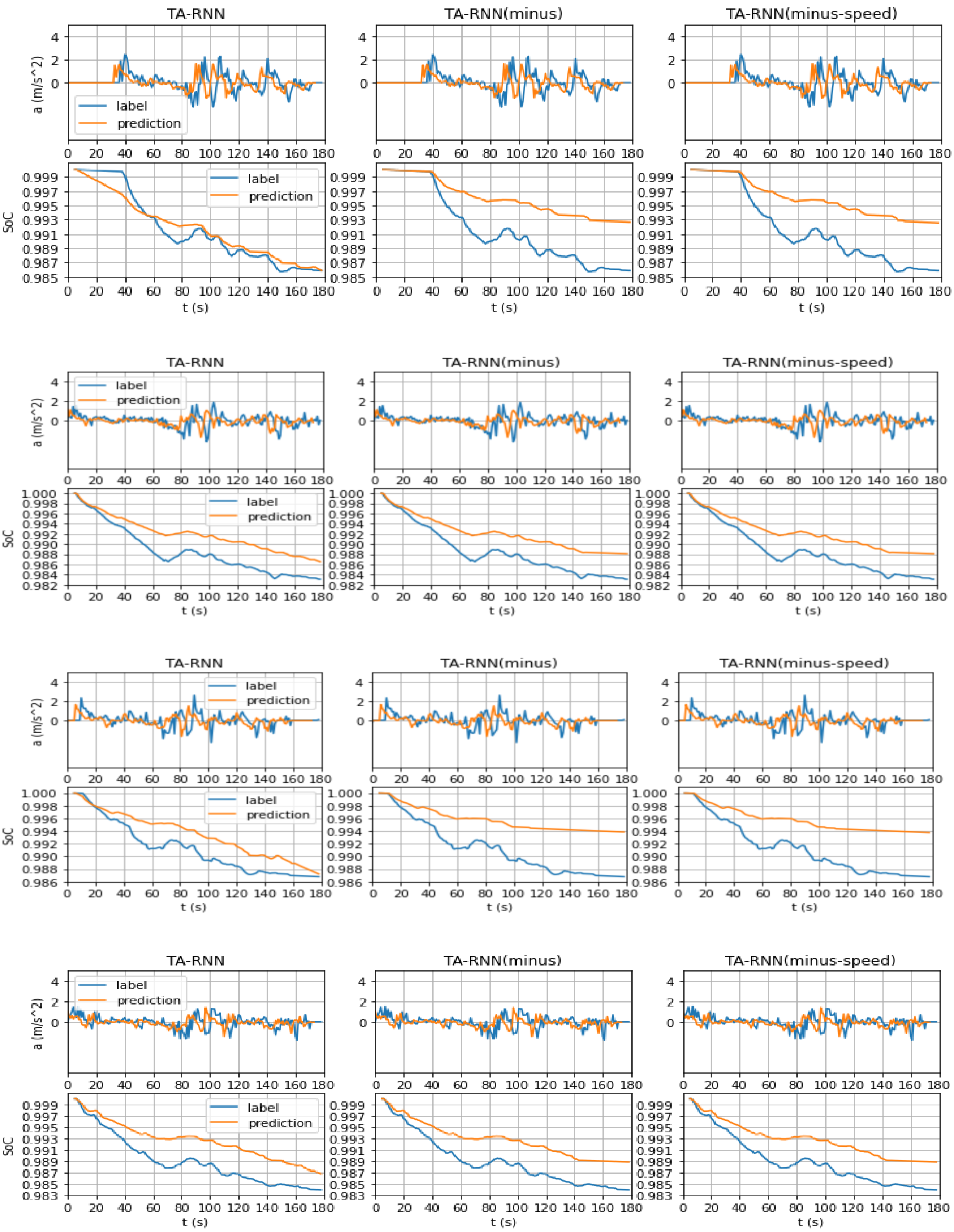


Fig.3.33 Prediction ARIMA Training Results for Urban flowing, Urban Congested, Subway, High way patterns

ARIMA (Auto Regressive Integrated Moving Average) is a powerful statistical modelling technique commonly used for time series forecasting, including the estimation of the State of Charge (SoC) in batteries. SoC estimation is crucial for managing battery systems in applications like electric vehicles and renewable energy storage, as it provides insights into the remaining energy and overall health of the battery. The ARIMA model consists of three main components: Auto-Regressive (AR), Integrated (I), and Moving Average (MA). The AR part uses past values of the series to predict future values, while the MA part uses past forecast errors. The Integrated component involves differencing the data to make it stationary, which is necessary for ARIMA modelling. Stationarity ensures that the statistical properties of the time series, such as mean and variance, do not change over time, which is vital for accurate forecasting. In the context of SoC estimation, ARIMA can be applied to historical battery data, such as voltage, current, and temperature readings, to forecast future SoC levels. By analyzing the time series of these parameters, an ARIMA model can learn the underlying patterns and trends, capturing the battery's charging and discharging behaviour. This predictive capability allows for real-time monitoring and accurate estimation of SoC, which is essential for efficient battery management and optimizing performance.

To implement ARIMA for SoC estimation, historical data is divided into training and testing datasets. The model is trained on the training set, where parameters are optimized to minimize forecasting errors. Evaluation metrics such as Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) are used to assess the model's accuracy. Visualizations, such as time series plots, help compare predicted SoC values against actual measurements, providing insights into the model's effectiveness. It is observed that the acceleration prediction is done for different driving patterns and the results show that the accuracy of prediction improved with ARIMA.

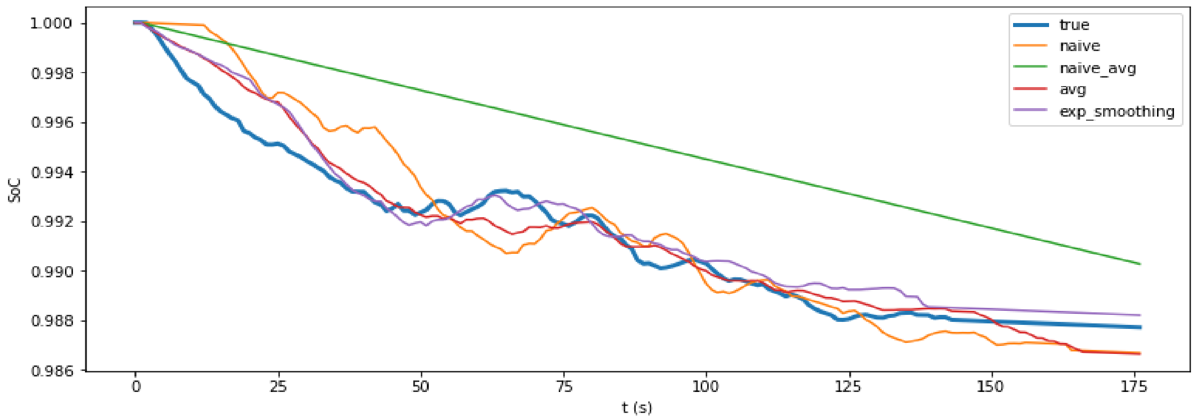


Fig 3.34 Comparison with other forecasting methods

The above Fig 3.34 represents the comparison of SoC estimation for different forecasting methods and it shows a lot of noise in present in the prediction.

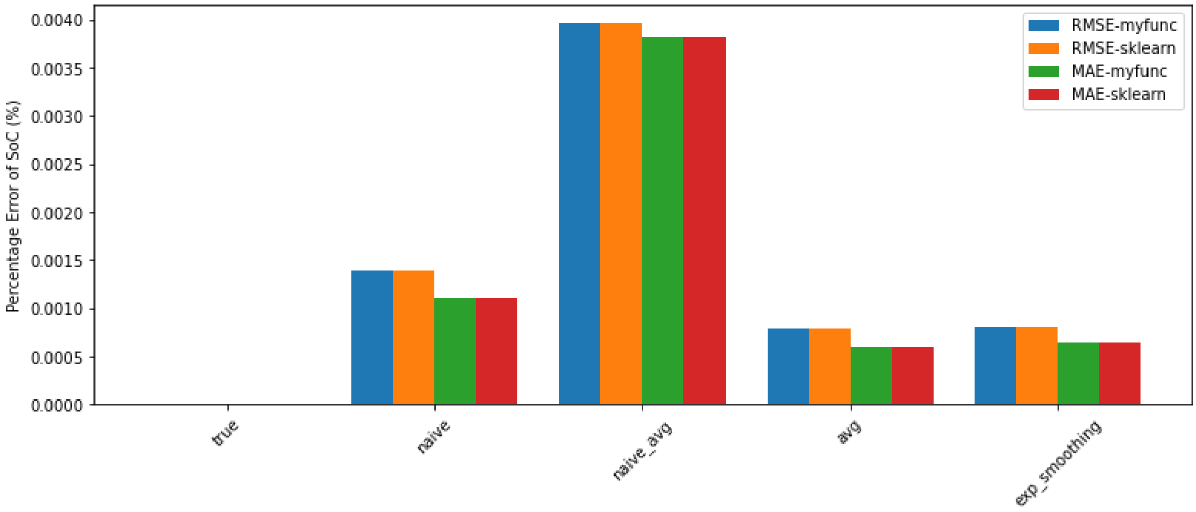


Fig 3.35 Comparison of percentage error with other methods

In Figure 3.35 Comparing the proposed method with the existing methods it is observed that the proposed method shows better performance in terms of predicting the driving cycle, acceleration and SoC. In Fig 3.35 the percentage error is compared with the standard methods like RMSE and it is observed that the proposed MAE has minimal error.

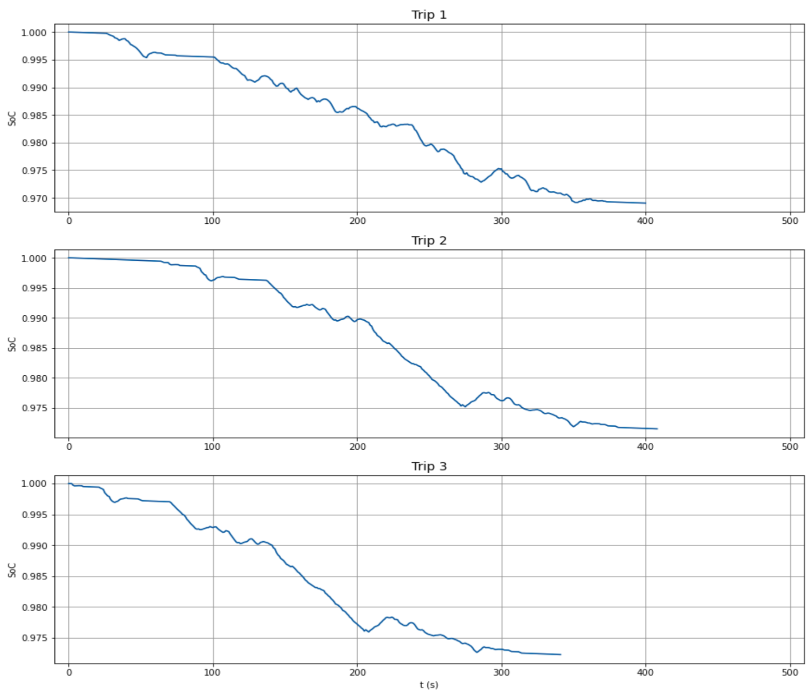


Fig 3.36Comparison of Various Trips with SoC Vs Time

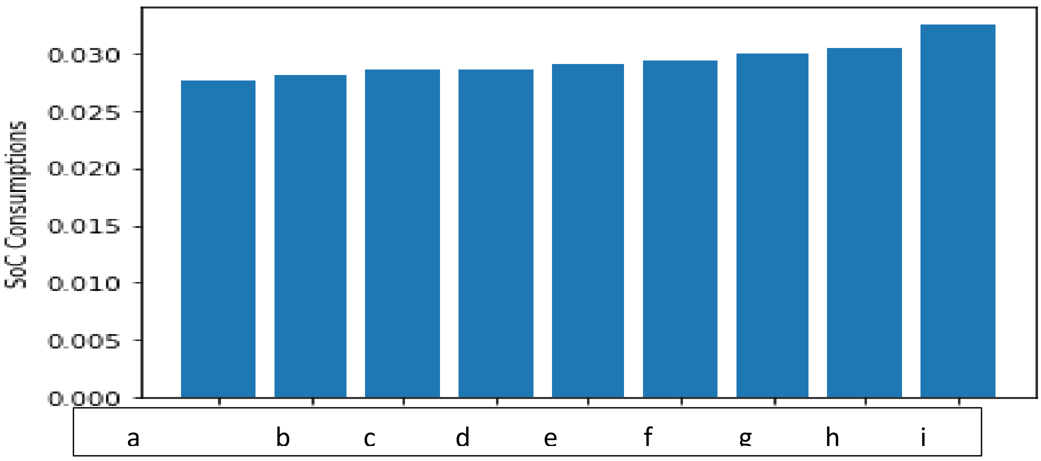


Fig 3.37 Comparison ofSoC consumption in different areas.

a) Banugudi to JNTUK
b) JNTUK to Sarpavarm
c) Sarpavaram to APSP
d) APSP to Beach Road
e) Beach Road toUppada
f) Uppada to Pithapuram
g) Pithapuram to Gollaparolu
h) Gollaparolu to APSP
i) APSP to JNTUK

The above Fig 3.36 shows the estimated SoC consumption details of the battery during different driving cycle patterns. The AIRA-obtained values are used to design the HESS for the hybrid vehicle and EVs. The predicted values of SoC are tested with the real-time trips represented in Fig 3.36.The value of SoC after each trip with the standard data is represented in Fig 3.37. The results show that the data generated is well validated both in practical and summation cases for accurate estimation of the SoC.

3.5 Summary:

In this Chapter, vehicle specifications like rolling resistance, drag coefficient, Total resistance, Air Drag, Torque calculations and Acceleration Gradient are determined. Data sets have been collected through electronic modules for Urban, subway, Highway, Rural, and semi-urbanterrain conditions and these datasets are trained for prediction through algorithms LMBT, LSTM, and ARIMA. Finally, the consumption of SoC and error percentages are presented.

CHAPTER 4
HYBRID ENERGY STORAGE

This chapter focuses on HESS, in a Pure Electric Vehicle (EV), integrating a Hybrid Energy Storage System (HESS) with a Battery, Super-capacitor, and Fuel Cell (BA+SC+FC model).HESS is the combination of strengths from multiple energy sources, enhancing reliability and performance through high energy density from the battery and high power density from the supercapacitor respectively. The LMBT-MNN model is employed to assess cost, power, and energy objectives by dividing the dataset into segments for prediction, testing, and validation. The analysis integrates mathematical and simulation-based approaches, incorporating auxiliary inputs like rolling resistance and aerodynamic drag coefficients.

The control parameters for different energy storage systems are given in Table 4.1.

4.1 Specifications of Various Energy Storages Used in the Research Work:

Table 4.1: Energy Storage Parameters

Li-ion	• State of Charge (SoC) • State of Health (SoH) • Terminal Voltage • Current Cell Temperature
Super capacitor	• Capacitance • Operating Voltage • Equivalent series resistance(ESR) • Power Density • Energy density
Fuel Cell	• Operating Voltage • Power output • Discharge current • Operating Temperature • Internal Cell Resistance

Electric vehicles (EVs) utilize various energy sources depending on the type of vehicle and its specific design. Below are the main energy sources used in this work. The table represents the merits, demerits and specifications of batteries, fuel cells and supercapacitors.

Table 4.2: Various Power Sources with Specifications

Power Sources	Advantages	Limitations	Specifications
Fuel cell	• Directly converts chemical energy into electrical energy. • Zero emissions of harmful gases. • More energy efficiency compound with IC engine. • Renewable Energy • Higher part load efficiency • Only Water as bi-product	• Expensive to fabricate due to the high cost of catalysts. • High inflammable. • Storage of hydrogen gas. Lack of infrastructure to support the distribution of hydrogen.	• Cell rated Voltage:0.65 V • Cell Exchange Area: 250 (mm2) • Reference Temperature: 303 (K) • Exchange Current Density: 0.1 (mA/cm2) • Maximum Current Density: 2.2(mA/cm2) • Icharge Transfer Coefficient: 0.5 • Hydrogen Gas Constant: 4124.36 • Oxygen Gas Constant: 259.81
Li-ion Battery	• High specific energy. • Self-discharge is much lower than that of other rechargeable batteries. • Low maintenance.	• Batteries cannot be charged or discharged at high currents. • Less cycle life. • Low specific power. • Requires protection circuit to maintain voltage and current within safe limits.	• Cell Voltage: 3.6 V (Nominal) • Charging Time: 10 to 60 min • Specific Energy(Wh/kg): 120 to 240 • Specific Power (W/kg): 1000 to 3000 • Cycle Life: 5 to 10 Years • Cost per kWh: \$200-1000(For large Systems)
• **Super Capacitor**	• High specific power and low resistance enable high load currents. • It can produce a sudden burst of powers with better performance and unlimited cycle life. • It can also charge as well as discharge at high currents.	• Low specific energy. • Low cell voltage requires series connections with voltage balancing. • High cost per Watt. • High self-discharge is even higher than most batteries.	• Cell Voltage: 2.3-2.75 V • Charging Time: 10 to 60 min • Specific Energy(Wh/kg): 120 to 240 • Specific Power (W/kg): 1000 to 3000 • Cycle Life: 5 to 10 Years • Cost per kWh: \$200-1000(For large Systems)

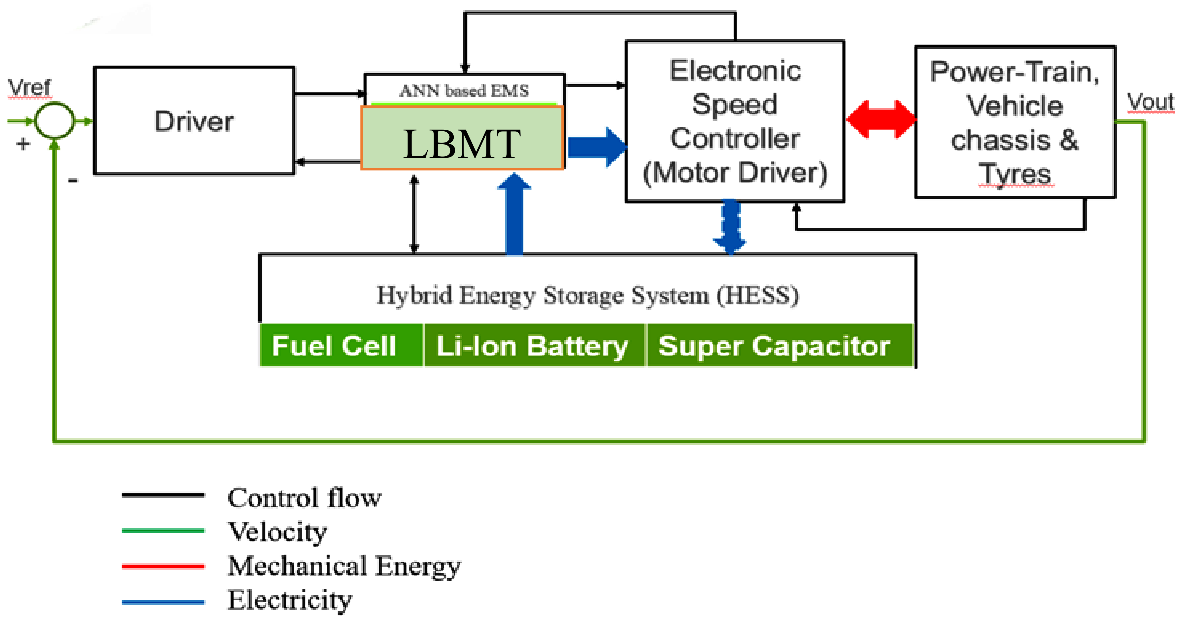


Fig. 4.1: Proposed Hybrid Energy Storage Based EV.

Fig.4.1 represents the details of the proposed control strategy for optimizing power utilization in the presence of different power sources in an EV.

4.2 Flow Chart for HESS:

The process of ANN performing design optimization is shown below in Fig 4.2.It is assumed to take input data of Energy Storage Systems from existing EVs. Also assumed the limits of each energy storage device and their approximate cost/kWh as per market trends. The ANN tends to compare the power density, energy density & cost of each scenario it has built from a combination of hybrid sources. After several iterations, we will get multiple recommendations that need to be again filtered to one best alternative by proper simulation with drive cycle sources.

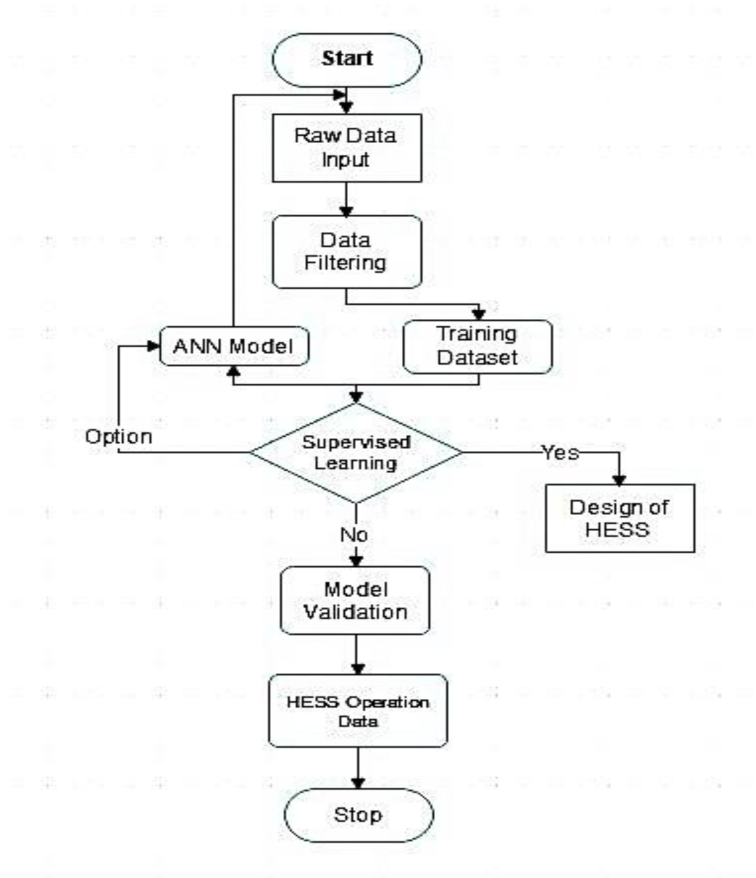


Fig .4.2: Proposed Flowchart for Design Optimization of HESS.

4.3 Modeling of Various HES:

4.3.1 Modeling of Battery:

Figure 4.3 shows the battery circuit modeling. The battery is a Hybrid energy storage system (HESS) key component. Here Lithium-ion (Li) battery is used.

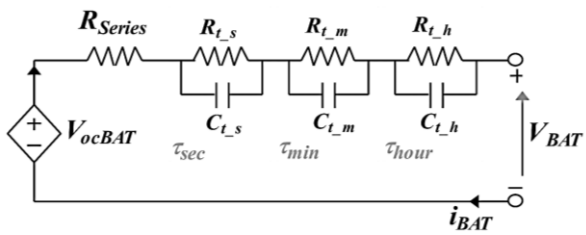


Fig. 4.3 Circuit Representation of Battery

Where, the battery open circuit voltage is denoted as V_{ocBAT}, an output voltage of the battery is V_{BAT} and the battery series resistance is denoted as $R_{Series.}$ Multiple time constants are there in the R-C circuit. They are τ_{hour}, τ_{sec} and τ_{min}. These parameters are called SoC functions and are also used to model the transient behavior of the battery as shown in Fig 4.4. Battery SoC- state of charge calculation is as used in the following Equation [36].

$$\mathrm{SoC} = \mathrm{S}o\mathrm{C}_0 + \frac{\eta_{BAT}}{(3600.C_{BAT})}\int i_{BAT}dt \tag{4.1}$$

Where the battery's initial parameters are i_{BAT} is the current of the battery, SoC_0 is the SoC of the battery and C_{BAT} is the battery capacity. .

4.3.2 Modeling of Fuel Cell

The Fuel Cell (FC) is the primary power source in the system, with hydrogen stored in a tank. The FC system consists of multiple auxiliary components that function together at different scales, each serving a specific purpose. It is primarily selected for low dynamic conditions, where power demand remains stable. The FC behaves like a voltage source and is influenced by ohmic resistance, mass transfer, and kinetic energy. Ohmic resistance causes energy losses within the cell, while mass transfer involves the movement of reactants and by-products, affecting efficiency. Kinetic energy refers to the flow of ions and electrons during the electrochemical reaction. The FC is ideal for steady-state driving, as it provides continuous, efficient power under low power fluctuations. This makes it suitable for longer trips and more energy-efficient operation.

The FC voltage and current relationships are noted as follows,

$$V_{FC} = N\begin{pmatrix} E_{cell} - R.j_{Stack} \\ -A.\ln\left(j_{Stack} + j_l\right) - m\exp(nj_{Stack}) \end{pmatrix} \tag{4.2}$$

$$\begin{cases} j_{Stack} = \frac{I_{Stack}}{A_{cell}} \\ I_{Stack} = \alpha + (1+\beta)i_{FC} + \gamma(i_{FC}) \end{cases} \tag{4.3}$$

Where V_{FC} is the FC voltage, the current for the FC is i_{FC}, each fuel area is A_{Cell}, the FC reversible voltage is E_{Cell}, FC stack number is N, the Density of the FC current is j_{Stack}, specific resistance of membrane area is R, mass the transfer two coefficients are m and n, coefficient of Tafel is A, Second order model approximating coefficients are α, β and γ, Fuel stack current is denoted as I_{Stack}, i_{FC} is the output current of FC [37].

4.3.3 Modeling of Super Capacitor

The traditional theoretical model for super-capacitors (SC) in hybrid systems utilizes a transmission line model, where the behaviour is governed by the voltage V_{SC} divided by the capacitance [38]. This model aims to accurately represent the SC's performance during both charging and discharging cycles. To capture the nonlinear behaviour of the electrodes, a resistance-capacitance (RC) model is employed. The SC itself is modelled as a simple capacitor, with losses being considered negligible due to their minimal impact compared to the transmitted power. Additionally, the SC current regulator incorporates a rectifier, which naturally compensates for any variations. A schematic of the SC circuit is shown in Figure 4.5

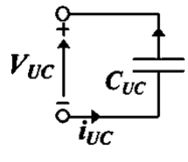


Fig. 4.4SC Circuit Diagram

4.4 Hybrid System Structure

The hybrid system structure consists of a battery, fuel cell (FC), and ultra-capacitor (SC). In this setup, a DC-DC boost converter is used to regulate the DC bus voltage, maintaining it at the desired level. The system also includes an integrated DC bus storage system and battery, each with a reversible DC/DC step-down converter for voltage regulation. The simulation results have been discussed in section 4.6. The state-space equation for the general system, of order 8, is provided in references[34-38]

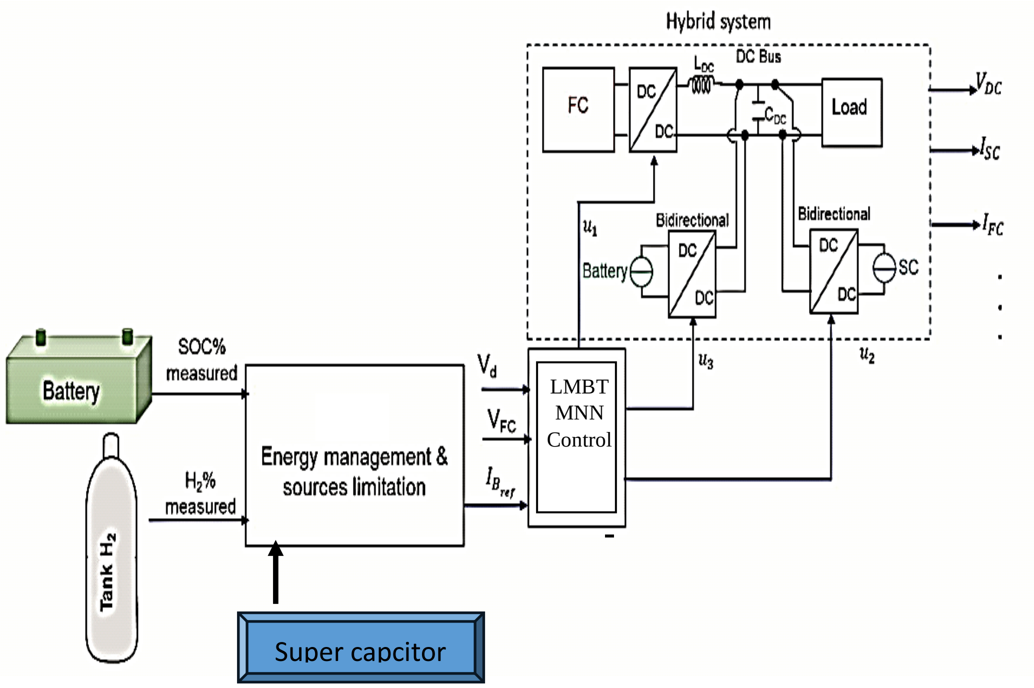


Fig. 4.5 LMBT-MNN Controllable EV Hybrid Structure.

To examine the limitations of the State of Charge (SoC) of the battery and the hydrogen level in the fuel tank, the LMBT-MNN strategy is implemented, as shown in Figure 4.6. In this setup, the battery current (I_{Bref}) is used as a reference, while the fuel cell voltage FC is V_{FC} and the reference voltage of the DC bus is V_d are also provided as inputs. These three parameters are fed into the LMBT-MNN to compute the control variables (u1,u2,u3)(u_1, u_2, u_3) which represent the control laws for the three converters. Using these converter control laws, various simulated variables can be obtained, including the DC bus current (I_{SC})the DC bus voltage (V_{DC}) and the fuel cell current (I_{FC}) [39].

The state-space equation of the hybrid system, which is of the 8th order, is as follows:

$$\begin{cases} \frac{dV_s}{dt} = \frac{1}{C_s}[(1-u_1)i_{FC} - i_{DC} \\ \frac{di_{FC}}{dt} = \frac{1}{L_{FC}}[V_{FC} - (1-u_1)V_s \\ \frac{dV_{DC}}{dt} = \frac{1}{C_{DC}}[i_{DC} - i_L + (1-u_2)i_{SC} + (1-u_3)i_B \\ \frac{di_{DC}}{dt} = \frac{1}{L_{DC}}[V_S - V_{DC}] \\ \frac{dV_{SC}}{dt} = \frac{-1}{C_{SC}} i_{SC} \\ \frac{di_{SC}}{dt} = \frac{1}{L_{SC}}[V_{SC} - (1-u_2)V_{DC}] \\ \frac{di_B}{dt} = \frac{1}{L_B}[V_B - (1-u_3)V_{DC}] \\ \frac{di_L}{dt} = \frac{1}{L_L}[-R_L i_L + V_L] \end{cases} \quad (4.4)$$

Therefore the defined state variables are,

$$x = [x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8]^T = [V_S, i_{FC}, V_{DC}, i_{DC}, V_{SC}, i_{SC}, i_B, i_L]^T \quad (4.5)$$

The static model provide VFC and VB=eB-rBiB.
The Hybrid EV must satisfy the electric power balance Equation as follows,

$$P_{FC} + P_B + P_{SC} = P_{Load} \quad (4.6)$$

This study's main objectives are:

- To control a hybrid multi-source system using the LMBT-MNN method.
- The SoC and H_2 quantity of the battery is subject to the source limit.
- Battery current reference is better for choosing LMBT-MNN methods in different situations. (Check if the battery is charged with this method.)

The above objectives are attained to use the following equations,

$$x = [\overline{x_1}, \overline{x_2}, \overline{x_3}, \overline{x_4}, \overline{x_5}, \overline{x_6}, \overline{x_7}, \overline{x_8}]^T = [V_d, \overline{x_2}, V_d, \overline{x_4}, \overline{x_5}, 0, \overline{x_7}, \frac{V_d}{R_L}]^T \quad (4.7)$$

To calculate the equilibrium control signals after simple calculations is

$$\bar{u} = [\overline{u_1}, \overline{u_2}, \overline{u_3}]^T = \left[\frac{V_{FC}}{V_d}, \frac{V_{SC}}{V_d}, \frac{e_B - r_B\overline{x_7}}{V_d}\right]^T \quad (4.8)$$

Here the SoC of the battery is considered an important parameter. LMBT-MNN is used to deliver the desired battery current [40].

$$SoC = SoC_0 - \int \frac{i_B}{Q_n} dt \quad (4.9)$$

where the nominal capacity of the battery is Qn, the battery current is i_B, and the battery's initial SoC is SoC_0. To determine the reference current of the battery, the SoC of the battery is given as input to the LMBT-MNN through the hydrogen level of the FC. The battery is charged fully, which helps to operate FC in a steady state. If the FC is damaged, the battery will be used according to its SoC level, allowing continuous operation in faulted mode.

4.5 The Hybrid Power Sources Proposed Control

The sum-of-squares error functions are minimized using the Levenberg-Marquardt (L-M) algorithm, which ensures optimal performance. In 1974, Paul Werbos developed the Backpropagation (BP) algorithm, and later, Rumelhart and Parker refined and reconstructed it [41-46]. The reconstructed BP algorithm has become widely used in neural network learning applications. In this context, the learning algorithm is applied to feed-forward multilayer neural networks (ANNs). The artificial neural network (ANN) utilizes parallel training techniques to enhance the efficiency of the Multilayer Perceptron (MLP) network through the Backpropagation (BP) algorithm. This approach is particularly effective for complex networks, making it easy to learn and highly popular due to its simplicity and effectiveness.

4.5.1 Flow Chart

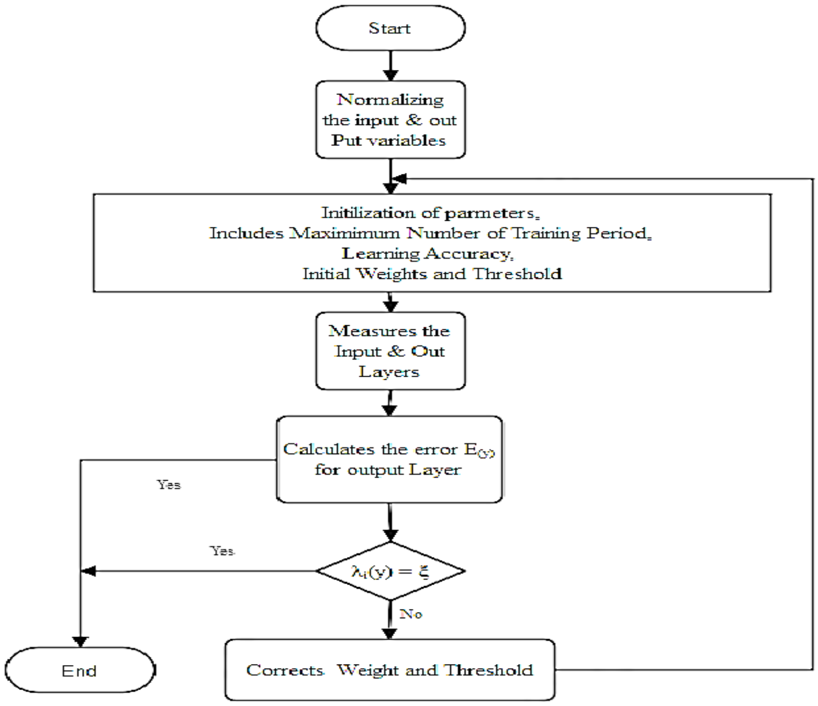


Fig. 4.6 LMBT Flowchart

To minimize the network error, the learning technique for BP is used and it's based on the method of Gradient Descent (GD) as shown in Fig 4.6. For multilayer networks and nonlinear activation functions its reflected delta rule generalization [47].

The feed-forward neural network's layered structure is considered and it is having an input and one or more parallel neurons [48]. The first layer is the input layer. Inputs do not perform any calculations. Their only role is to feed the model to other parts of the network. The first layer of neurons is connected to the next layer of all neurons. In this connection, no other neurons are there. The final layer is the output layer, this is the neural network output. Before the output, the layer is called the hidden layer. The LMBT working flowchart is shown in Figure 4.7.

Levenberg – Marquardt algorithm is designed to minimize sum-of-square error functions [49],

$$E = {}^{1}/_{2} \sum k(e_k)^2 = {}^{1}/_{2} \|e\|^2 \tag{4.10}$$

Where the vector with element $e_k$is denoted as e and k^{th} pattern error is denoted as ek.

The error vector is defined as the difference between the weight of the vector for the new and old one. So the error vector follows the Taylor series first-order methods. This as follows,

$$e_{(j+1)} = e_{(j)} + \partial e_k / \partial w_i \left(w_{(j+1)} - w_{(j)}\right) \tag{4.11}$$

The function of error for the above consequence can be expressed as

$$E = {}^{1}\!/_{2}\left\| e_{(j)} + \partial e_k / \partial w_i \left(w_{(j+1)} - w_{(j)} \right) \right\|^2 \tag{4.12}$$

The vector weight of the new one is used to Minimizing function of the error,

$$w_{(j+1)} = w_{(j)} - (Z^T Z)^{-1} Z^T e_{(j)} \tag{4.13}$$

$$\text{Where, } (Z)_{ki} = \partial e_k / \partial w_i \tag{4.14}$$

The function of sum-of-square error for the Hessian is

$$(H)_{ij} = \frac{\partial^2 E}{\partial w_i \, \partial w_j} = \sum \left(\frac{e_k}{\partial w_i} \right) \left(\frac{e_k}{\partial w_i} \right) + e_k \, \partial^2 e_k / \partial w_i \, \partial w_j \tag{4.15}$$

Neglecting the second term, the Hessian can be written as $H = Z^T Z$

Therefore, the weight updating process involves nonlinear networks or the inverse Hessian. The computation of the Hessian is relatively straightforward since it involves the first-order derivatives with respect to the network's weights, and its backpropagation can be easily implemented.

However, while the modified formula can be applied iteratively to reduce the error, it may cause large updates to the weights. These large steps can lead to instability in the model, resulting in incorrect prediction paths or convergence to suboptimal solutions. Thus, careful management of the step size is necessary to ensure the model learns effectively without overshooting the optimal solution.

$$E = {}^{1}\!/_{2}\left\| e_{(j)} + \partial e_k / \partial w_i \left(w_{(j+1)} - w_{(j)} \right) \right\|^2 + \lambda \left\| \left(w_{(j+1)} - w_{(j)} \right) \right\|^2 \tag{4.16}$$

Where the step size parameter governing is λ.

$$w_{(j+1)} = w_{(j)} - (Z^T Z + \lambda I)^{-1} Z^T e_{(j)} \tag{4.17}$$

The λ value is very large represent standard gradient descent, while λ value is very small represent Newton's method.

4.6 Simulation Results

It was created using Matlab, Simulink, and Sim Power Systems Toolbox software. Figure 4.7shows a representation of Simulink EMS on an LMBT-MNN-based battery, FC and ultra-capacitor. The power management subsystem is shown in Figure 4.9.

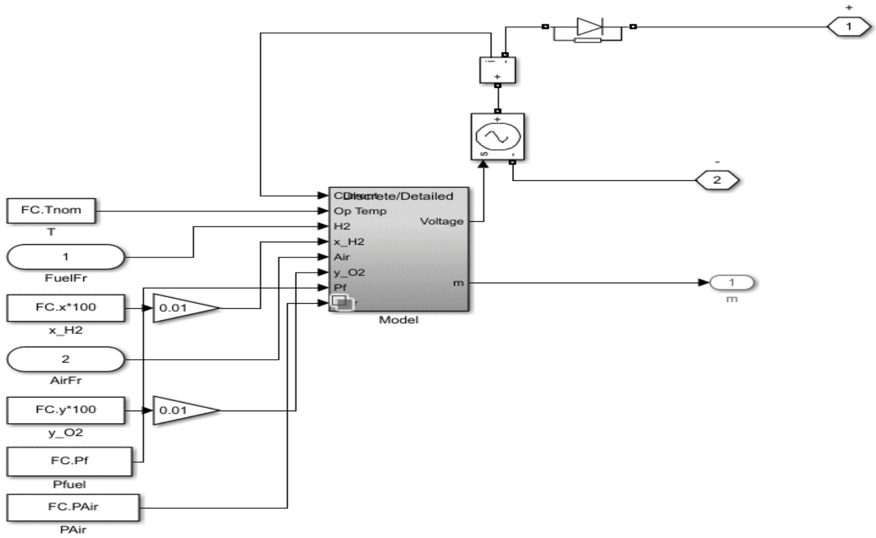


Fig. 4.7 Simulink representation of the proposed hybrid system

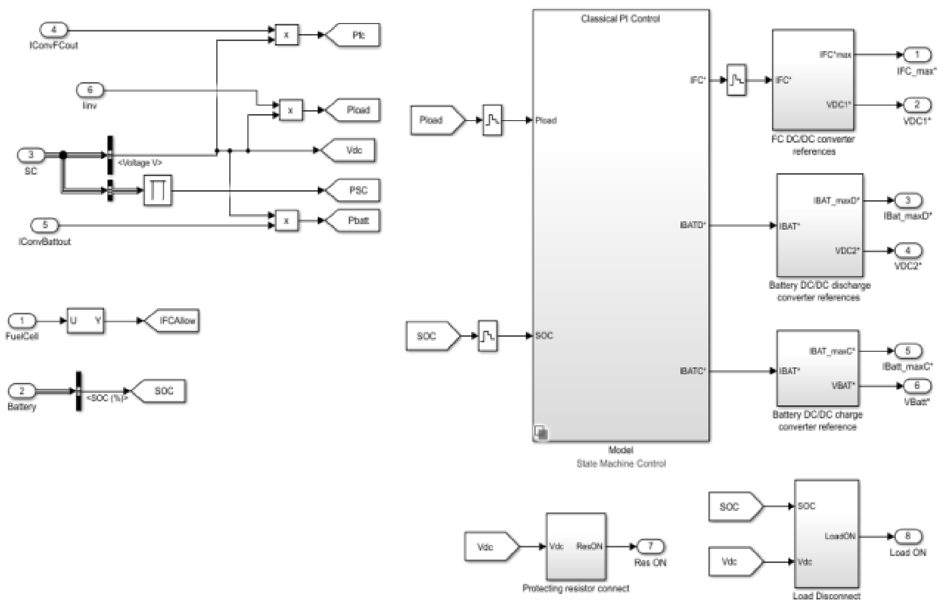


Fig .4.8 Simulink Representation of E M System

FC output voltage and current are shown in Figure 4.8. Consider two cases for comparison. In the first case, without the use of the LMBT strategy, the fuel cell (FC) operates at a voltage of 52V and a current of 20A. This scenario represents the baseline system performance.In the second case, the LMBT-based multi-layer neural network (MNN) approach is employed. The FC voltage and current remain the same as in the first case, but the oscillations are significantly reduced. This is achieved by using the LMBT-MNN concept, which helps to smooth out fluctuations and improve system stability.Furthermore, the LMBT-MNN generates a pulse signal, which is then fed to the DC-to-DC converter, as illustrated in Figure 4.8. This approach enhances the control and regulation of the power conversion process, leading to more stable system behavior compared to traditional methods.

Table.4.3 Parameters for Battery, Super Capacitor and FC

Battery Parameters:				
S.No	**Parameters Considered**	**Values**		
1.	Nominal Voltage	48 V		
2.	Rated Capacity	80 Ah		
3.	Initial SoC	85 %		
4.	Battery Response Time	15 sec		
Super Capacitor Parameters:				
1.	Rated Capacitance	15.6 F		
2.	Equivalent DC Series Resistance	150e-3 Ohms		
3.	Rated Voltage	291.6 V		
4.	Capacitors Series	108		
5.	Parallel Capacitors	1		
6.	Initial Voltage	290 V		
7.	Operating Temperature	25 Celsius		
FC Stack Parameters:				
1.	Voltage at 0A and 1A [V0,V1]	52.5	52.46 V	
2.	Normal Operating Point [I_{nom}(A), V_{nom} (V)]	250A	41.15 V	
3.	Maximum Operating Point [I_{end}(A), V_{end} (V)]	320	39.2	
4.	Number of Cells	65		
5.	Operating Temperature	45 Celsius		
6.	Nominal Stack Efficiency	50		
7.	Nominal Air Flow Rate	732 lpm		
8.	Nominal Supply Pressure [Fuel (bar), Air (bar)]	1.16	1	
9.	Nominal Composition [H_2 O_2 H_2O]	99.95	21	1

FromFigure 14, the battery discharging characteristics can be observed clearly as the nominal current discharge characteristics

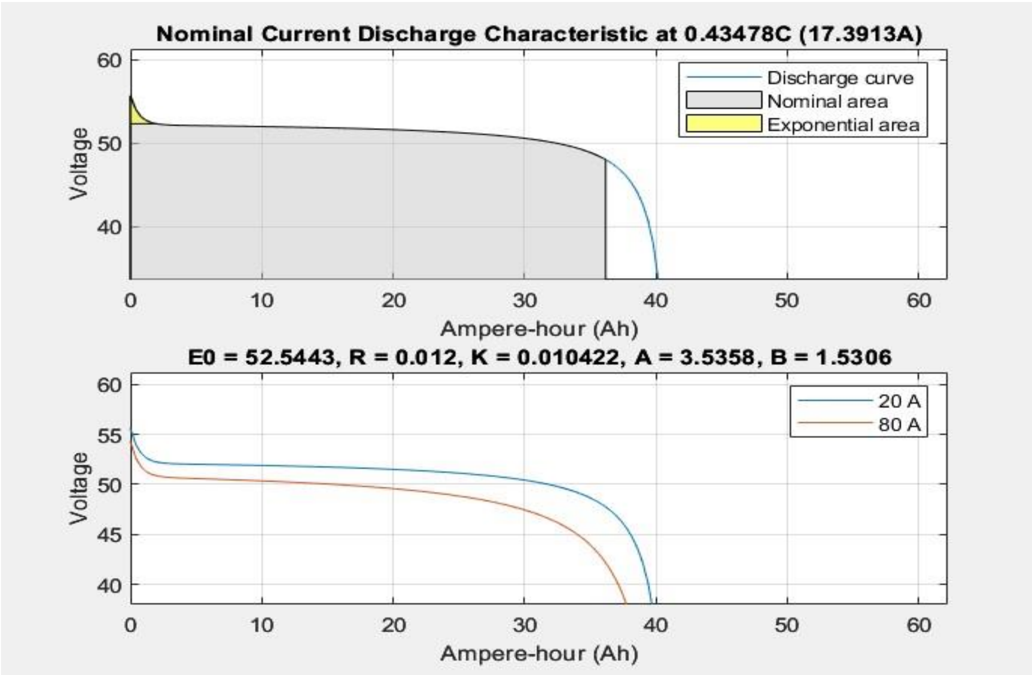


Fig. 4.9 Battery Discharging Characteristics

In Figure4.9, the details of supercapacitor charging characteristics can be observed with various current values like 10A, 20A, 100A and 500A along with voltage and time.

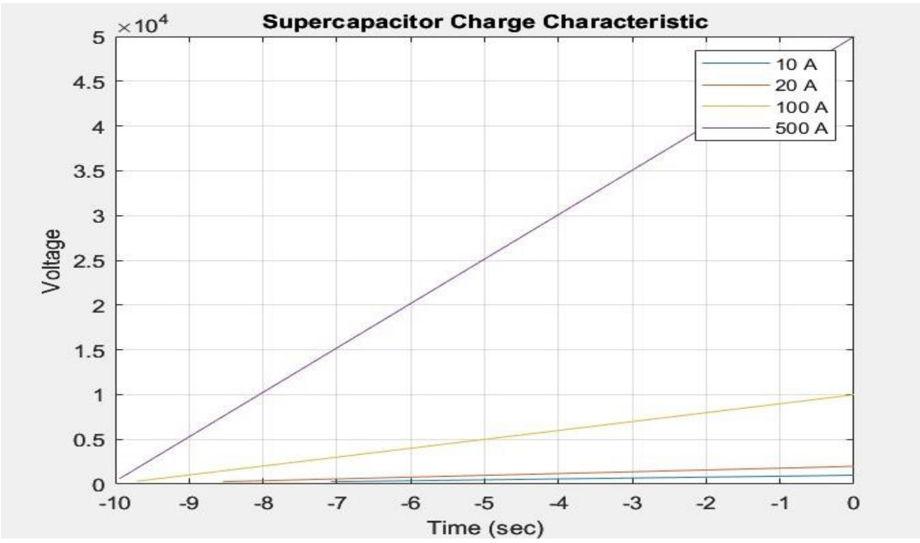


Fig. 4.10Supercapacitor charging Characteristics

Figure 4.10 illustrates the fuel cell (FC) curves, showing the relationship between the stack voltage and current. In this graph, the voltage is approximately 53V, while the current ranges between 250A and 320A.Additionally, the Figure compares the power output with the current. The stack current increases from the initial stage, reaching power outputs of approximately 10.18 kW and 12.54 kW. It is evident from the graph that the power rises rapidly as the current increases, highlighting the efficient response of the fuel cell to varying load conditions. This rapid rise in power reflects the fuel cell's ability to deliver higher energy output as its current demand increases.

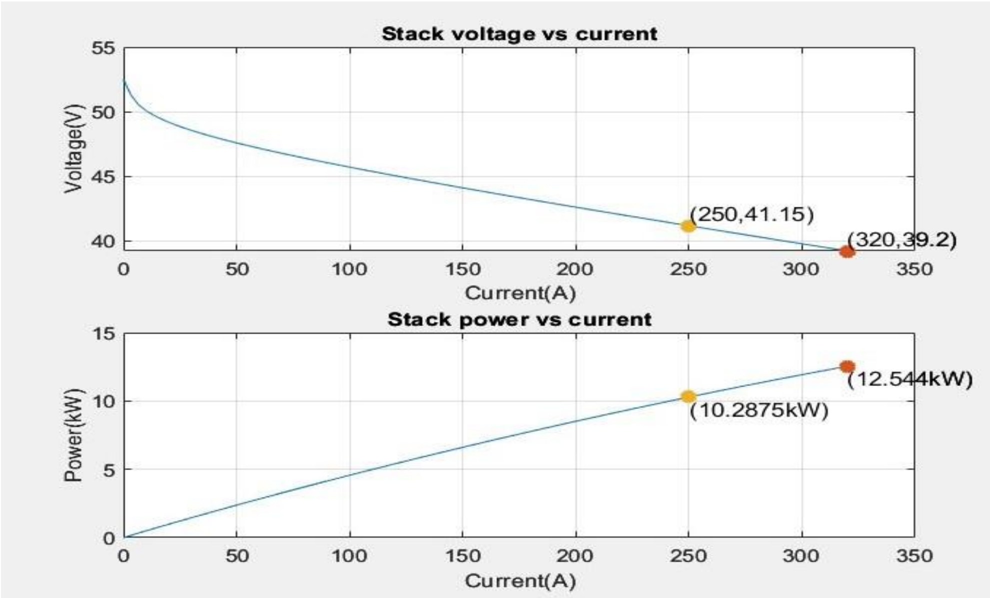


Fig. 4.11 FC Curves

The power from Fig 4.11 consists of the power drawn from load, FC, battery and supercapacitor. The first graph in red colour represents the load the next one in blue colour represents the variation of the FC, the yellow colour represents the battery variations and finally the green colour represents the supercapacitor. From the graph, FC and battery power vary more compared to the others.

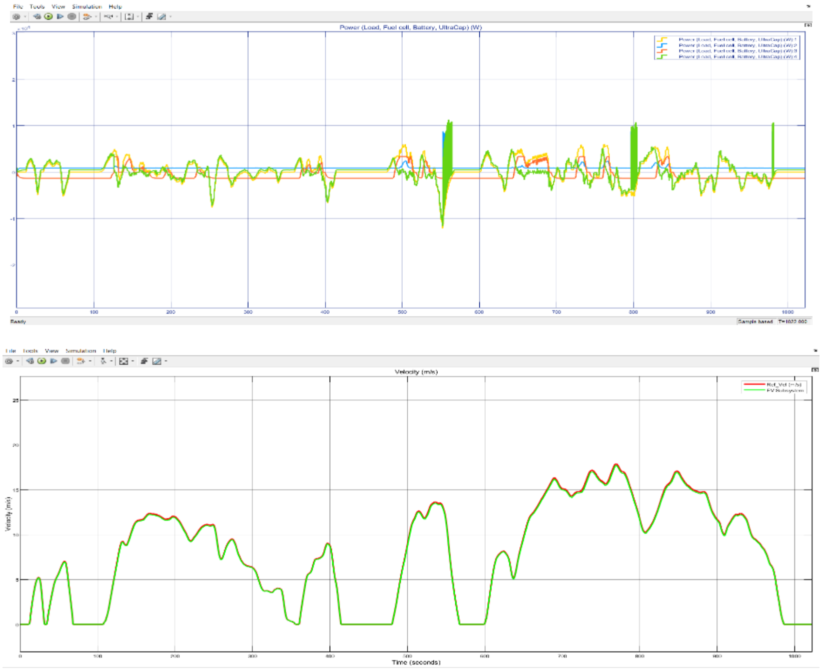


Fig. 4.12 Power Graph for load, FC, battery, super capacitor.

Figure 4.12 shows the input voltage of the fuel cell (FC) converter and the battery. The graph illustrates how the voltage varies with respect to time. As the power demand increases, the input voltage rises accordingly, reflecting the system's response to higher load requirements. After reaching a peak, the graph stabilizes, indicating that the system adjusts to the new power demand and maintains a stable output. This variation clearly shows how the system dynamically adjusts to varying power needs, with the voltage increasing during high power demand and stabilizing once the required power is met.

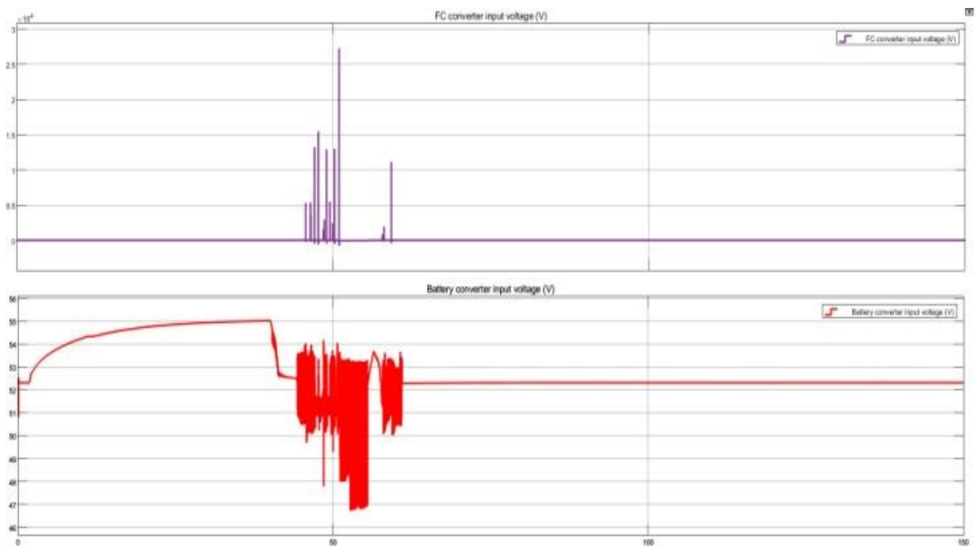
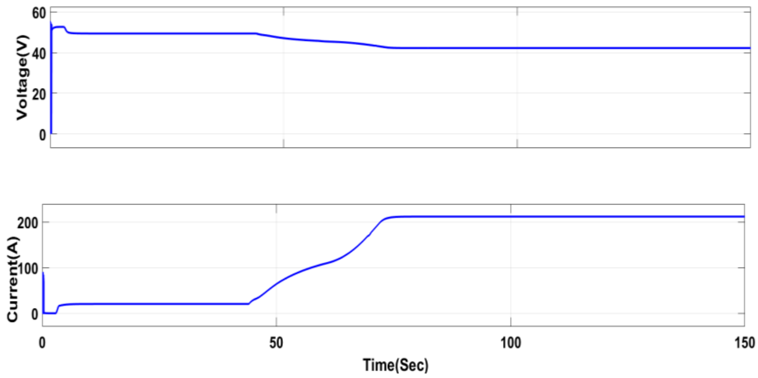
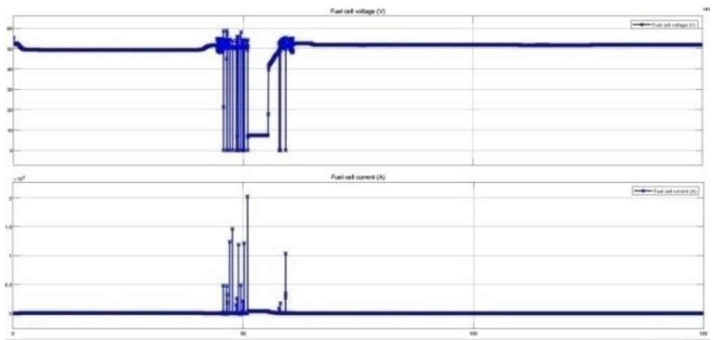


Fig. 4.13 Input voltages for battery and FC.

As shown in Figure 4.13 (a) and Figure 4.13 (b), during operation, both fuel cell (FC) voltages settle at 52V, but with noticeable distortions in the waveform.Figure 4.13 (a) illustrates the system's behaviour without using optimization techniques. In this case, the FC voltage remains at 52V, with a current of 30A, but the voltage waveform exhibits some distortions due to the lack of optimization in the control strategy. In contrast, Figure 4.13 (b) presents the results when the LMBT-based Multi-Layer Neural Network (MNN) optimization is applied. Here, the FC voltage shows improvements, with less distortion and better overall stability. The LMBT-based MNN helps reduce fluctuations and enhances the system's decision-making process, leading to smoother and more controlled voltage behavior.



(a) Without using Optimization Technique

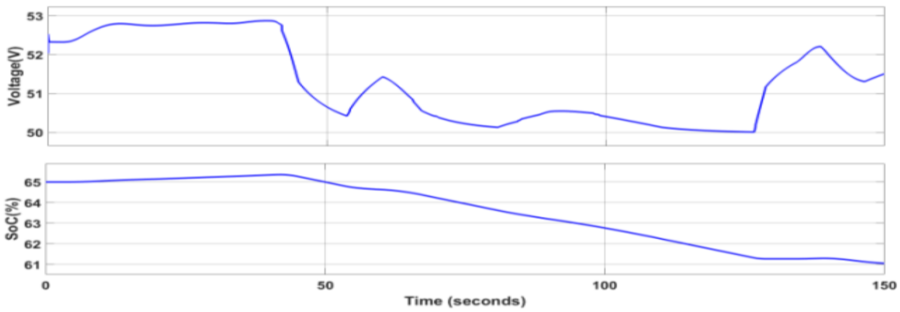


(b) With LMBT-MNN Technique

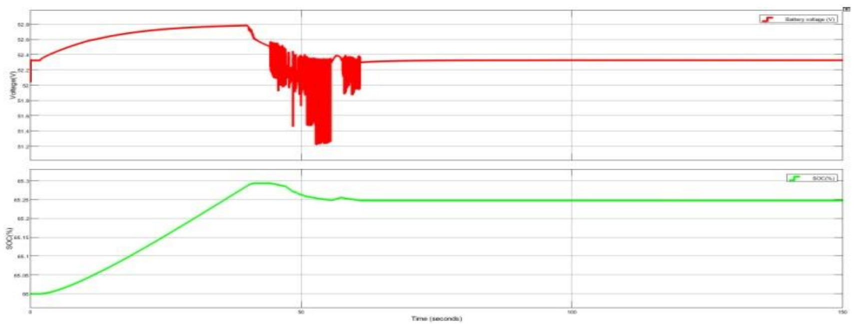
Fig. 4.14: FC output voltage and current (a)without using optimization technique (b) With LMBT-MNN.

Figure 4.14 illustrates the battery output voltage and State of Charge (SoC) over time, highlighting various changes in the battery’s behaviour. As previously mentioned, the battery's health (SoC) drops sharply from 85% to 0.3%. During the recovery process, the fuel cell (FC) provides extra energy that is stored in both the ultra-capacitor and the battery. The Energy Management System (EMS) is controlled using the proposed LMBT-MNN, which regulates the power distribution among the battery, FC, and ultra-capacitor to meet the required demands.

Figure 4.14(a) shows the system's performance without any controller, where the battery's SoC and output voltage fluctuate significantly, reflecting the absence of optimization and control. In contrast, Figure 4.14(b) demonstrates the performance using the LMBT-MNN technique. With this control strategy in place, the battery output voltage remains stable, and the SoC discharge time is significantly reduced compared to the uncontrolled case. The LMBT-MNN helps optimize the energy flow, ensuring the battery operates more efficiently, with better stability and a quicker recovery in SoC.



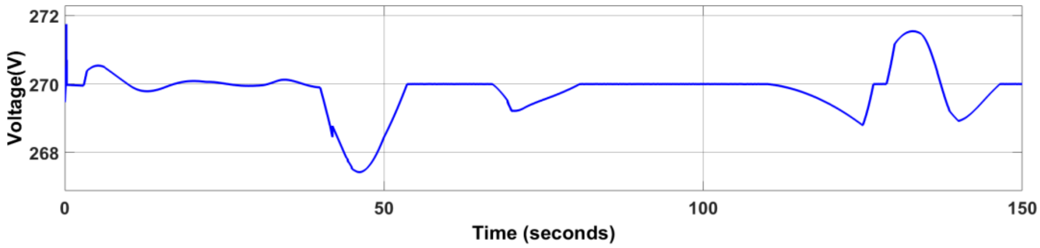
(a) Without using Optimization Technique



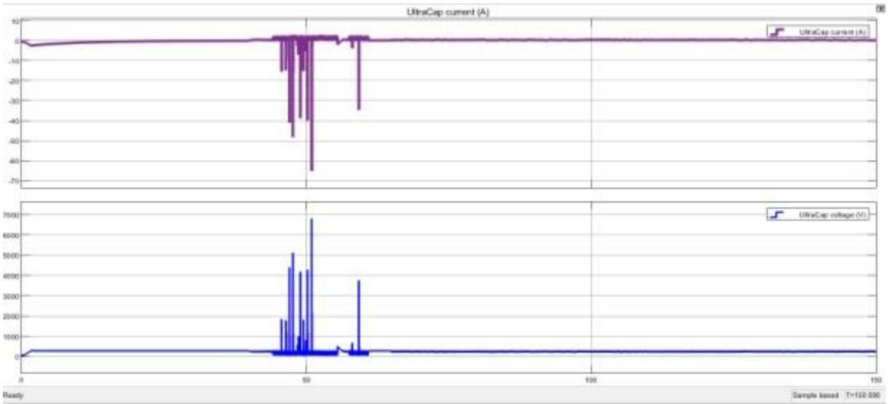
(b) With LMBT-MNN Technique

Fig.4.15: Battery output voltage and SoC (a) without using optimization technique (b) LMBT-MNN

Figure 4.15 illustrates the ultra-capacitor (UC) voltage behaviour both with and without control techniques. The Figure shows how various parameters can impact the system's performance, with fluctuations and variations observed in the UC behaviour throughout the simulation time. In **Figure 4.15 (a)**, the UC operates without any control technique. Here, the UC voltage exhibits significant disturbances due to the lack of optimization or regulation. These fluctuations highlight how uncontrolled variables can negatively affect the system's stability and performance. In **Figure 4.15 (b)**, the UC voltage is regulated using the LMBT-MNN control technique. With this control in place, the UC voltage is much more stable, and the system's performance improves. The EMS control reactions, guided by the LMBT-MNN, optimize the operation of the UC subsystems, allowing them to function sequentially and efficiently. The use of LMBT-MNN minimizes voltage fluctuations, ensuring smoother operation throughout the simulation period.



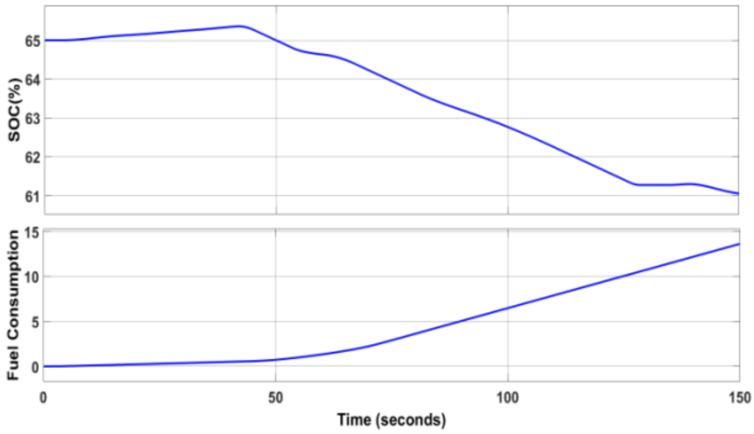
(a) Without using Optimization Technique



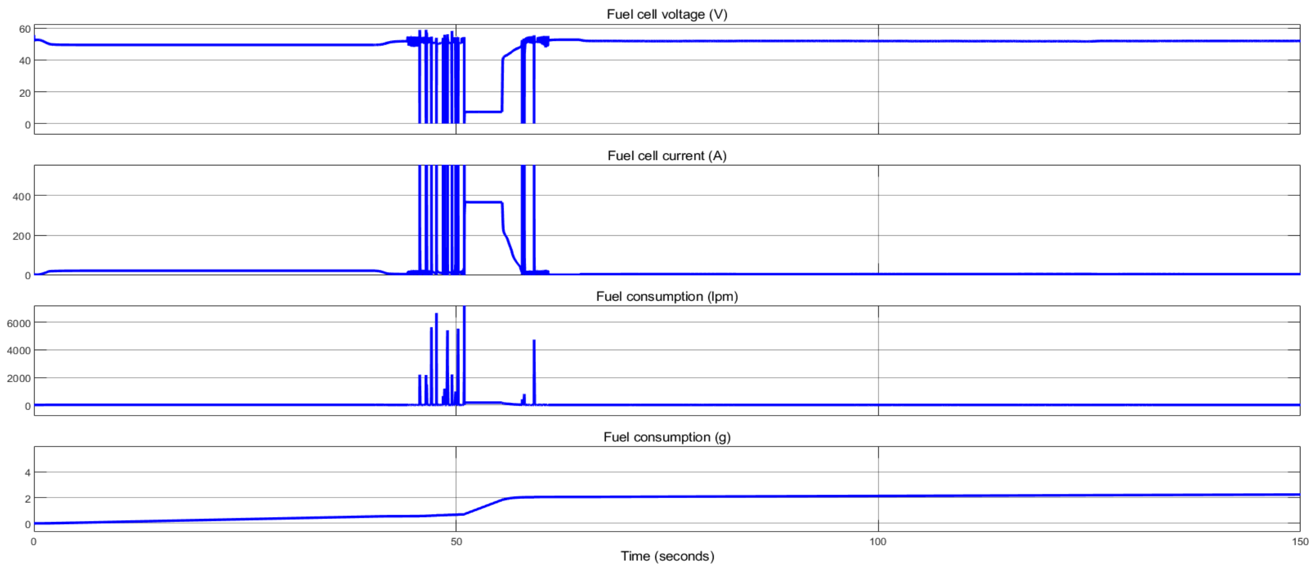
(b) With LMBT-MNN Technique

Figure 4.16 Ultra-capacitor (UC) voltage behaviour with and without using the optimization technique.

In Figure 4.16 (a), where no optimization technique is applied, the UC voltage shows more fluctuations and instability. In contrast, Figure 4.16 (b) demonstrates the UC voltage under the control of the LMBT-MNN technique, which results in a more stable and controlled voltage response. Additionally, the comparison incorporates the State of Charge (SoC) and H2 battery levels, which are used as inputs to the Multi-Layer Neural Network (MNN) for optimization. From the comparison curve, it is clear that the LMBT-MNN control technique leads to significantly lower fuel consumption compared to the system without optimization. The system utilizing the LMBT-MNN also experiences a faster settling period for fuel consumption, meaning that the fuel usage stabilizes more quickly and efficiently with the proposed optimization technique. This results in improved overall system performance and efficiency in terms of energy consumption and fuel usage.



(a) Without using Optimization Technique



(b) With LMBT-MNN Technique

Fig. 4.17 Comparison of SoC and Fuel consumption

(a) without using optimization technique (b) LMBT-MNN

The Levenberg Marquardt training process is shown below Figures. Figure 4.17 shows the LMBT-MNN performance. From the Figure4.18 the epoch achieved is 15. The graph is plotted 15epoch Vs Mean Square Error. In this LMBT network, the input variables are two, the hidden layer having eight nodes and one output.

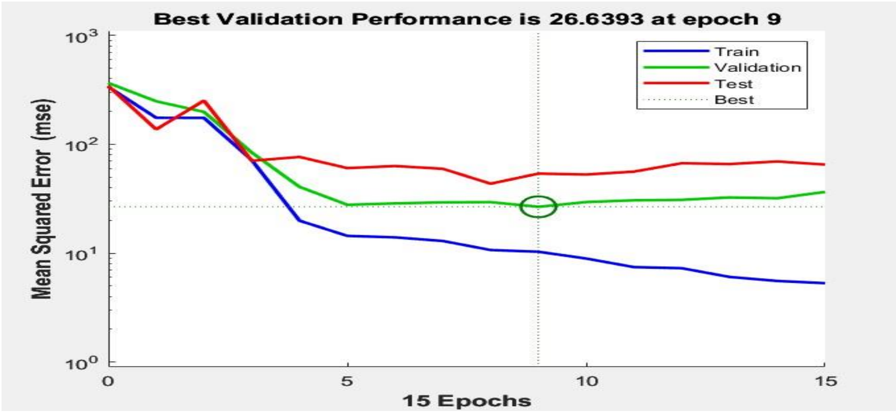


Fig. 4.18: LMBT-MNN Performance

Finally, several studies have explored the architecture of battery/fuel cell (FC)/ultra-capacitor hybrid electric vehicles (EVs), such as those in references [50, 51]. The proposed work offers enhancements in the control strategies, ensuring that the units—battery, FC, and ultra-capacitor—work efficiently and in coordination to meet the load requirements. A comparison of the proposed approach with existing techniques is summarized in **Table 4.4**, highlighting the improvements in performance, stability, and energy efficiency provided by the proposed control strategy.

TABLE – 4.4:

SoC Discharging Time Comparison

Optimization Techniques Used	**Reference No.**	**SoC Discharging Rate**
ANN – PSO	[49]	45 %
ACO	[50]	25 %
ABC	[51]	19%
LMBT-MNN	Proposed Work	05 %

4.7Summary:

The proposed HESS optimally balances power and energy density, reducing energy loss and enhancing motor-to-wheel efficiency. Proposed control strategies ensure seamless coordination of the battery, fuel cell, and supercapacitor to meet dynamic loads. The comparative analysis highlights significantly lower SoC discharging rates, with the LMBT-MNN approach achieving just 5% compared to existing methods higher rates.

CHAPTER5

ENERGY MANAGEMENT SYSTEM

In this chapter, the fractional braking power distribution strategy is developed by considering the braking power and safety together, and the PMSG drive system model is based on low and high-speed conditions. A model of a vehicle braking system is built by mechanics and a regenerative braking system. Then Levenberg-Marquardt back propagation training multi-layer neural networks with three weighting factors are defined, the output power, torque efficiency and current efficiency are selected as the optimization objectives of driving range, braking comfort and battery life respectively. In addition, a Levenberg-Marquardt back-propagation trained multi-layer neural networks controller is used with variable turning angles and coupled to the vehicle braking system.

Finally, braking energy recovery efficiency, braking efficiency and charging current smoothness are analysed in the Levenberg-Marquardt backpropagation multilayer neural network controller for PMSG and compared with those in the output power optimization (OPO) controller. The PMSG drive system regenerative braking control concept based on LMBT neural network can achieve balance between the comfort of the braking, battery life, and electric vehicle driving range.

5.1 Energy Management System (EMS):

- For a better operation of an EV, the ESS (Energy Storage System) should be able to have good performances in terms of energy density and power capabilities during acceleration and braking phases.
- It has been recognized that the adoption of systematic model-based optimization methods using meaningful objective functions to improve the energy management controllers is the pathway to go to achieve near-optimal results in designing the vehicle EMS.
- As it mainly consists of Transmission Control Unit (TCU), Battery Management System (BMS), Motor Control Unit (MCU).
- And the power allocation between them reduces the energy loss in the vehicle. In this research, an optimized combination of energy storage for smooth running &a high range of vehicles using optimization with ANN learning algorithm is designed.

- An optimization and intelligent control strategy are used for the efficient running of the Energy Management System (EMS) to improve the performance.
- An off-line/online learning method is adopted to the EMS for accurate decision-making of the power required by the vehicle.
- In the proposed model the algorithms are based on Supervised learning which establishes a learning process and compares the predicted results with the actual results of the training data, the predictive model is varied until it attains the expected result.
- Algorithms employed:
    - Levenberg-Marquardt Back Propagation Algorithm.
    - Broyden Fletcher Goldfarb Shannon (BFGS),
    - Quasi-Newton Back Propagation Algorithm.
    - Hyper parameter optimization with Random Forest Algorithm.
    - Long Short Term Memory (LSTM)

In this work, a novel combination of energy storage systems, along with an optimal control strategy, is integrated into the Energy Management System (EMS) to ensure the smooth operation of hybrid vehicles. This approach leverages machine learning algorithms and optimization techniques to enhance the system's performance. Python programming is used to facilitate better coordination and matching of the system components. To prevent energy wastage, the proposed energy management system efficiently captures excess energy and stores it for use when necessary. The optimal control strategy ensures the EMS operates efficiently, optimizing energy flow between the battery, fuel cell, and ultra-capacitor for improved vehicle performance.

This work addresses various conditions related to hybrid energy storage systems, incorporating two-way communication with the Energy Management System (EMS). The system monitors the State of Charge (SoC) of the battery, tracks battery levels, and observes degradation over time using machine learning techniques. The specifications for the vehicle and energy storage are based on the latest vehicle models, and the system is simulated using these specifications. The proposed results are then compared with actual results to evaluate the system's performance.

For the electric motor, either a Permanent Magnet Synchronous Motor (PMSM) or a Brushless Direct Current Motor (BLDC) is utilized, depending on the application. Different driving cycles and conditions, sourced from the latest data and literature, are considered for simulation. These prescribed cycles are compared, and the results are plotted in graphs for further analysis.

Long Short-Term Memory (LSTM), an advanced version of the recurrent neural network (RNN), is employed to model chronological sequences and their long-range dependencies. LSTM is used for training datasets, and the code is written in Python.

After all the models are arranged and calculated, the implementation is done using MATLAB 2022a, , the State of Charge (SoC) blockset, Vehicular Dynamics blockset, Python coding on the Python IDLE platform, Powertrain blocks, tools are used for simulation and analysis.

5.2 EMS Overview:

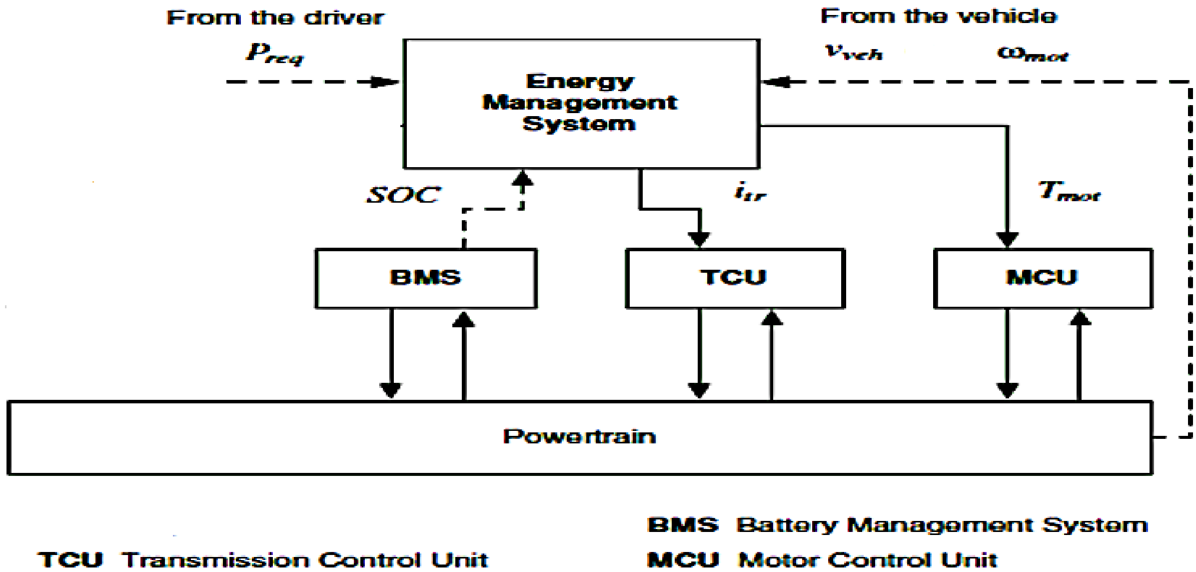


Fig. 5.1 Energy Management System overview

The Artificial Neural Network (ANN) based optimizations are now widely popular among several AI techniques. It mimics biological neural networks to make the right decision for any task from the given raw data. In the genre of Electric Vehicles, there are various subsystems like Motor & its control unit, Steering & Human Interface Control unit (HICU), Energy Storage System (ESS), Energy Management System (EMS), Cyber-Physical Security System (CPSS) as shown in Fig 5.1. Each subsystem is very important to get proper control, efficiency & stability of the vehicle. The main problem to achieve that success is the highly non-linear nature of the systems, data errors, insufficient data, data lost during communication, and improper coordination between the above subsystems.

This problem is more common in EMS due to the presence of a Hybrid Energy Storage System (HESS) supplying the EV due to unpredictable electrochemical reactions, improper data, lack of coordination between different sources, etc. So, we may not get satisfactory energy & power densities ultimately leading to less mileage (range) & faster draining of source (HESS).In this proposed work to design an ANN to get the appropriate level of hybridization i.e; no of Li-ion pack, Fuel Cell &Supercapacitors required and then we extend it to map their capacities to supply our Permanent Magnet Synchronous Motor (PMSM) according to various loading situations (Vehicle-Road interaction scenarios or Drive cycles). This data will be helpful to extend the ANN controller as EMS.

The main advantage of optimizing is initially the cost objective, power, and energy objective, with improved range, efficient regenerative braking, and ideal position gives raise from efficient Energy Management Systems (EMS). The excess power is utilized for charging the battery as well as the super capacitor which increases the efficiency of the energy storage as well as the motor.

The energy density (Wh/kg) can be given as the amount of energy stored per unit (mass (kg), area (cm2), or volume (L)) and corresponding power density (W/ kg) means the amount of energy flow per unit (mass, area, volume) per unit time (s). Energy density is the amount of energy in a given mass (or volume) and power density is the amount of power in a given mass. The distinction between the two is similar to the difference between Energy and power. For example, Batteries have a higher energy density than capacitors, but a capacitor has a higher power density than a battery. This difference comes from batteries being able to store more energy, but capacitors can give off energy more quickly. just think about the water tank with the fixed tap at its bottom. More simply said, energy density can be taken as the volume of the water tank and power density can be taken as the rate of water flow from the tap.

5.3 Electric Vehicle Regenerative Braking System (RBS)

5.3.1 Dynamic Model of Vehicle:

The vehicle driving force is denoted as Ft, which can be calculated as follows using the external force under the indicated driving conditions:

$$\boldsymbol{F_t = F_f + F_w + F_i + F_j} \tag{5.1}$$

Where, the resistance of the acceleration is denoted as F_j, the Resistance of the wind is denoted as F_w, the resistance of the gradient is denoted as F_i, and the resistance of the rolling is denoted as F_f. To express the balance equation is

$$m\frac{du}{dt} = mgfcos\alpha + \frac{1}{2}C_D A\rho u^2 + mgsin\alpha + F_b \quad (5.2)$$

Where, the mass of the vehicle is denoted as m, the vehicle speed is called u, vehicle braking force is F_b. In relation to the front and rear axles, the braking force Fb can be divided into two components, which can be expressed as

$$F_b = F_{bf} + F_{br} \quad (5.3)$$

Where, the front axels force of the braking is F_{bf} and rear axels force of the braking is F_{br}.

5.4 Distribution of Braking Force:

In this Figure, the I- Curve shows the braking condition of vehicle stability. Here the regenerative braking energy for a front-wheel drive electric vehicle is not enough below the I-Curve, and the RBS control under curve I is very difficult. The regenerative braking energy for a front-wheel drive electric vehicle is maximum below ECE-Curve[20,21].

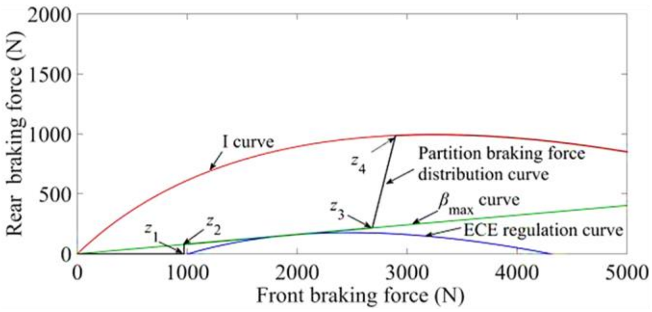


Figure 5.2 : Distribution Curve of The Braking Force

When designing the braking system for electric vehicles, much attention should be paid to recovering braking energy. In this article, Figure 5.2 shows the sectional braking force distribution strategy is designed and divided into five regions [22].

The braking intensity is calculated from Figure 1 as follows:

$$\begin{cases} \begin{cases} F_{bf} = mgz \\ F_{br} = 0 \end{cases} & ,0 < z < z_1 \\ \begin{cases} F_{bf} = mgz_1 \\ F_{br} = mgz - F_{bf} \end{cases} & ,z_1 < z < z_2 \\ \begin{cases} F_{bf} = \beta_{max} mgz \\ F_{br} = (1 - \beta_{max})mgz \end{cases} & ,z_2 < z < z_3 \\ \begin{cases} F_{bf} = \varphi \frac{mg}{L}(b + zh_g) \\ F_{br} = \left(mgz - F_{bf}\right) \end{cases} & ,z_3 < z < z_4 \\ \begin{cases} F_{bf} = z\frac{mg}{L}(b + zh_g) \\ F_{br} = \frac{1}{2}\left[\frac{mg}{h_g}\sqrt{b^2 + \frac{4h_gL}{mg}F_{bf}} - \left(\frac{mgb}{h_g} + 2F_{bf}\right]\right. \end{cases} & ,z > z_4 \end{cases} \tag{5.4}$$

where, the intensity of the braking is denoted as z.

5.5 Control For the Coupling Braking Force

The PMSG is used to generate the torque maximum. This maximum torque is denoted as T_m . Then this is determined by consider the vehicle speed condition is u_a and SoC is called as battery state of charge. So need to adjust the EVs regenerative braking force, in this paper to propose the two influence factor K_1 and K_2. K_1 is for speed of the vehicle and K_2 is for SoC of the Battery. These influence factors are written in Equation (5) and Equation (6). According to that the regenerative braking maximum torque is calculated by the following Eq.(7)

$$k_1 = \begin{cases} 0, & u_a < 10km\ per\ h \\ 0.2(u_a - 10), & 10km\ per\ h \le u_a < 15m\ per\ h \\ 1, & u_a \ge 15m\ per\ h \end{cases} \tag{5.5}$$

$$k_2 = \begin{cases} 1, & SOC < 0.9 \\ 20(0.95 - SOC), & 0.9 \le SOC \le 0.95 \\ 0, & SOC \ge 0.9 \end{cases} \tag{5.6}$$

$$T_{reg-max} = k_1 k_2 T_m \tag{5.7}$$

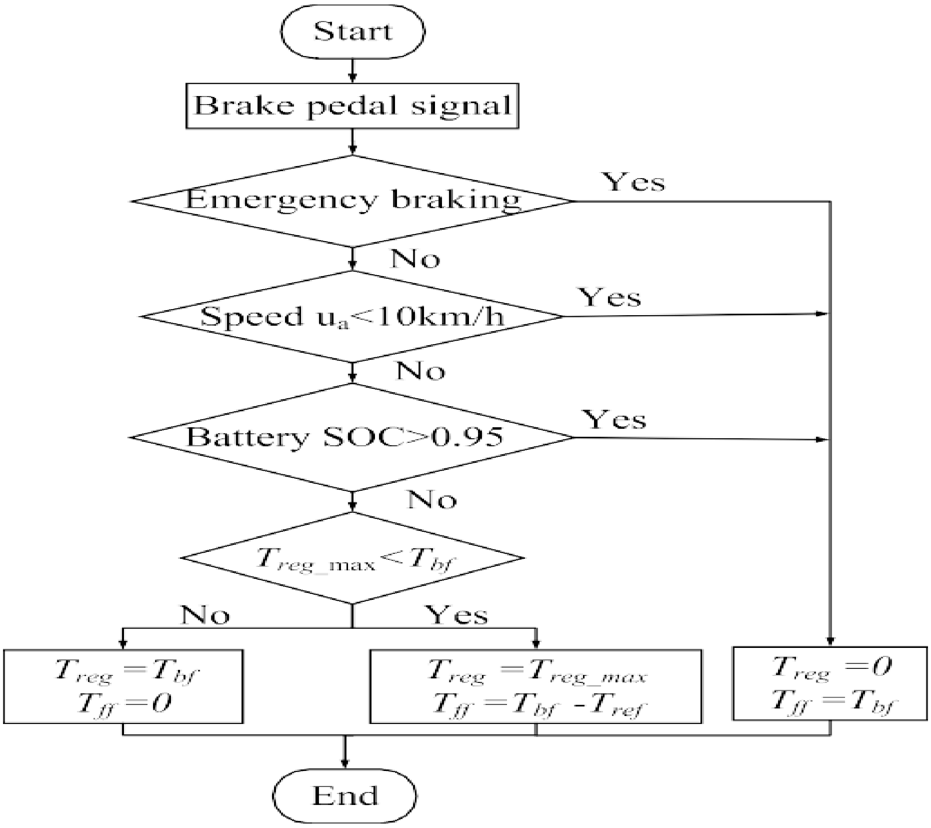


Figure 5.3: Flow Chart for Control process of coupling braking force

Figure 5.3 shows the Control process of coupling braking force**.** For the Electrical vehicle front drive consists of the braking force of the front and rear. Regenerative and Mechanical braking is enabled to develop the front force of braking and mechanical braking force alone to develop the rear braking force.

$$T_{ff} = T_{bf} - T_{reg} \tag{5.8}$$

Where, $T_{ff}$is denoted as mechanical braking torque, T_{bf} is denoted as a mechanical braking force, T_{reg} is denoted as regenerative braking torque.

5.6 Permanent Magnet Synchronous Generator (PMSG)

The operation of the PMSG relies on the field created by a permanent magnet attached to the generator rotor to convert mechanical energy into electrical energy. On the copper ground of the generator stator 6, the windings are wound and fixed in the respective places. The permanent magnet rotor is connected to a bearing that rotates on the shaft. This generator has 2 rotors, the first is behind the stator and the second is outside. These two are connected to each other by long pins that move through the stator opening. The blades are also mounted on these pins that connect the rotors to each other. These blades turn the rotor to produce electricity. Figure 5.4 shows the PMSM drive system model.

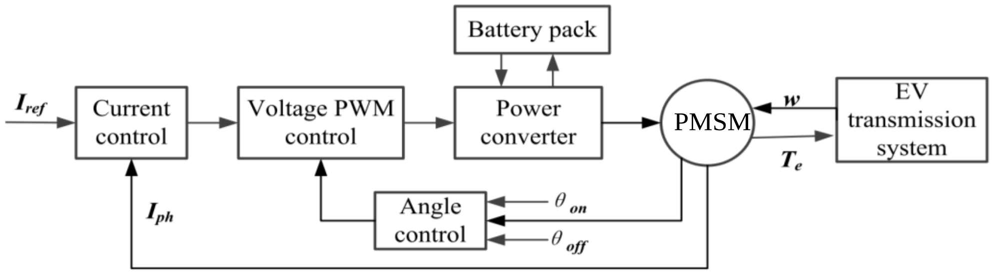


Figure 5.4:PMSM Drive System Model.

Neglecting the phase winding voltage drop,

$$U = \frac{dL(i,\theta)i}{dt} = L(i,\theta)\frac{di}{dt}U_E \tag{5.9}$$

where, I is the phase current, θ is the rotor angle, L is the phase inductance, ω is the angular velocity, and U is the phase voltage. The BEMF (Back Electromotive Force) is denoted as U_E. This is given as follows,

$$U_E = i\omega \, \frac{dL(i,\theta)}{d\theta} \tag{5.10}$$

5.7 The Braking System of EVs

The permanent magnet synchronous generator is used for the application of electric vehicle. The desired goal for the LMBT has driving range is higher, braking performance is better and battery life is longer. To optimize these objectives, to consider the three optimization parameters, namely the generation of power, ripple of the torque and fluctuation of current. The PMSG generated output power is denoted as P_{out}, is as follows,

$$P_{out} = P_g - P_e \tag{5.11}$$

where, the excitation power is P_e and the generating power is P_g.

To reduce the torque ripple is the second objective. It is denoted as τ and called as torque smoothness. This is calculated as follows,

$$\tau = min\left\{\frac{T_a}{T_{max}-T_a}.\left\{\frac{T_a}{T_a-T_{min}}\right\}\right\} \tag{5.12}$$

where, the torque maximum is T_{max}, the torque minimum is T_{min}.

The current flows frequently to the battery during the condition of regenerative braking. This causes current fluctuation. The fluctuation of the current is very harm to damage the lifetime of the battery. So the fluctuation of the of the current I_r must reduce. To evaluate the current fluctuation, Smoothness of the current $I_s$is used. And The Current smoothness is measured from the following equation.

$$I_s = \frac{1}{I_r} = \frac{I_{ave}}{I_{max} - I_{min}} \tag{5.13}$$

where, Imax is the bus current maximum value and I_{min} is bus current minimum value. The bus current average is I_{ave}.

The three objectives for smoothness of the current, efficiency of the torque, and generated output power is selected for improving the performance of the parameters are braking comfort, driving range and lifetime of the battery. And the values of these objectives are expected to be high. A Levenberg-Marquardt back-propagation multilayer neural networks strategy is proposed to improve the regenerative energy and braking performance of the vehicle.

5.8 Levenberg-Marquardt Backpropagation Training (LMBT) of Multilayer Neural Networks (MNN)

A Levenberg-Marquardt back propagation multilayer neural network strategy is presented in this paper to improve regenerative energy and braking performance of the vehicle control strategy was proposed

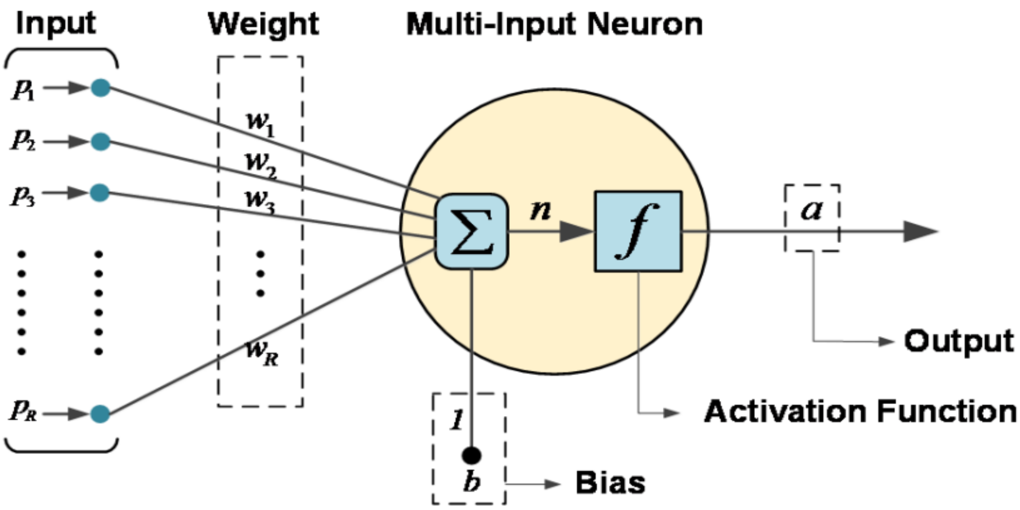


Figure 5.5: Multi Input Neuron Structure

Considering the multilayered structure of a neuron, it is shown in Figure 5.5. Typically, a neuron has more than one input [Lv, Chen et al., 2017]. The vector input elements are $p =$

$p_1, p_2, \ldots . p_R$ are elements of weighted, the weight matrix is $w_1, w_2, \ldots . w_j$ denoted as W respectively. Figure 2 operation can be described using the following formula

$$a^{m+1} = f^{m+1}(W^{m+1}a^m + b^{m+1}) \tag{5.14}$$

Where the mth layer output is a^m and (m+1)th output is a^{m+1}. $(m+1)^{th}$The layer bias vector is b^{m+1}. m= M 0,1,..., M-1, where the number of layers of the neural network is referred as M. The first layer of neuron input is

$$a^0 = p \tag{5.15}$$

$$a = a^m \tag{5.16}$$

5.9 Analysis of Results and Comparison:

The PMSG dynamic performance are measured using the proposed LMBT of MNN. The results are compared with OPO (Output Power optimization). Equation (45) shows the generated output power K_{Pout}, smoothness of the torque ($K\tau$), and smoothness of the current (K_{Is}) is as follows,

$$\begin{cases} K_{P_{out}} = \frac{P_{opt}}{P_{max}} \\ K_\tau = \frac{\tau_{opt}}{\tau_{max}} \\ K_{I_s} = \frac{I_{sopt}}{I_{smax}} \end{cases} \tag{5.17}$$

From Equation (46), it can be analysed that when the values of the three factors approach 1, PMSG dynamic performance improvement becomes more obvious

5.10 PMSG Dynamic Characteristics:

Figure 5.6 to Figure 5.8 shows the comparison of two optimization strategies results and the analysis of PMSG running conditions at low speed. The low-speed generated output power using output power optimization (OPO) and LMBT is shown in Figure 5.6.

From Figure 5.6 the dotted line denotes the output power optimization techniques and the thick line denotes the proposed LMBT of the multilayer neural network. However, the generated output power is improved significantly using the LMBT of the MNN strategy.

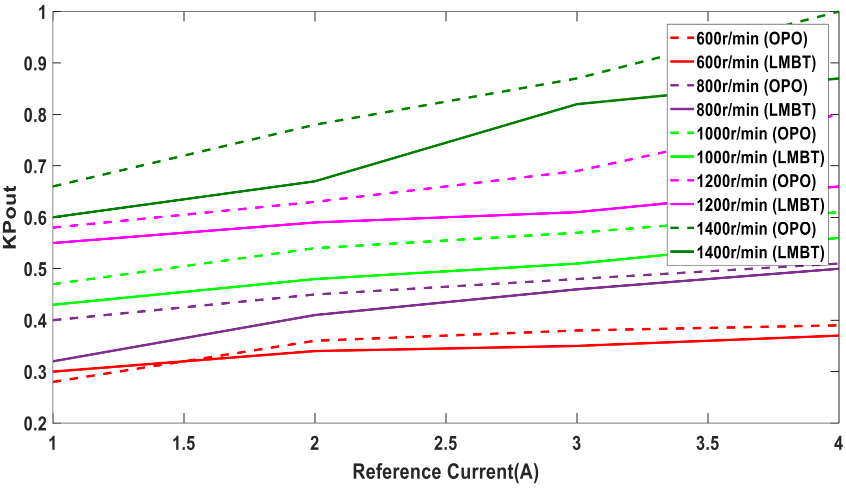


Figure 5.6: Low-Speed output power factor.

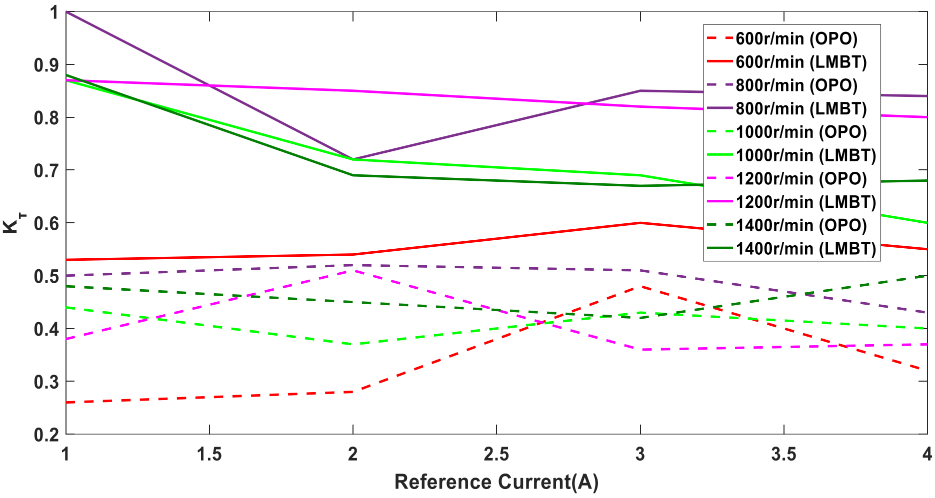


Figure 5.7: Low-speed Torque smoothness factor

The low-speed torque smoothness factor of OPO varies between 0.26 and 0.51, as shown in Figure 5.7. However, the torque smoothing value in the Levenberg-Marquardt multi-neural network training strategy is 0.53 to 1, which is much better than the OPF strategy. This shows that the strategy significantly improves driving efficiency and effectively reduces the ripple of the torque, certifying braking efficiency and increasing EV braking comfort.

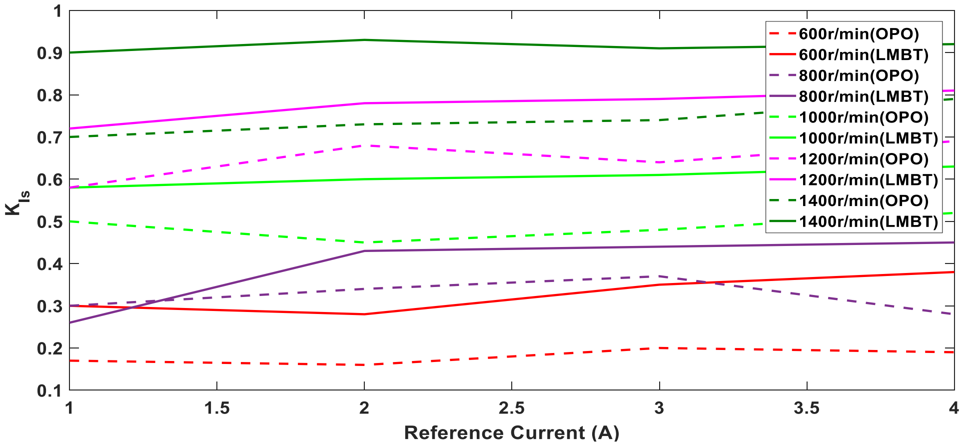


Figure .5.8: Low-speed Current smoothness factor.

The low-speed current smoothness factor of OPO varies between 0.14 and 0.84, as shown in Figure 5.8. The fact that the multi-layer neural network strategy in Levenberg-Marquardt backpropagation training is higher than the energy optimization strategy is in the range of 0.27 - 0.92. Therefore, compared with the optimization of the output power, the Levenberg-Marquardt backpropagation training multilayer neural network strategy can significantly reduce current fluctuations and achieve the goal of extending battery life. Figure 5.8 to Figure5.10 shows the three objective factors at High-speed output power. Due to the power output from the multi-layer neural network (MNN) training using the Levenberg-Marquardt (LM) backpropagation algorithm, the Levenberg-Marquardt control strategy is able to optimize the system's performance. Specifically, it reduces the speed range of the motor from 2210 to 2820 RPM (rotations per minute). This reduction in speed variation helps in efficiently managing the energy flow within the system. Additionally, the optimization strategy ensures that energy is effectively directed towards charging the battery, thereby increasing the driving speed. The LM backpropagation helps maintain stability while improving the efficiency of energy management, allowing for faster and more efficient vehicle operation.

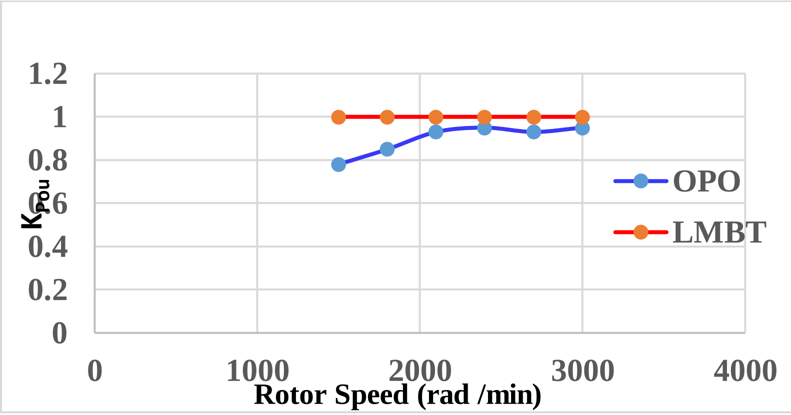


Figure 5.9:High-Speed Output Power

As shown in Figure 5.9, the LMBT strategy of the multi-layer neural network increases the torque efficiency at speeds from 2000 to 2600 r per minute. Speed. In addition, the current state of fluency can be improved by comparing the control strategy of the Levenberg-Marquardt backpropagation training multi-layer neural network with the optimization strategy of output power, as shown in Figure 10. Therefore, come to the results, the LMBT based Multi-layer neural network is used to reduce the PMSG current fluctuation and increase the life of the battery.

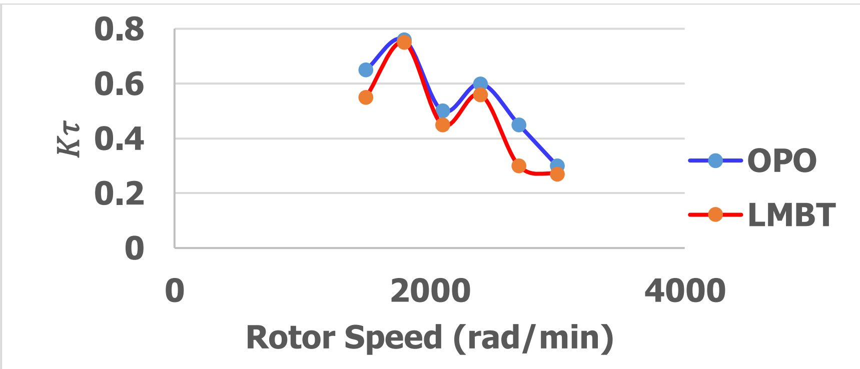


Figure 5.10: High-Speed Torque Smoothness Factor

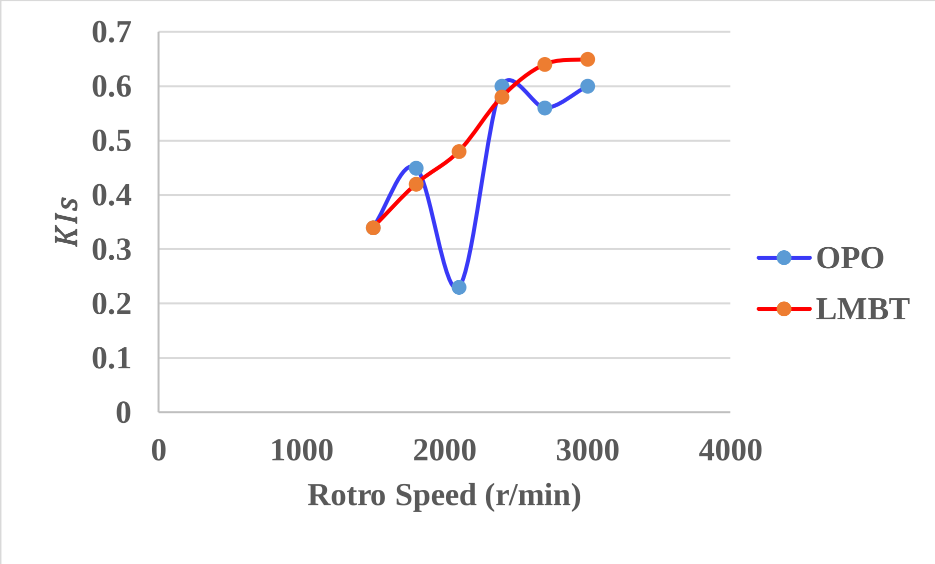


Figure 5.11 High-SpeedCurrentSmoothness Factor

5.11 Dynamic Characteristics of Vehicle:

Considering the result in two cases, the power generation in PMSG is very well, although the cost of power output is slightly reduced in some comparison to the OPO strategy. Obviously, the LMBT of MNN is better than the power optimization strategy for increasing torque waveforms and current fluctuations. In general, the LMBT control strategy can achieve the balance of energy consumption, energy consumption and current performance as well as weight, which can improve the PMSG the work of high and low. Moreover, using regenerative braking the battery life is extended and also improves the electric vehicle's performance

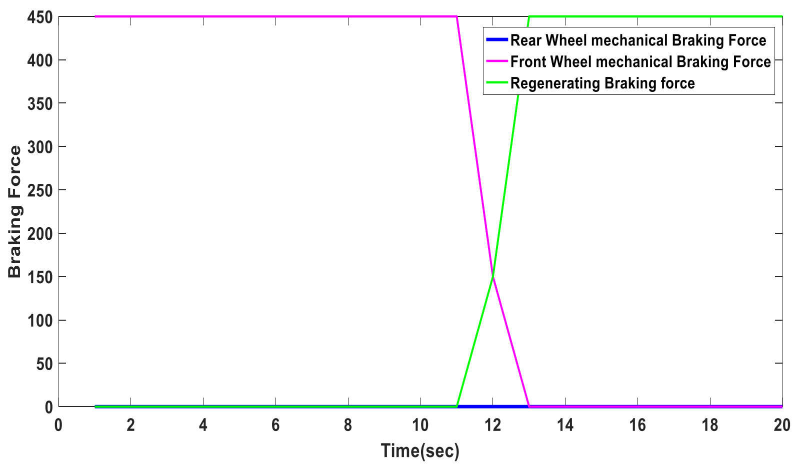


Figure 5.12. Braking at low intensity of z=0.06

The intensity of low, medium and emergency situations were simulated with a Levenberg-Marquardt rear propagation trained multi-layer neural network scheme to evaluate the vehicle's dynamic characteristics and braking force distribution controller (BFDC) performance. In low braking conditions is 0.05 and 0.1 and in the middle and current braking conditions, the braking intensity is 0.4 and 0.7, respectively. In order to analyse the recovery process for EV, braking power, speed of the vehicle and stopping distance, SoC of battery, and recovery power are analysed, which is shown in Figure 5.12 to Figure 5.15.

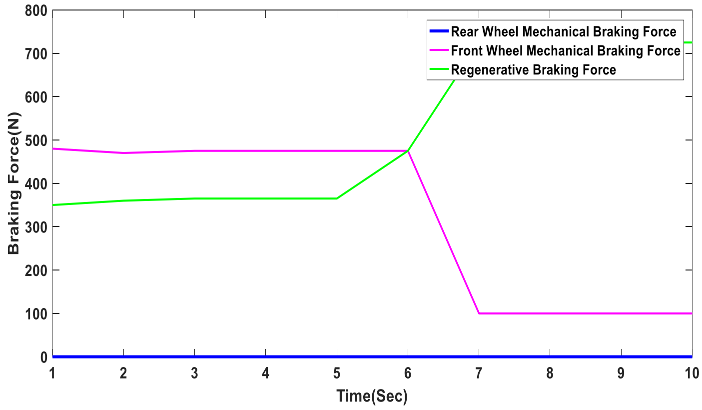


Figure 5.13. Braking at low intensity of z=0.12

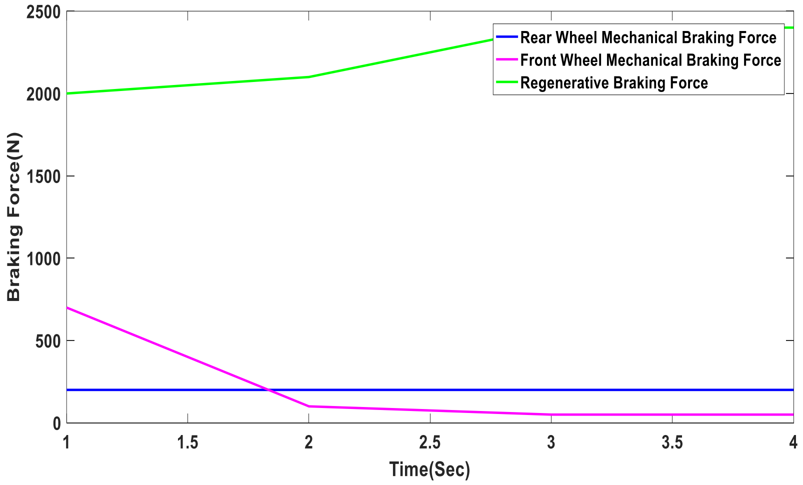


Figure.5.14. Braking at medium intensity of z=0.5

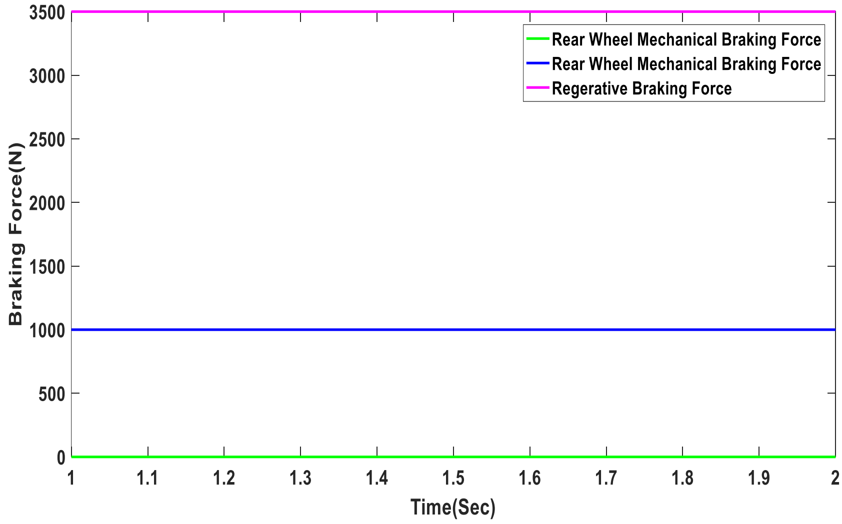


Figure 5.15. Braking at emergency for z = 0.8.

Figure 5.12 illustrates the braking performance at different intensities. At a low braking intensity of 0.06, only the motor supplies the required braking power to the front wheel. During this phase, the State of Charge (SoC) rate increases by 0.16%, the gained braking power extends the range by 25 km, and the braking distance is 94 meters.

Figure 5.13 shows the braking intensity increased to 0.12, where the gained energy is 15 kJ and the SoC of the battery grows by 0.1%. At this intensity, both the front and rear wheels supply the braking force, which reduces the amount of regenerative braking force. As a result, the SoC growth is only 0.027%, and the gained power is 4.3 kJ. The involvement of the mechanical braking system in moderate-intensity braking results in much lower SoC development and energy recovery compared to low-intensity braking, where regenerative braking is more prominent.

At medium braking intensity (0.5), the front and rear wheels both contribute braking power, but due to the mechanical system's involvement, regenerative braking is less effective. This results in reduced SoC growth and energy recovery. In contrast, at low-intensity braking, the regenerative braking system is more efficient, and the vehicle can stop quickly due to rapid deceleration, as shown in Figure 5.14.The performance for the braking system of an EV is compared with the two strategies are output power optimization and LMBT of the Multilayer neural network. The speed of the braking is selected as 60 km per hour, 40 km per hour and 20 km per hour to simulate the rates of different braking.

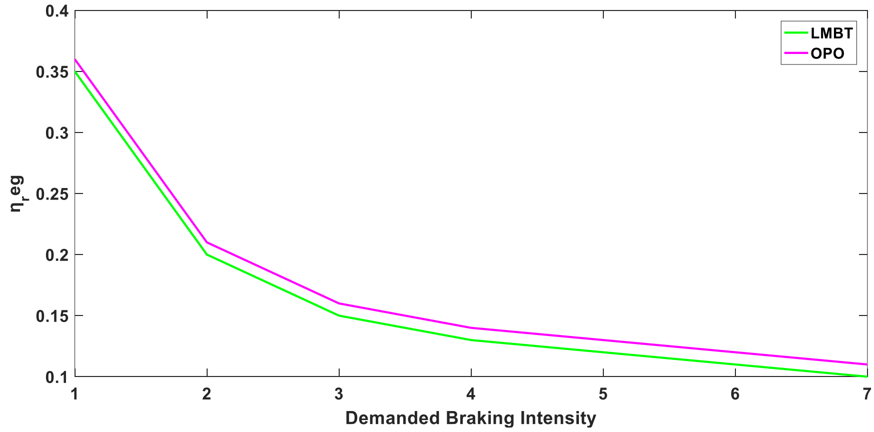


Figure 5.16 Demanded Braking Intensity Vs Efficiency

Figure 5.16 shows Demanded Braking Intensity Vs Efficiency for the Levenberg-Marquardt backpropagation braking system's power recovery efficiency of the multi-layer neural network strategy braking system is slightly lower than the OPO strategy. Under the two control strategies the efficiency of the energy recovery is basically 60km per h initial speed. Under the LMBT-based multi-layer neural network strategy the efficiency of energy recovery occurs at 20km per h and 40km per h initial braking speed. Also the rate of the reduction is .34% and 7.24%. For the OPO strategy, longitudinal braking smoothness is small and the LMBT longitudinal braking smoothness is higher, which is shown in Figure 5.17. For 60km per h initial speed, LMBT longitudinal braking smoothness is 9.6 and output power optimization strategy longitudinal braking smoothness is 8.5. At this time 0.5 is the demanded braking intensity. For the comparison of LMBT and Output Power Optimization strategy, LMBT maintains braking smoothness is better.

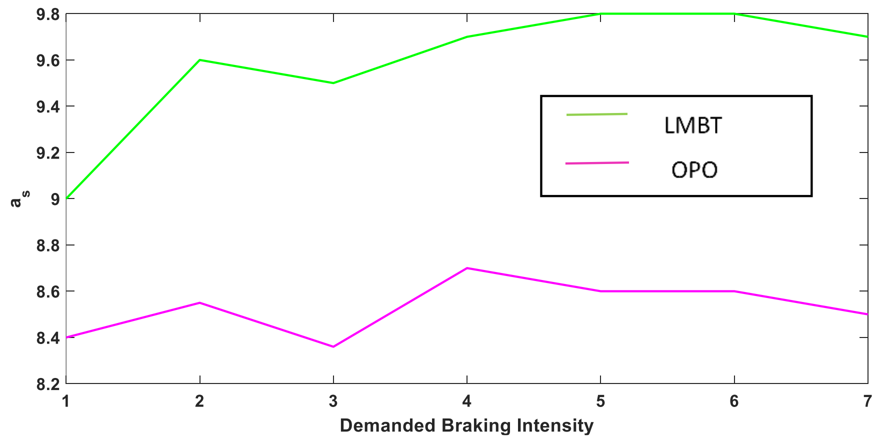


Figure 5.17.Smoothness of Braking.

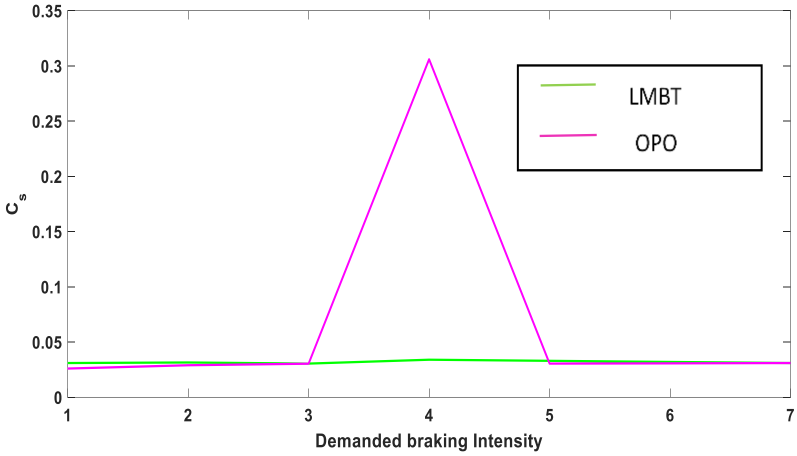


Figure .5.18. Lifetime Coefficient of Battery.

Similarly, compared to the performance optimization strategy of the output power, the longitudinal braking efficiency improvement score was from 2.83 to 3.43 with the Levenberg-Marquardt multilayer neural network strategy for backpropagation training at 45 km per h. It increased its peak by 19.7%, while 3.31% is the maximum increase at 22 km per hr an initial speed. In addition, the battery life of the Levenberg-Marquardt Backpropagation Multilayer Neural Network strategy is much higher than that of the OPO strategy, with an increase of 12.02%. Similarly, compared to the OPO performance, the longitudinal braking efficiency improvement score was from 2.81 to 3.42 with the Levenberg-Marquardt multilayer neural network strategy for backpropagation training at 40 km per h. Besides, the lifetime of the battery for the Levenberg-Marquardt multilayer backpropagation neural network is much higher than that achieved by the output power of optimization techniques.

Compared the proposed techniques with the other optimization techniques link PSO (Particle Swarm Optimization) (Y.Qin et al., 2020) (, the battery life is 89%, using Ant Colony Optimization (ACO) (S.Zhang et al., 2018) is 94%. The proposed technique battery life is 98%.

Table.5.1 Comparison of Results with Parameters Considered

Parameters Considered	Output Power Optimization (OPO) Controller	Levenberg-Marquardt Back-Propagation Trained Multi-Layer Neural Networks Controller (LMBT-MLNN) Controller	Comparing with OPO, LMBT And LMBT has the following advantages.
Low Speed Torque Smoothness Factor	0.26 - 0.51	0.53 – 1.00	Improves Diving efficiency and Effectively reduces ripple of the torque, increasing braking comfort
Low speed current smoothness factor	0.14 - 0.84	0.27 - 0.92	It reduces current fluctuations and achieves the goal of extending battery life.
High speed Output power	2000 to 2650 rad per minute	2210 to 2820 rad per minute	The reducing range of, To charge battery to increase the driving speed.
High speed Torque smoothness factor	2000 to 2500 rad per min	2000 to 2600 rad per min	reducing range of, To charge battery to increase the driving speed.
High speed Current smoothness factor	-------	-----------	It is used to reduce the PMSG current fluctuation and increase the life of the battery.
Cost	Medium	High	--
Longitudinal Braking Efficiency Improvement Score	2.81% at 40 KM speed 2.83% at 45KM speed	3.42% at 40 KM speed 3.43% at 45KM speed	The PMSG drive system regenerative braking control concept based on LMBT neural network can achieve the balance between the comfort of the braking, battery life, and electric vehicle driving range.

Table – 5.2Comparison of Results with Various Algorithms

Optimization Techniques	Battery Life	Ref No.
Partial Swarm Optimization – (PSO)	89%	12
Output Power Optimization (OPO)	92%	52
Ant Colony Optimization – (ACO)	94%	47
Proposed Technique- (LMBT)	97%	-

Table 5.3 Parameters of the vehicles in the market for comparison of real time performance 1.

S. No	Specification of the Vehicle	TATA NEXON EV	HYUNDAI KONA	MG ZS EV	TATA TIGOR	NISSAN	MAHINDRA E-VERITO	Proposed
1.	Kerb Weight (Kg)	1400	1535	1518	1126	1567	1265	1500
2,	No. of Passengers	5	5	5	5	5	5	5
3.	Avg. Mass of Passenger (Kg)	75	75	75	75	75	75	80
4.	Extra Payload (Kg)	0	0	0	0	0	0	0
5.	Drag Coefficient	0.18	0.29	0.28	0.25	0.28	0.25	0.32
6.	Frontal Area of Vehicle (Sq. m)	2.477	2.4	2.528	2.19	2.276	2.27	2.33
7.	Avg. Velocity of Vehicle (Kmph)	48	60	56	40	60	35	60
8.	Rolling Resistance	0.02	0.02	0.02	0.02	0.02	0.02	0.02
9.	Transmission Efficiency (%)	85	85	85	85	85	85	85
10.	Overall Gear Ratio (___:1)	9.1	7.981	7.5*	9*	8.193	10.83	9
11.	Tyre Diameter (mm)	664.4	668.3	668.3	583.1	646.8	614.6	660.2
12.	Battery Pack of Vehicle (KWh)	30.2	39.2	44.5	21.5	40	13.91	48

The above table 5.2 represents the specification that are to be considered for validating the proposed model

Table 5.4 Parameters of the vehicles in the market for comparison of real time performance 2.

S. No	Specification of the Vehicle	TATA NEXON EV	HYUNDAI KONA	MG ZS EV	TATA TIGOR	NISSAN	MAHINDRA E-VERITO	Proposed
1.	Claimed Range (Km) (ARAI/EPA)	312	452	340	213	241	110	**400**
2.	Actual Range (Km) User Reported	200-220	250-280	220-270	150-170	180-240	80-110	**NA**
3.	Calculated Range (Km) for the Proposed System	219	229	269	184	235	113	**285**
4.	CALCULATED RANGE WITH AC & OTHER EQUIP. (KM)	157	187	215	110	192	64	**220**

From table 5.4 it is evident that the proposed model of considering the driven cycle, participation of HESS when optimized with the proposed algorithm will increase the mileage and power efficiency of the system

5.12 Summary

A control strategy using the Levenberg-Marquardt Backpropagation Training (LMBT) of Multilayer Neural Networks was proposed to enhance regenerative energy, braking performance, and optimize braking comfort, battery life, and driving range. The optimization objectives included output power, torque smoothness, and current smoothness. Results proved that the LMBT-based strategy, reduced torque fluctuations and ripples effectively, increasing battery life by 12.02% compared to the OPO strategy. This approach balances braking comfort, battery longevity, and vehicle range.

CHAPTER6

CONCLUSION

This chapter summarizes the work presented and highlights potential directions for future research.

The vehicle specifications such as rolling resistance, drag coefficient, total resistance, air drag, torque, and acceleration gradient have been calculated. Now the data from urban, subway, highway, rural, and semi-urban terrains are collected using electronic modules. Then the ANN-based prediction training various driving cycles in different driving conditions. It is observed that ECMS converges in fewer epochs, while BFGS requires more epochs but achieves higher validation performance. The PI strategy demonstrates a superior R-value of 0.87702, indicating a strong correlation. BFGS is found to generate the best training set for feature correlation. Using the test data, the LMBT Algorithm effectively determines the velocity required for the driving cycle. ARIMA was implemented for SoC estimation by training the model on historical data and optimizing parameters to minimize forecasting errors. Evaluation metrics, including Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE), assessed accuracy. Time-series visualisations compared predicted and actual SoC values, highlighting the model's effectiveness. The results demonstrated improved prediction accuracy across various driving patterns, confirming ARIMA's suitability for SoC.

AHESS combination of battery, supercapacitor, and fuel cell addresses critical challenges in ESS for electric vehicles, such as safety, size, and management complexities. Then LMBT-MNN is used to evaluate cost, power, and energy objectives, utilizing a 70%-15%-15% split for prediction, testing, and validation. Mathematical and simulation-based analyses incorporated auxiliary inputs such as rolling and aerodynamic drag coefficients, with key outputs including state-of-charge and torque. By integrating these components, the HESS achieves a balance between power density and energy density, reducing energy loss and enhancing motor-to-wheel efficiency. The proposed work enhances control strategies, ensuring efficient and coordinated operation of the battery, fuel cell, and super-capacitor to meet load requirements. A comparative analysis with existing techniques shows SoC discharging rates of 45% (ANN-PSO), 25% (ACO), 19% (ABC), and 5% for the proposed LMBT-MNN approach. This demonstrates significant improvements in performance, stability, and energy efficiency achieved by the proposed control strategy.

This work demonstrates the effective use of the LMBT Algorithm for optimizing energy management and braking performance in an electric vehicle. The Simulation results demonstrate the superior performance of the LMBT-based neural network strategy compared to the Output Power Optimization (OPO) method. The findings reveal a significant reduction in torque ripple and fluctuation, contributing to improved braking efficiency and enhanced driving comfort. Additionally, the battery life is extended by 12.02%, highlighting the effectiveness of the PMSG strategy in achieving a balance between energy efficiency, braking performance, and overall EV reliability.

Future Scope:

In the future, this work can be extended by incorporating various types of motors and comparing their performance with a prototype 1 kW motor across all models. Leveraging advanced simulation tools such as OPAL-RT can provide a comprehensive understanding of system performance, particularly under real-time scenarios.

This approach aims to enhance the model's accuracy and applicability to practical scenarios. Additionally, integrating LIDAR technology can be explored to assess real-time road conditions, offering valuable insights for optimizing the energy management system. Incorporating Control Area Network (CAN) protocols can enable energy sharing between vehicles (Vehicle-to-Vehicle or V2V), fostering more efficient and collaborative energy distribution systems.

Lastly, adopting the Digital Twin concept could significantly advance the design process of the vehicle's energy system, real-time monitoring, analysis, and optimization further improving EV system performance and reliability.

CHAPTER 7

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List of Publications:

- Shanmukha Naga Raju Vonteddu, Ravindra Kollu and Prasanthi Kumari Nunna, "Energy Based PMSM Drive Electric Vehicle to Eliminate High Frequency Switching," 2021 IEEE Electrical Power and Energy Conference (EPEC), 2021, pp. 390-395, doi: 10.1109/EPEC52095.2021.9621431. **Published on (29th-30th October 2021) (Scopus). DOI:** 10.1109/EPEC52095.2021.9621431**(Conference Paper)**

- Shanmukha Naga Raju Vonteddu, Ravindra Kollu and Prasanthi Kumari Nunna, "Dynamic Modeling For Hybrid Electric Vehicles With Its Performance Optimization Using Different Control Strategies and Energy Management Systems " in the Journal of Electrical Engineering, Electronics, Control and Computer Science. **(Free Journal-DOJ), (Published), 2023.** Published on 24th December, 2023.

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Journal Papers Under Review Process:

- Shanmukha Naga Raju Vonteddu, Ravindra Kollu and Prasanthi Kumari Nunna, "Using Regenerative Braking Control Strategy For Electric Vehicles Based On Levenberg-Marquardt Backpropagation Training Of Multilayer Neural Networks" in Advances in Electricaland Computer Engineering,**(SCIE)** submitted on 18th November 2024.

- Shanmukha Naga Raju Vonteddu, Ravindra Kollu and Prasanthi Kumari Nunna, "An Efficient Energy Management Based Control Strategy Using Levenberg-Marquardt Training Algorithm For Electric Vehicles" in Result in Engineering**, Elsevier. (ESCI)** submitted on 04th January 2025.

<u>Other Publications Details:</u>

- Shanmukha Naga Raju Vonteddu, Ravindra Kollu and Prasanthi Kumari Nunna, patent on “An IoT Based Battery Swapping System for Electric Vehicle and Method Thereof” **Indian Utility Patent** has been **Published on (22nd July 2022**).

- Shanmukha Naga Raju Vonteddu, Ravindra Kollu and Prasanthi Kumari Nunna “Design and Evaluation of Battery Management Systems for Electric Vehicle Application with Harris hawk Optimized Algorithm - HHOA Based on Fuzzy Logic Controller” in the **Book Chapter** "Artificial Intelligence Applications in Battery Management Systems and Routing Problems in Electric Vehicles“in IGI Global Publication.(**Published on March 2023) (Scopus).**

- Shanmukha Naga Raju Vonteddu, Ravindra Kollu and Prasanthi Kumari Nunna, patent on “Foldable Electric Scooter” **Indian Design Patent** has been **Accepted on (15th March 2024**).

Appendix A

A1. Specifications of PMSM(RTML-032) considered for simulation.

Model	100k_D_D_I-
Model name	PMSM
Max. Power	100(kW)
Voltage/Current	DC500(V)/400(A)
Number of Poles	12
Number of Slots	72
Number of Phases	3
Rotor	IPM
Stator (Outside Diameter)	400(mm)
Stator (Inside Diameter)	260(mm)
Stator	Distributed winding
Number of Turns	3
Height	65(mm)
Magnet	Neodymium sintered
Inertia Moment	1.39e-1(kg·m^2)
Mass	62.95(kg)
Max. Current	283(Apeak)

A2. Hybrid Energy Storage Parameters Considered:

Battery Parameters:				
S.No	**Parameters Considered**	**Values**		
1.	Nominal Voltage	48 V		
2.	Rated Capacity	80 Ah		
3.	Initial SoC	85 %		
4.	Battery Response Time	15 sec		
Super Capacitor Parameters:				
1.	Rated Capacitance	15.6 F		
2.	Equivalent DC Series Resistance	150e-3 Ohms		
3.	Rated Voltage	291.6 V		
4.	CapacitorsSeries	108		
5.	Parallel Capacitors	1		
6.	Initial Voltage	290 V		
7.	Operating Temperature	25 Celsius		
Fuel Cell Parameters:				
1.	Voltage at 0A and 1A [V0,V1]	52.5	52.46 V	
2.	Normal Operating Point [Inom(A), Vnom (V)]	250A	41.15 V	
3.	Maximum Operating Point [Iend(A), Vend (V)]	320	39.2	
4.	Number of Cells	65		
5.	Operating Temperature	45 Celsius		
6.	Nominal Stack Efficiency	50		
7.	Nominal Air flow Rate	732 lpm		
8.	Nominal Supply Pressure [Fuel (bar), Air (bar)]	1.16	1	
9.	Nominal Composition [H2 O2 H2O]	99.95	21	1

A3. Gains of the neural Network

Parameter	Typical Gain Value Range	Impact on Drive Train
Motor Torque	1.1 to 1.5	Affects acceleration and overall driving performance.
Battery State of Charge (SoC)	-0.3 to -0.7	Lower SoC reduces performance and range.
Regenerative Braking Efficiency	1.0 to 1.3	Higher efficiency improves energy conservation.
Motor Efficiency	1.0 to 1.2	Higher efficiency reduces energy consumption.
Power Distribution	1.0 to 1.4	Balanced distribution improves overall drive quality.
Temperature Management	1.0 to 1.2	Proper management ensures optimal performance and longevity.
Drive Train Gear Ratio	0.95 to 1.05	Impacts acceleration and top speed.
Battery Temperature	-0.2 to -0.6	High temperatures can reduce battery life and performance.
Charging Efficiency	1.0 to 1.2	Better efficiency reduces charging time and energy loss.
Weight of Drive Train	-0.5 to -1.0	Reducing weight improves acceleration and range.

A4: Algorithm for LMBT

- net.trainFcn = 'trainlm'
- [trainedNet,tr] = train(net,...)
- The process taking place in the training:
- [trainedNet,tr] = train(net,...) trains the network with trainlm.
- Trainlm is a network training function that updates weight and bias values according to Levenberg-Marquardt optimization.
- Trainlm is often the fastest backpropagation algorithm in the toolbox, and is highly recommended as a first-choice supervised algorithm, although it does require more memory than other algorithms.
- The "epoch" serves as a reference point from which time is measured.
- Training occurs according to trainlm training parameters, shown here with their default values:

- net.trainParam.epochs — Maximum number of epochs to train. The default value is 1000.
- net.trainParam.goal — Performance goal. The default value is 0.
- net.trainParam.max_fail — Maximum validation failures. The default value is 6.
- net.trainParam.min_grad — Minimum performance gradient. The default value is 1e-7.
- net.trainParam.mu — Initial mu. The default value is 0.001.
- net.trainParam.mu_dec — Decrease factor for mu. The default value is 0.1.
- net.trainParam.mu_inc — Increase factor for mu. The default value is 10.
- net.trainParam.mu_max — Maximum value for mu. The default value is 1e10.
- net.trainParam.show — Epochs between displays (NaN for no displays). The default value is 25.
- net.trainParam.showCommandLine — Generate command-line output. The default value is false.
- net.trainParam.showWindow — Show training GUI. The default value is true.
- net.trainParam.time — Maximum time to train in seconds. The default value is inf.

Battery Specifications:

S.No	Parameters of the Battery:	Lithium Ferrophosphate (LPH)	Lithium Manganese Oxide(LMO)	Lithium Cobalt Oxide (LCO)	Lithium Titanate (LTO)	Lithium Nickel Manganese Cobalt Oxide (NMC)
1	Nominal Cell Voltage: (V)	3.2	3.8	3.6	2.4	3.6
2	Energy Density:(Wh/Kg)	90 to 160	100 to 150	150 to 190	50 to 80	150 to 220
3	Life Cycle:	2000 to 12000	300 to 1000	500 to 1000	3000 to 7000	1000 to 2000
4	Specific Power:(W/kg)	200	250 to 340	250 to 340		250 to 340
5	Self Discharge Rate:	<5%/Month	<5%/Month	<5%/Month	<5%/Month	<5%/Month

Supercapacitors Specifications:

S.No	Parameter	Aluminum	Supercapacitors			Lithium-ion
			Double-layer	Pseudo capacitors	Hybrid (Li-ion)	
1	Temperature range,	−40 … +125 °C	−40 … +70 °C	−20 … +70 °C	−20 … +70 °C	−20 … +60 °C
2	Maximum charge,	4 … 630 V	1.2 … 3.3 V	2.2 … 3.3 V	2.2 … 3.8 V	2.5 … 4.2 V
3	Recharge cycles,	< unlimited	100 k … 1 000 k	100 k … 1 000 k	20 k … 100 k	0.5 k … 10 k
4	Capacitance,	≤ 2.7 F	0.1 … 470 F	100 … 12 000 F	300 … 3 300 F	—
5	Specific energy,	0.01 … 0.3 Wh/kg	1.5 … 3.9 Wh/kg	4 … 9 Wh/kg	10 … 15 Wh/kg	100 … 265 Wh/kg
6	Specific power,	> 100 W/g	2 … 10 W/g	3 … 10 W/g	3 … 14 W/g	0.3 … 1.5 W/g
7	Self-discharge	short	medium	medium	long	long
8	time at room temp.	(days)	(weeks)	(weeks)	(month)	(month)
9	Efficiency (%)	99%	95%	95%	90%	90%
10	Working life at room	> 20 y	5 … 10 y	5 … 10 y	5 … 10 y	3 … 5 y

OPO Parameters:

Parameter	Description	Value
Braking Intensity (z)	Determines the level of energy recovery during braking.	Low: 0.05–0.1, Medium: 0.4–0.7, High: 0.8+
Energy Recovery Efficiency	Efficiency of recovering energy during braking.	75%
Battery State of Charge (SoC)	The amount of energy stored in the battery as a percentage.	85% initial, varies during operation
Torque Distribution	Distribution of torque between front and rear wheels during braking/acceleration.	50/50 to 70/30 (front/rear)
Current Fluctuations	Variation in current drawn from the energy storage systems.	< 10% of nominal value
Energy Consumption	Total energy consumed by the vehicle during operation.	Varies with driving conditions, approx. 10-15 kWh/100 km
Energy Distribution Strategy	The distribution of energy between FC, battery, and supercapacitors.	FC: 40%, Battery: 30%, Supercapacitor: 30%
Vehicle Speed (Initial Speed)	Speed of the vehicle before braking.	60 km/h, 40 km/h, 20 km/h
Braking Smoothness	Measures the smoothness of braking power application.	9.6 (LMBT), 8.5 (OPO)
Efficiency of Power Conversion	Efficiency of converting power from energy storage to the motor.	85%–95%
Peak Power Demand	The maximum power required by the vehicle during acceleration.	80 kW (high acceleration)
Control Algorithm Performance	Performance of the algorithm used in OPO to control power flow and energy recovery.	High accuracy, < 5% deviation from ideal power distribution

Hyper Parameters:

Hyperparameter	Description	Selected Value	Optimization Method
Number of Layers	The depth of the LSTM network (e.g., 2-3 layers)	2 layers	Manual tuning based on performance evaluation
Neurons per Layer	The number of units in each LSTM layer (e.g., 50-100)	100 neurons per layer	Grid search and cross-validation
Learning Rate	Step size for weight updates (e.g., 0.001)	0.001	Adaptive learning rate schedule during training
Epochs	Number of full passes over the dataset (e.g., 100-300)	200 epochs	Cross-validation to find the optimal number of epochs
Batch Size	Number of samples processed before updating model weights	64	Grid search and performance testing
Dropout Rate	Fraction of input units set to zero during training (e.g., 0.2)	0.2	Manual tuning to prevent overfitting
Activation Function	Function applied to neurons (e.g., ReLU, sigmoid)	ReLU (Rectified Linear Unit)	Selected based on network type and task requirements
Optimizer	Algorithm used for weight update (e.g., Adam, SGD)	Adam	Grid search to find optimal optimizer

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