Received 18 February 2024, accepted 4 March 2024, date of publication 11 March 2024, date of current version 21 March 2024.
Digital Object Identifier 10.1109/ACCESS.2024.3375753

RESEARCH ARTICLE

Assessment of Adaptive Self-Learning-Based BLDC Motor Energy Management Controller in Electric Vehicles Under Real-World Driving Conditions for Performance Characteristics

PEMMAREDDY SAITEJA[1], BRAGADESHWARAN ASHOK[1], BYRON MASON[2], AND P. SURESH KUMAR[1]
[1]School of Mechanical Engineering, Vellore Institute of Technology, Vellore, Tamil Nadu 632014, India
[2]Department of Aeronautical and Automotive Engineering, Loughborough University, LE11 3TU Loughborough, U.K.

Corresponding authors: Bragadeshwaran Ashok (ashokmts@gmail.com) and Byron Mason (B.Mason2@lboro.ac.uk)

This work was supported in part by Indian Council of Social Science Research under Grant ICSSR/RPD/MN/2023-24/G/39, in part by the British Council-Going Global Partnerships Industry Academia under Grant 2023-24 (Application Unique ID-28), and in part by the Open Access funding from the Engineering and Physical Sciences Research Council (EPSRC) Project under Grant EP/L014998/1.

ABSTRACT The superior performance of an electric vehicles (EVs) is dependent on the related energy management controller (EMC). The current study devoted to develop various EMCs such PID, intelligent, hybrid and supervisory strategy to enhance the performance of EVs under real-time driving conditions. Also, the work integrates the various novel methodologies to develop EV model, efficiency maps and real-time driving cycle (DC). In this instance, a mathematical model of an EV with BLDC motor is developed using MATLAB/Simulink. Further, the efficiency maps for the motor and controller with different EMC's are generated using the innovative experimental approach. Then, the developed efficiency maps are incorporated into model-in-loop (MIL)-based EV test platform to analyze the performance of various EMCs. Additionally, to validate the EV model, a real time DC has been developed for different types of road conditions, including urban, rural, and highway. Subsequently, the developed DC is integrated with MIL-based EV test platform for analysis of energy consumption and battery discharge behavior under real-time conditions. From the results, the proposed supervisory controller (68.4%) exhibits minimal SOC drop than the PID (21.5%), intelligent (44.9%) and hybrid (59.1%) controllers. As well, the energy consumption (EC) of the various EMCs is 85.63, 60.14, 44.67 and 33.4 Wh/km. In the case of regenerative efficiency of the developed EMCs under real-time driving conditions are −27.73, −41.64, −58.28 and −77.6 Wh respectively. The overall outcome of this work demonstrates that the proposed supervisory controller achieves a considerable improvement in battery consumption as well as a reduction in EC as compared to PID, intelligent, and hybrid controllers.

INDEX TERMS Electric vehicles, energy management controllers, adaptive supervisory self-learning strategy, real-time driving cycle, efficiency maps.

ABBREVIATIONS

ASSC	Adaptive Supervisory Self-Learning Controller.
BLDC Motor	Brushless Direct Current Motor.
BMP	Battery Motoring Power.
BRP	Battery Regenerative Power.
DC	Driving Cycle.
DOE	Design of Experiments.
DOF	Degree of Freedom.
EC	Energy Consumption.

The associate editor coordinating the review of this manuscript and approving it for publication was Wonhee Kim.

EMC	Energy Management Controller.
EMs	Electric Motors.
EMS	Energy Management System.
EOT	End of Trip.
EV	Electric Vehicle.
FLC	Fuzzy Logic Controller.
GHG	Green House Gas Emission.
GPS	Global Positioning System.
GVM	Grass Vehicle Mass.
GVW	Grass Vehicle Weight.
HEV	Hybrid Electric Vehicles.
HIL	Hardware In Loop.
IM	Induction Motor.
MANFIS	Multi Adaptive Neuro Fuzzy Inference System.
MBC	Model Based Calibration.
MEP	Motor Electric Power.
MIL	Model In Loop.
MMP	Motor Mechanical Power.
MRP	Motor Regenerative Power.
Ms	Motor Speed.
Mt	Motor Torque.
NN	Neural Network.
OBD	On-Board Diagnosis.
PID	Proportional Integral Derivative.
SOC	State of Charge.
SR Motor	Switched Reluctance Motor.
Ws	Wheel Speed.
Wt	Wheel Torque

I. INTRODUCTION

The adoption of electric transportation is a significant solution for reducing air pollution and greenhouse gas (GHG) emissions. Advancing towards a more ecological automotive industry is also critical in dealing with the world's ever-increasing need of fossil fuels, despite their scarcity [1]. An Electric Vehicles (EVs) and Hybrid Electric Vehicles (HEVs) have been identified as crucial remedies for present environmental issues. An EVs are battery-powered vehicles and it provide several benefits such as no pollutants, high efficiency, and effortless driving experience with minimal environmental noise [2]. However, there is potential for further advancements in EV technology, including in the fields of driving range extension, battery and motor technology. Therefore, the development of EVs and the examination of their performance are significant interest to both the automotive sector and the research community [3]. In addition, to evaluate EV performance and optimize EM, battery, controller, and converter characteristics, the power required for propulsion and accessories must be assessed under real-world operating circumstances. However, the actual operation of the vehicle is highly unpredictable, as it is influenced by a variety of factors including energy consumption (EC), road conditions, temperature, road grade, driving behavior, etc [4], [5]. As a consequence, EC evaluations of EV are commonly conducted using the standardized driving cycle (DC) mandated by legislation. Diverse DCs are utilized globally, including new european driving cycle (NEDC), worldwide harmonized light vehicles test cycle (WLTC), federal test procedure (FTP), Indian modified driving cycle (IMDC), US06, etc [6], [7]. In [8] studied the effect of temperature on EC using the urban dynamometer driving cycle (UDDC) and NEDC, and the optimal EC for UDDC and NEDC were identified to be 1.547 kWh and 1.648 kWh, respectively. Then, in [9] investigated the influence of gearbox on the EC of EVs and discovered that dual and continuously variable gearbox systems save much more energy than single gear transmission. Even so, the energy consumption of EVs is majorly influenced by component sizing, operating regions of powertrain components (motor & battery), state of charge (SOC), driving range, etc. To address these issues, an optimal modelling environment is required to improve the vehicle performance and EC under various real-time driving conditions. As well, to ensure the effectiveness of vehicle modelling and validation procedures, critical design and control decisions must be considered. In particular, efficient modelling, simulation, and analysis of the EV powertrain components are required [10]. The primary components of an EV propulsion system are an electric motor (EM), battery, controller, and power converters. In EV propulsion system various types of EM are used such as Brushless Direct Current (BLDC) motor, Permanent Magnet Synchronous Motor (PMSM), Switched Reluctance Motor (SRM) and Induction Motor (IM). The performance of EVs is significantly influenced by the choice of the EM and its associated controller. The selection of the suitable motor and controller is critical to maximizing the performance and energy consumption of an EV, taking into account performance needs, energy efficiency objectives, economic concerns, and the desired driving experience [11], [12]. In this study, the BLDC motor has been chosen due to its favorable characteristics such as high starting torque, high efficiency, and high-power density. So, the development of an optimal energy management system (EMS) is a universal concern, particularly for EVs, to optimally distribute power demand without losing drivability and performance.

Today, there are several EMS techniques for enhancing the performance of EVs under different real-time conditions, such as proportional integral and derivative (PID) control, direct torque control (DTC), model predictive control (MPC), field-oriented control (FOC), fuzzy logic control (FLC), hybrid control, etc. Therefore, these controllers may be characterized by their capacity to accomplish one or multiple goals, such as minimizing energy consumption, optimizing dynamic responsiveness, enhancing drivability, etc. The DTC provides greater torque control and is thought to be a superior control approach for BLDC motors used in EVs. On the other hand, it has several flaws, such as torque and current ripples in low-speed conditions. As a result, it is difficult to achieve a maximal vehicle performance and minimal energy consumption under real-time driving conditions [13], [14], [15]. To accomplish high performance and maintain the battery SOC in a depleting phase around the desirable value, DTC and FOC techniques are integrated into BLDC motors for EV propulsion. When these two controllers are used, EVs operating in a variety of driving conditions exhibit poor EC and regenerative braking efficiency results [16]. So, the MPC approach is used to minimize the EC of EV under real-time driving conditions. It is used to forecast future behaviour EV and identify the optimum operating condition. As well, the capability to manage numerous dynamic constraints in realtime. Anyway, due to the EV system's high complexity, the MPC technique fails to achieve appropriate battery discharge limits under real-time driving circumstances [17], [18]. This technique is challenging to implement in real-time systems due to its high iterative and computational costs; also, it necessitates prior knowledge of future driving actions. The PID approach is gaining significant interest for the implementation of optimum EMS in real-world driving scenarios because to its dependability, short processing time, and efficient use of memory resources in real-time systems. It dynamically adjusts the control signals to improve the efficiency and driving range of the EV under various conditions. In [8], the PI variables have been optimized using the particle swarm optimization (PSO) and genetic algorithm (GA), which led to an enhancement in the transient response under real-time driving circumstances. A well-tuned PID controller can facilitate smoother transitions between different driving conditions, optimizing energy recuperation during regenerative braking and enhancing battery efficiency. In comparison to conventional vector control methods such as DTC and FOC, the PID controller demonstrates the capability to minimize EC and enhance the operational range of EVs during dynamic situations. The optimization of PID parameters and energy conservation in unpredictable circumstances is achieved in [19] via battery SOC feedback and vehicle velocity. In terms of vehicle performance, PID control ensures precise tracking of desired speed and torque, resulting in smooth acceleration and deceleration under real-time driving conditions. However, it can struggle in dealing with nonlinearities and uncertainties in the EV system, which can affect battery state of charge (SOC) estimation accuracy. Due to these reasons, the tuning of the PID parameters is difficult at various transient conditions. As a result, the designers have adopted intelligent controllers such as fuzzy logic controller (FLC), neural network (NN) to enhance the performance of the EV under unpredictable conditions [20], [21]. From the literature, to regulate the nonlinear operations of the EVs, the FLC employs a rule base and membership functions that integrate the input and output variables at different conditions. The optimal calibration of the membership functions and rule base will give more accurate responses under various dynamic conditions. Consequently, a FLC is more effective than a PID controller in terms of various characteristics such as EC, SOC, regen-efficiency, etc under varying speed and load conditions [22]. However, the non-linear behaviour of battery usage introduces numerous uncertainties into the battery SOC feedback system. Hence, it is critical to adjust the FLC settings to improve EV performance, which has yet to be addressed by researchers.

To address the uncertainties in battery state-of-charge (SOC) while driving in real-time, a novel hybrid learning approach is suggested [23]. It is an integration of FLC and PID technique that govern the EV's varied transient error responses under diverse scenarios. The FLC duty is to modify the PID parameters based on the most suitable rules and membership functions. The combination of FLC and PID controllers is referred to as a revolutionary hybrid strategy for reducing EC and improving battery performance under variety of transient conditions. It offers the advantage of both accuracy and robustness, which can result in improved battery health and lifespan. In addition, the hybrid technique is utilized to improve EV performance under various road circumstances (Urban, Rural, and Highway) by using battery SOC, vehicle speed, driving behaviour, and current flow direction (i.e., regeneration) as feedback [24]. However, a variety of hybrid control techniques have been implemented in research studies to manage nonlinear systems whose control parameters are unknown and which operate under limited conditions. With the data-driven nature of these approaches, it is challenging to establish a suitable mathematical model for nonlinear systems in the context of real-time driving situations. Besides, NN is a sort of control mechanism that has the capability to adapt and learn via the adjustment of neuron weights, sizes, relationships between neuron layers, and activation functions [25]. But, the precision of neural network control is contingent upon both the quality and quantity of the data used for training. Also, it exhibits longer time for data training and provide questionable control outside the training domain. It is noted that relying only on a single learning approach might lead to negative outcomes to some extent. Therefore, integrating several control strategies (FLC, NN), known as hybridization, have more promise for achieving greater efficiency in real-time conditions [26]. In this context, an Adaptive Supervisory Self-Learning Controller (ASSC) is a hybrid learning control approach that combines the reasoning mechanism of FLC with the self-learning capability of NN. The NN improves the output decisions of the fuzzy inference system by defining the optimum membership functions on the basis of the training data. This integration aims to improve the performance and minimize the EC of EVs in real-time scenarios. By employing the ASSC approach, the variations of speed, torque and unfavorable chattering consequences under different conditions are reduced quickly. The implementation of a supervisory control technique improves the dynamic behaviour of the EV in terms battery SOC, EC, battery C-rate, regenerative efficiency, etc [27]. Therefore, ASSC is a more effective control strategy than FLC and NN for controlling battery SOC fluctuations under real-time conditions. The implementation of a non-linear ASSC strategy have the potential to enhance the utilisation profile of the battery SOC in EVs, hence extending their operational range. The ASSC approach is implement with BLDC motor used in EV applications under real-time conditions. In this study, the entire procedure of design and performance assessment is conducted using the model-in-the-loop (MIL) simulation. In MIL simulation, it is generally more efficient and computationally straightforward to define a system behaviour using a mapped experimental response technique rather than relying on numerical representations to depict the behaviour of the BLDC motor, controller, and battery systems. Using a model-based calibration technique, an efficient BLDC motor and controller maps (lookup) have been developed. This process includes the following stages: design of experiments (DOE), model fitting, optimization, and lookup table generation. During the process of map (lookup table) generation, the use of experimental design allows for a systematic examination of the impact of BLDC motor and controller behaviour under various conditions, while minimizing the number of test cases required. This use of Design of Experiments (DOE) effectively decreases the complexity, time, and expense associated with the map development process. As the field of EVs continues to evolve, advancements in control strategies will play a pivotal role in achieving greater energy efficiency, prolonged battery life, and enhanced driving experiences.

In the present context, vehicles manufacturers have recognized that an efficient EMS is required for the effective performance outcomes of EVs under real-time driving conditions. The importance for sophisticated EMS that improve the energy efficacy of EVs in real-world conditions is addressed in this research. Numerous studies have been carried out on numerical simulation of EV performance characteristics with various EMS approaches under real-time driving conditions. Particularly, the estimation of accurate driving range by evaluating the EC of EVs is the key factor for eradicating driver anxiety. Moreover, it is substantially more difficult to identify the optimal discharge path for EVs owing to variations in driving actions, road grade, travel distance, and initial SOC. To address the issue of battery utilisation in EVs, this study aims to provide an advanced self-learning control strategy that can effectively achieve real-time optimum energy management. This study aims to bridge the gap between theoretical advancements and practical implementation by evaluating the optimal EMS effectiveness within an BLDC motor equipped EV under real-world driving conditions. According to the extensive literature review on EV performance with different control methods, no publication thoroughly examines the performance characteristics of EVs with various energy management approaches. In this context, the objective of this study is to develop a mathematical model of an EV through integrating the mapped BLDC motor and controller efficiency with various EMS techniques. This study also develops different energy management strategies such as PID, FLC, hybrid, and adaptive supervisory self-learning controllers for minimize the EC and extend the range of EV under different operating conditions. Compared to traditional approaches such as PID, FLC and hybrid, the ASSC approach improves the dynamic behaviour of the EV in terms battery SOC, EC, battery C-rate, regenerative efficiency, etc. Further, the novelty of the present work is the development of a real-time driving cycle across a variety of road conditions, including urban, rural, and highway to examine the effectiveness of EVs in real-time operating conditions. In addition, this research employs an innovative methodology to develop DC and efficiency maps of the controller and BLDC motor under real-time conditions. Then, the developed DC and efficiency maps are loaded into the EV model to verify different performance parameters as EC, regeneration efficiency, motor power, Battery SOC, battery current, C-rate, etc with various energy management controllers (EMC) under real-time operating conditions. Subsequently, the different energy management controllers (PID, Fuzzy, hybrid and ASSC) are compared with numerous performance parameters to assure the energy management real-time performance superiority. The proposed adaptive supervisory self-learning controller is anticipated to yield improved battery utilisation, therefore ultimately enhancing the real-time operational performance of electric vehicles. With the specified objectives, this study will deliver readers with knowledge and a critical perspective regarding the design and development of an effective energy management controller for electric vehicles. Finally, this work provides assistance in critical areas and proposes potential areas for future research concentration.

II. PROPOSED METHODOLOGY

This methodology examines the performance of EV with different energy management controllers by integration of efficiency maps and real-time driving cycle under different operating conditions. In this study, the entire procedure of design and performance assessment is conducted using the model-in-the-loop (MIL) simulation. The workflow and proposed methodology of the present study have been organized in accordance with the four aspects illustrated in Fig 1. First, an EV model is developed with BLDC Motor via the MATLAB/Simulink software, employing the reference parameters of the Ather 450 plus vehicle. The specification details of the developed EV model are presented in Table 1. The present study employs the backward-facing modelling approach to construct the electric vehicle configuration. The generic structure for backward-facing model consists of sub-models related to longitudinal block, transmission block, battery block, mapped motor and controller block. To validate the performance of the EVs, various efficiency maps (motor and controller) of energy management controllers (PID, FLZ, Hybrid and ASSC) and a real-time driving cycle are installed in EV model. Secondly, under real-time operating conditions, this study develops different energy management controllers, including PID, FLZ, Hybrid, and ASSC, to ensure the battery utilisation path and increase the driving range of electric vehicles. The motor and controller behavioral maps (lookup tables) are developed experimentally with different energy management controllers using the point-by-point model-based calibration technique under transient situations. Next, this work developed a real-time DC

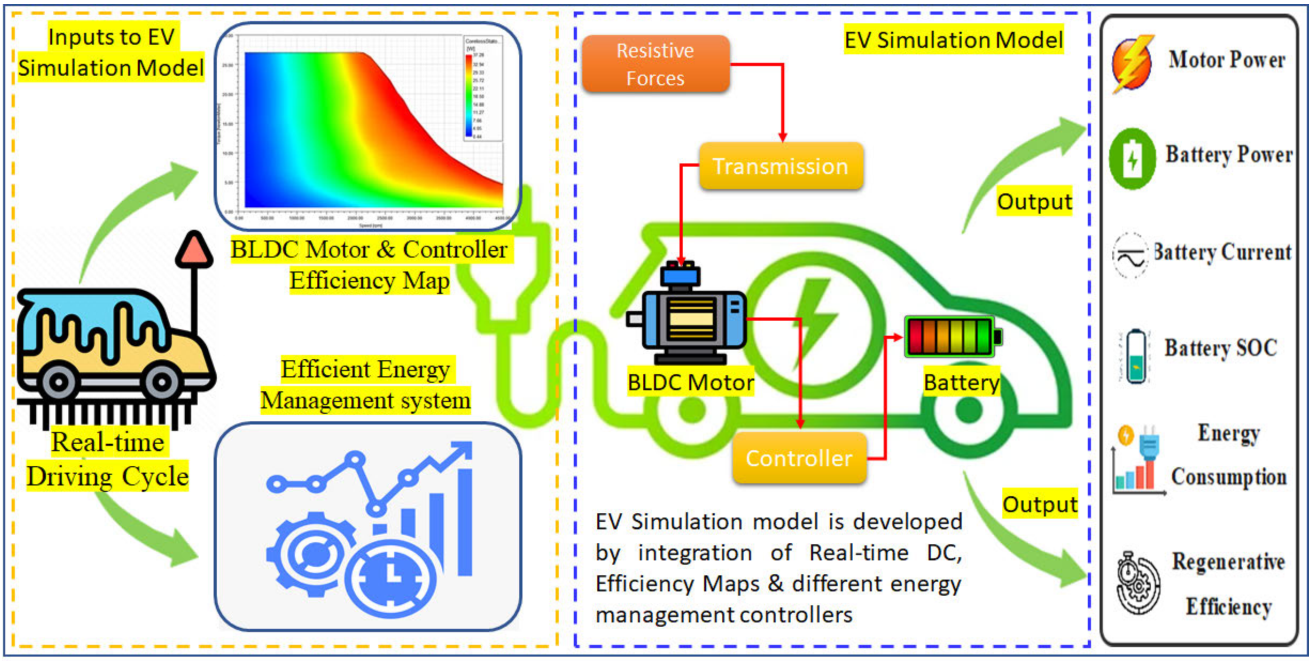


FIGURE 1. Proposed methodology of the present research.

TABLE 1. Technical specifications of the developed electric vehicle.

SNO	Parameters	Features	Value	Unit
1	Vehicle	Model	Electric Scooter	-
		Rolling resistance	0.015	-
		Mass	111	kg
		Garde Angle	0	Degree
		Area	0.875	m^2
		Velocity	Driving Cycle	kmph
2	Transmission	Type	Belt Drive	-
		Gear ratio	7.8:1	-
		Transmission Efficiency	85	%
3	Motor	Type	BLDC Motor	-
		Driving Cycle Time	33.45	km
4	Battery	Type	Lithium-ion	-
		Battery Capacity	2400	Wh
		Battery Voltage	51.1	V
		Battery Initial SOC	100	%
		Cell Voltage	3.6	V
		Cell Capacity	2.7	Ah

across a variety of road conditions, including urban, rural, and highway to examine the performance of various energy management controllers in real-time operating conditions. Further, the developed efficiency maps and DC are loaded in EV model to verify the performance with EC, regeneration efficiency, motor power, Battery SOC, battery current, C-rate, etc. However, the battery utilisation characteristics vary based on the travel distance and the starting battery

SOC. Utilizing the various energy management controllers to optimize sudden energy distribution ensures the battery utilisation path remains unchanged during real-time operation, thereby extending the vehicle's driving range. Finally, the different energy management controllers are compared with numerous performance parameters to assure the energy management real-time performance superiority. The proposed ASSC approach is anticipated to yield improved battery utilisation, therefore ultimately enhancing the real-time operational performance of electric vehicles.

III. DEVELOPMENT OF ELECTRIC VEHICLE MODEL TO VALIDATE THE PERFORMANCE OF THE PROPOSED CONTROL SYSTEM

In this article, a backward-facing EV model has been designed and tested on the Matlab-Simulink platform using a BLDC motor EV configuration. Fig 2 shows a simplified schematic architecture of the potential EV configuration. The Simulink model comprises five main functional blocks, which have been derived from the physical components arranged in the EV system: longitudinal block, transmission block, battery block, mapped motor and controller block. The architecture of the developed Simulink function block for simulating the EV model is depicted in Fig 2. In this section, the relevance and mathematical relationships of vehicle dynamics, battery, motor, and controller are examined to increase the accuracy of EC and driving range estimates.

A. LONGITUDINAL VEHICLE DYNAMICS MODEL

Vehicle modelling begins with an examination of the dynamics and the impact of numerous parameters on its performance. To calculate these parameters, the forces acting on the vehicle must be specified. The model has only one degree of freedom (DOF) (longitudinal motion) therefore lateral and vertical motions are neglected [28]. In essential powertrain modelling, the assessment of the EV performance is conducted by considering its longitudinal vehicle dynamics. An aerodynamic force, acceleration force, rolling force, and gradient forces are considered as longitudinal resistive forces [29]. The driving cycle is a critical input to the longitudinal vehicle dynamics block. Then, it involves a comprehensive consideration of various resistive forces exerted on the vehicle during its longitudinal motion. These encompass rolling forces (Equation 1), arising from the interaction between the tires and the road surface; aerodynamic forces (Equation 2), influenced by the vehicle's shape and speed; gradient forces (Equation 3), stemming from inclines or declines in the terrain; and acceleration forces (Equation 4), reflective of changes in velocity. After that, the estimation of the total tractive force is illustrated in Equation 5. Finally, the output of the longitudinal vehicle dynamic block is wheel speed and torque, as specified in equations (6) and (7).

$$Fr = Crf * GVW * Cos(\theta \tag{1}$$

$$Fa = 0.5 * \rho * Af * Cd * V^2 \tag{2}$$

$$Fg = Sin(\theta) * GVW \tag{3}$$

$$Facc = a * GVM \tag{4}$$

$$Ft = Fr + Fa + Fg + Fa \tag{5}$$

$$Wt = Ft * Rw \tag{6}$$

$$Ws = \frac{V * 60}{2 * \pi * Rw} \tag{7}$$

where, GVW -grass vehicle weight, GVM-grass vehicle mass, Crf-co-efficient of rolling resistance, Fr-rolling force, Fa-aerodynamic force, Fg-gradient force, Facc-acceleration force, Ft-total tractive force, Cd-drag co-efficient, A_f- frontal area, a-acceleration, ρ- density, Wt-wheel torque, Ws- wheel speed, Rw-wheel radius and V-velocity (rpm).

B. TRANSMISSION MODEL

To meet a wide range of EV tractive needs, efficient power electronics-controlled BLDC motor in EVs substitutes multi-speed with gearless or single-speed gear transmission [30]. In this study, the transmission model is based on single speed transmission with gear ratio of 7.8:1. Based on the inputs from the longitudinal model (wheel speed and torque), it estimates the motor speed and torque and sent to BLDC motor model. The outputs of the transmission model are presented in equation (8) and equation (9).

$$Mt = \frac{Wt}{GR * Teff} \tag{8}$$

$$Ms = Ws * GR \tag{9}$$

where, GR-gear ratio, Mt- Motor speed, Ms- Motor speed (rpm), Teff- Transmission efficiency.

C. MAPPED BLDC MOTOR AND CONTROLLER MODEL

The performance parameters of EVs including acceleration, maximal speed, passing capability and gradeability are dependent operating range of BLDC motor and controller. The incorporation of a mathematically modelled BLDC motor and controller into EV simulation introduces an extra computational obstacle and represents the complex dynamic characteristics of the transient BLDC motor [31]. Hence, the optimal response behavior maps are constructed utilizing the steady state empirical model of BLDC motor and controller behavior. Further elaboration on the process of map construction and experimentation will be presented in the subsequent section. Based on this contemplation, the developed BLDC motor and controller efficiency maps with different EMS's (PID, FLZ, Hybrid and ASSC) are used in the EV simulation model. Further, based on the inputs from the transmission model (Mt & Ms), the mapped BLDC motor model estimate the motor mechanical power (MMP) (equation (10)) and motor electrical power (MEP) (equation (11)) under different real-time operating conditions. The MEP is calculated by the integration of various energy management controllers BLDC motor efficiency maps. As well, the motor model estimates the motor regenerative power (MRP) (equation (12)) by the inclusion of different controllers' regenerative efficiency maps under numerous operating conditions. Then, to analyze the performance of mapped controller under real-time conditions, the outputs of the motor block (MEP & MRP) are sent to the controller block.

$$MMP = \frac{2 * \pi * Ms * Mt}{60} \tag{10}$$

$$MEP = MMP > 0 \div Meff = f\,(S, T > 0) \tag{11}$$

$$MRP = MMP < 0 * Meff = f\,(S, T < 0) \tag{12}$$

were, Meff-Motor efficiency, S-Motor Speed, T-Motor Torque. The controller block regulates the operations of the BLDC motor and battery. The controller block determines any modifications in the operation of the vehicle related with the demand energy based on the signals received from the motor model block. Based on the inputs (MEP & MRP) from the motor block, the controller block estimates the battery motoring power (BMP) and battery regenerative power (BRP) by the integration of various motor controller and regenerative controller efficiency maps. The functions of the expressions are shown in equations 13 and 14. Finally, the outputs of the mapped controller block (BMP & BRP) are sent to the battery bock to estimate the EC and regenerative efficiency of different control algorithms under real-time operating conditions. In section IV contains comprehensive information about the proposed control algorithms.

$$BMP = MEP \div MCeff = f\,(S, T > 0) \tag{13}$$

$$BRP = MRP * MCeff = f\,(S, T < 0) \tag{14}$$

where, MCeff- Motor controller efficiency, BMP- Battery motoring power, BRP- Battery regenerative power.

D. BATTERY PACK MODEL

The battery is a complex and nonlinear system, making the modeling of its function challenging. Its functioning is affected by SOC, temperature, aging, and internal resistance. The parameters related to battery performance need to be evaluated for understanding its variations and limitations under real-time driving conditions [32]. As a result, to simplify the battery model, the influence of battery aging and temperature is not studied in this work. The lithium-ion battery is often used as an energy source in EVs because of its unique characteristics such as high voltage potential, high energy density and lightweight with minimal self-discharge. Based on the inputs (BMP & BRP) from the controller block, the battery model predicts the E/km, battery current, driving range, SOC, C-rate, and regeneration efficiency with different energy management controllers (PID, FLC, hybrid and ASSC) under real-time driving cycle. The magnitude and direction of battery current in EVs are varying based on the position of the accelerator and brake pedal. Then, battery SOC acts as a direct indicator of the total available energy in the battery during the trips which is a key factor to evaluate the remaining driving range of EVs. Moreover, the total driving range of EVs is directly correlated with the amount of energy consumed and recovered during acceleration and barking, which is primarily depending on the atmospheric conditions and characteristics of road segments, vehicle physical parameters, speed and acceleration. Finally, the functional equations of the energy consumption per km (E/km) and SOC are presented in equation (15) & (16).

$$\frac{E}{km} = \int BMP > 0 \div \left(distance * 3.6 * 10^6\right) \tag{15}$$

$$SOC = ISOC - \left(\int Bc \div 3600 * Bcap\right) \tag{16}$$

where, BMP- Battery motoring power, ISOC- Initial SOC, Bc- Battery current, Bcap- Battery Capacity.

IV. DESIGN AND DEVELOPMENT OF EFFICIENT CONTROL SYSTEMS TO EVALUATE PERFORMANCE OF ELECTRIC VEHICLE

An efficient energy management controller improves the range and efficiency of EVs while minimizing EC under a variety of operating conditions. This research investigates different kinds of energy management controllers, such as PID, fuzzy, hybrid, and supervisory techniques, for improving EV performance under real-time driving conditions. These controllers have the ability to accurately predict the battery utilization path while minimizing EC and improving regeneration efficiency under a variety of dynamic circumstances. These controllers are constructed and tested (steady state experimentation) under a variety of dynamic conditions in order to generate efficiency maps for the motor and controller. An efficiency maps are generated for the motor and controller in real-time using various energy management controllers. In subsequent sections, the experimental procedure and development of the control system for BLDC motor are detailed.

A. PID CONTROLLER

The PID Controller is the most often utilized controller for controlling industrial operations and EV BLDC motor speed. It uses a closed loop system to continually check the output and change the input values to get the desired output with little to no volatility in the values despite the different disturbances. The PID controller removes the incorrect response caused by the discrepancy between the feedback and reference speeds. This erroneous response is multiplied by the proportional (Kp), integral (Ki), and derivative (Kd) sections of the controller and then summed to estimate the final controller output [33]. This output regulates the duty cycle of the PWM pulses necessary for the BLDC motor to run in a continuous loop. The continuous output control signal (u(t)) of the PID controller is represented in equation (17). However, the selection of PID settings has an effect on the efficiency of the EV BLDC motor. It leads to improve the EC and decrease regenerative efficiency under real-time operating conditions. As a result, estimating PID settings is essential for the smooth operation of an EV BLDC motor. In this proposed work, the PID parameters are chosen using the Ziegler Nichols method. The Ziegler Nichols method is used to fine-tune the P, I, PI, and PID controllers when the BLDC motor dynamics are available or not precisely known [34]. The Ziegler Nichols rules are used to predicted the PID controller gains based on the various transient responses of the EV BLDC motor. The proportional controller is connected to the BLDC motor in a closed loop system. This method begins by zeroing the Ki and Kd gains and the Kp value is then increased from zero to the utmost value until the system exhibits stable oscillations. The maximal value of Kp is denoted by Kcr (Kcr-Critical value of Kp), whereas the period of oscillations is denoted by Tcr (Tcr-Critical period of oscillations). The PID tuning parameters are determined based on the optimal tuning of the Kcr and Tcr values and the tuning methodology of the Ziegler Nichols approach are depicted in Fig 3.

$$U(t) = K_p * e(t) + K_i * \int e(t)\,dt + K_d * \frac{d}{dt} e(t) \qquad (17)$$

Further, the MATLAB/Simulink is utilized to construct the mathematical model of the EV BLDC motor with PID controller during steady-state experimentation. The EV BLDC motor is operated in accordance with the optimal experimental design to estimate the various output parameters for the purpose of generating efficiency maps. The findings lead to the development of an EV BLDC motor and controller PID approach efficiency map under various dynamic conditions. Finally, to analyze a variety of performance parameters, including battery SOC, EC, motor power, and regenerative efficiency, the developed PID controller efficiency maps has been integrated into an EV simulation model. The simulation findings indicate that the PID controller fails to achieve minimum EC, SOC drop, and maximum regenerative efficiency as a consequence of the intricate nature of the EV system.

B. INTELLIGENT CONTROLLER

The intelligent controller is generally acknowledged as an appropriate controller for complex linear and nonlinear EV systems. It is used to manage a large variety of input and output variables, resulting in efficient and acceptable outcomes. The detailed design and development processes of the intelligent controller is discussed in [35]. Further, this work combines the developed intelligent controller with a steady-state EV BLDC motor experiment to generate intelligent controller efficiency maps under real-time driving situations. With the intelligent control approach, the EV BLDC motor and controller efficiency maps are developed under various real-time operating conditions. Subsequently, the developed efficiency maps are loaded into EV simulation model to estimate the EC and regenerative efficiency with real-time driving cycle. The intelligent controller control rule tuning is challenging due to the complexity of real-time EV operation. So, the intelligent controller exhibits a sub-optimal result with the EV simulation model. However, the findings reveal that the intelligent controller has a lower EC, battery SOC drop, and a higher regeneration efficiency than the PID controller. Finally, the intelligent controller improves the performance of the EVs than PID controller under real-time driving condition.

C. HYBRID CONTROLLER

The process for developing and enhancing intelligent controllers in real-time is typically complex since many elements must be altered, such as MFs, control rules, input and output gains, and so on. Also, the selection of appropriate PID controller parameters is of utmost significance, and various methodologies are proposed for the estimation of PID controller advantages. Despite the fact that adjusting the controller gains can improve the performance of the PID controller. As a consequence, a self-tuning hybrid controller is implemented to modify the PID gains in response to the static and dynamic speed of the EV BLDC motor. It is the combination of PID and intelligent controller. The gains of the PID controller are adjusted in real-time by means of an intelligent controller. The detailed design and development processes of the hybrid controller is discussed in [35]. Hence, the output control signal of the hybrid controller can be described by the subsequent equation (18):

$$\mathrm{UPID} = K_{p2} * e(t) + K_{i2} * \int e(t)\,dt + K_{d2} * \frac{d}{dt} e(t) \qquad (18)$$

where Kp2, Ki2 and Kd2 are the modified gains of the PID controller. Based on the optimal tuning of PID gains though the fuzzy rules, the self-learning controller is developed under real-time conditions. Then, in an effort to analyze and generate efficiency maps in real-time, the developed hybrid controller is integrated into an EV BLDC motor steady state experiment. The EV BLDC motor and controller maps are produced using a hybrid technique in steady state testing under varied dynamic situations. Afterwards, the developed efficiency maps are plugged into an EV simulation to examine performance characteristics of vehicle through a real-time driving cycle. According to the data, the self-learning controller outperforms the PID and intelligent controllers in terms of battery SOC, EC, and energy recovery. However, the tuning rules and gains in a self-learning controller under real-time operational circumstances is tricky. So, this work presented an adaptive supervisory self-learning controller to improve vehicle performance with low EC and maximum energy recovery under various dynamic circumstances. The subsequent section provides a comprehensive explanation of the supervisory self-learning controller.

D. ADAPTIVE SUPERVISORY SELF-LEARNING CONTROLLER

This research integrates NN and FLC into an adaptive supervisory self-learning controller for EV analysis in a variety of real-time scenarios. The integration of FLC and NN produced an innovative method that consolidated the benefits of both techniques, resulting in significant progress in nonlinear mapping, modeling, and learning. In EVs, the optimization of controller parameters has become a challenging task due to recent developments in BLDC motors. As a result, to maximize the efficiency of BLDC motors in EVs, controller developers must adopt some sophisticated self-learning control strategies. The versatility of the ASSC renders it suitable for implementation in an extensive range of control applications. The internal architecture of the ASSC approach is presented in Fig 4. The detailed design and development procedures of the ASSC approach is discussed in [35]. The schematic representation of proposed energy management controllers in rea-time is presented in Fig 5. The developed ASSC controller is integrated into an EV BLDC motor steady state experiment. The investigations are conducted in accordance with the DoE's design plan. Subsequently, the ASSC method is employed to generate efficiency maps for the EV BLDC motor and controller across a range of dynamic conditions. Next, the developed efficiency maps are loaded into EV simulation model for the investigation of vehicle performance characteristics with real-time driving cycle. The results obtained from the EV simulation model utilizing the ASSC approach indicate that various performance parameters, including battery state of charge, energy recovery, battery current, battery power, and motor power, reveal optimal performance across a range of real-time driving conditions. Finally, the adaptive supervisory self-learning controller shows optimal performance results than PID, FLC and hybrid controller under real-time driving conditions. In a subsequent section, the experimental setup and efficiency map development process for the EV BLDC motor and controller are detailed.

V. DEVELOPMENT OF CONTROLLER AND MOTOR OPERATING MAP UNDER VARIOUS REAL-TIME OPERATING CONDITIONS

This section outlines the experimental setup of an optimal BLDC motor and controller efficiency maps, which will be used to build the Simulink EV simulation model within the MATLAB software.

A. EXPERIMENTAL SETUP FOR MAP DEVELOPMENT

In this study, a 4.5 kW BLDC motor is employed to generate efficiency maps for various energy management controllers (PID, FLC, Hybrid & ASSC) under real-time driving conditions. The BLDC motor is securely placed in the testbed, as illustrated in Fig 6, and the eddy current dynamometer of 12 kW is safely connected to the shaft of the BLDC motor. From Fig 6, The stepdown transformer receives a 230 V AC power and converts it to 60 V AC since the BLDC motor works at 60 V DC. The technical specifications of the BLDC motor are presented in Table 2. The reduced voltage is subsequently sent to the rectifier, which converts 60 V AC to 60 V DC to power the BLDC motor. In this case, a 400 V capacitor is used to stabilize the BLDC motor's DC voltage under fluctuating load and speed situations. To verify the effectiveness of the various energy management controllers, the 60 V DC output is directly linked to the BLDC motor's drive or inverter. The controllers (PID, FLC, Hybrid & ASSC) mentioned above have been developed in real-time using MATLAB/Simulink and are linked to the STM32 microcontroller or DAC in an encrypted way via USB. Following that, the STM32 microcontroller is connected to the drive/inverter through a serial port (RS 232) to broadcast and receive information under diverse operating situations. Moreover, the dynamometer control interface allows for manual load regulation of a BLDC motor under different speed conditions. At that time, in different real-world situations, the BLDC motor drive/inverter receives control signals from the developed energy management controllers such as PID, FLC, hybrid and ASSC. Based on the control signals from various EMC's, the BLDC motor and drive operates under different operating conditions. Finally, the output responses (current & voltage) of the controller and motor are estimated based on the feedback data received from the real-time system. Finally, the efficiency maps of the controller/drive and motor are generated using various energy management controllers such as PID, fuzzy, hybrid, and supervisory approaches based on the experimental predicted output responses of the motor and controller under various dynamic scenarios. The detailed procedure of map development is discussed in further section.

B. OPTIMAL ENERGY EFFICIENT RESPONSE MAPS UNDER VARIOUS DYNAMIC OPERATING CONDITIONS

In this work, the Model Based Calibration (MBC) technique is used to develop motor and controller efficiency maps with various EMCs for the EV simulation model. The MBC technique stepwise process entails DoE, modeling, optimization, and map production. The MBC methodology in MATLAB is a complex strategy that is utilized in this research to investigate the influence of certain variables on future outputs. A one-stage model approach is employed in this study to generate motor and controller efficiency maps for PID, intelligent, hybrid and supervisory controllers under real-time operating conditions. The behavior of the motor and controller is heavily influenced by its operating and control parameters. Torque and speed are the operational parameters for the motor, while energy management controllers (control algorithms such as PID, FLC, and so on) are the control parameters. To achieve the optimum BLDC motor and controller response maps, the control parameters (control algorithms) must be optimized at various dynamic circumstances. Experimental motor response behaviors are captured using the DoE technique in order to create the model. An experimental control and operational parameter ranges are shown in Table 3. The design plan had been created in collaboration with the DoE (50 test conditions) employing the I-optimal technique. The tests are carried out in accordance with the design plan, and the Sobol-series DoE is utilized to gather the motor and controller data for various EMC's based on the test circumstances. The gathered data is processed through data transformation such that it roughly matches a normal distribution, which increases the model forecasting capability's efficiency. In this research, a Gaussian elimination technique is employed to generate the motor and controller empirical model behaviors under dynamic situations. With the empirical models of the motor and controller, the optimal efficiency maps for different EMCs of BLDC

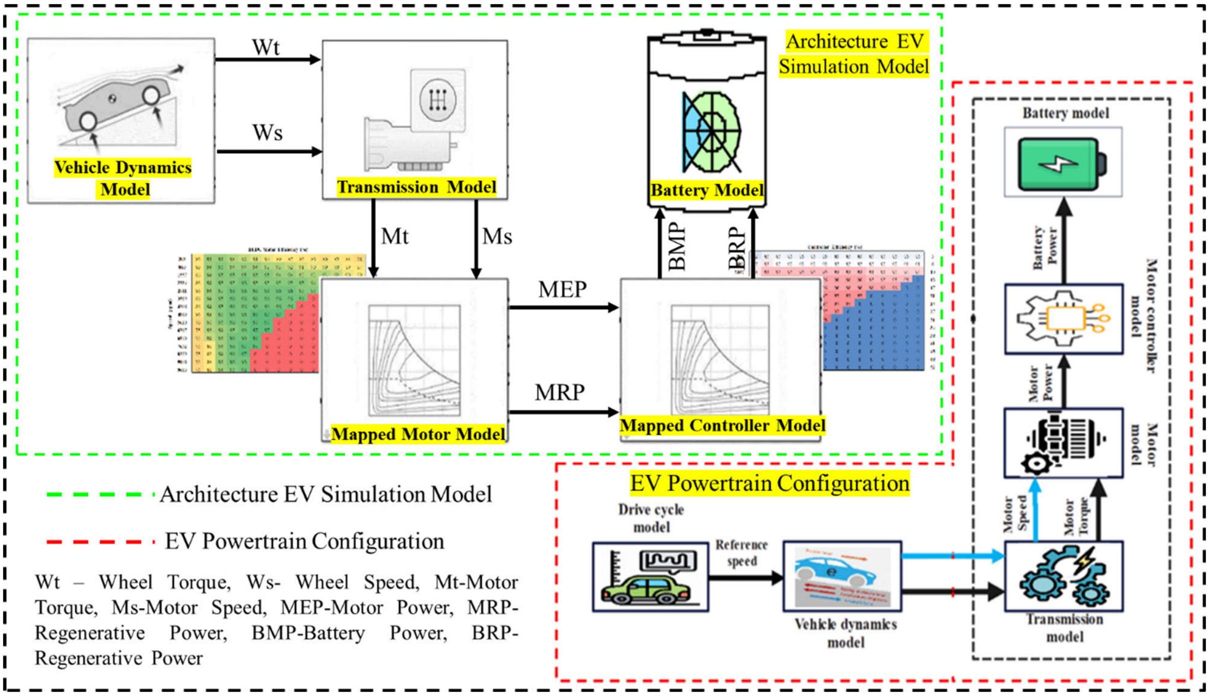


FIGURE 2. Schematic representation of EV simulation model and EV powertrain configuration.

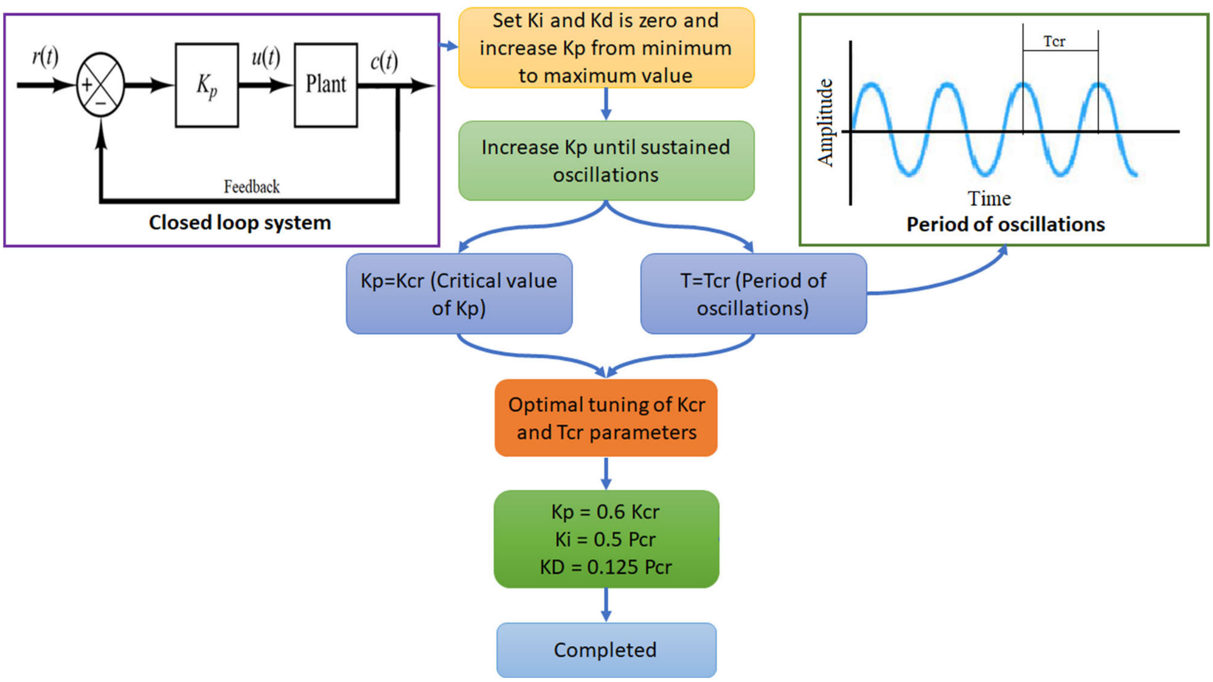


FIGURE 3. Tuning methodology of PID controller gains using ziegler nichols approach.

motor and controller are developed under real-time operating conditions. Figure 7 (a-d) depicts the developed BLDC motor and controller efficiency maps with different energy management strategies such as PID, FLC, hybrid and ASSC approach under real-time Condition, which will be utilized in vehicle modeling. Finally, to examine the performance characteristics of the vehicle, the developed controller and motor efficiency maps are loaded into EV simulation model.

VI. SIMULATION AND VALIDATION OF THE DEVELOPED MOTOR AND CONTROLLER MAPS WITH THE REAL-WORLD DRIVING CYCLE

The driving cycle source is required to estimate the EC and battery discharge behavior in the simulation. In this study, a real-time DC is developed for all types of road conditions, including urban, rural, and highway. Fig 8 depicts the experimental methodology for developing real-time DC under

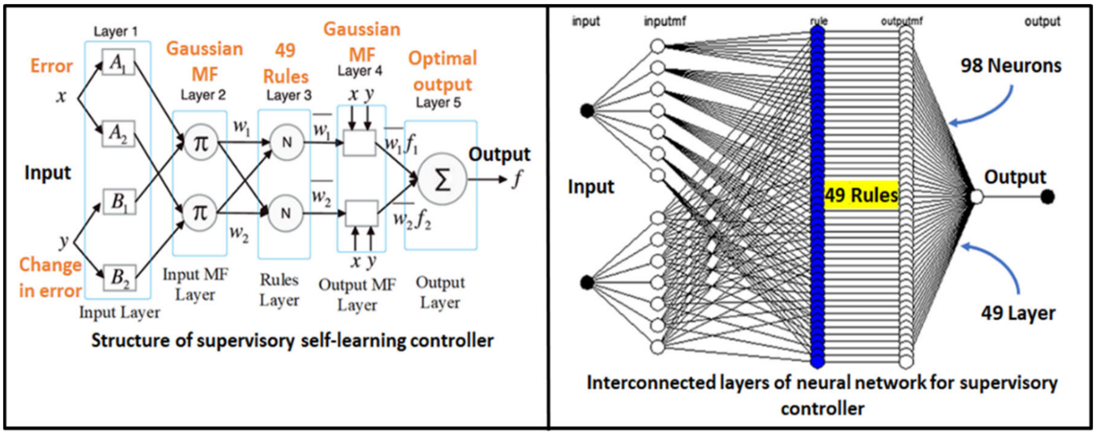


FIGURE 4. Internal architecture of the proposed supervisory controller.

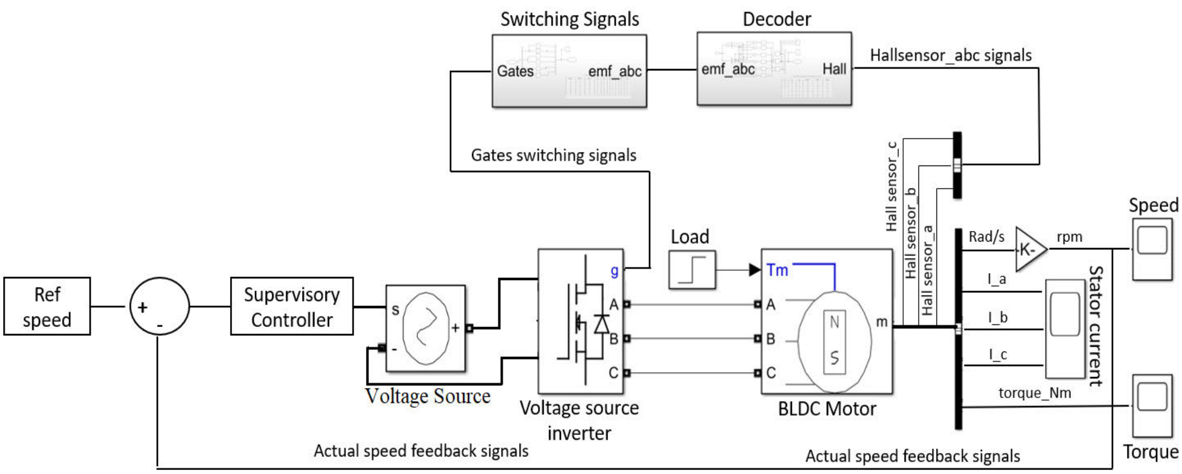


FIGURE 5. Schematic representation of a proposed energy management controller for the development of BLDC motor efficiency map.

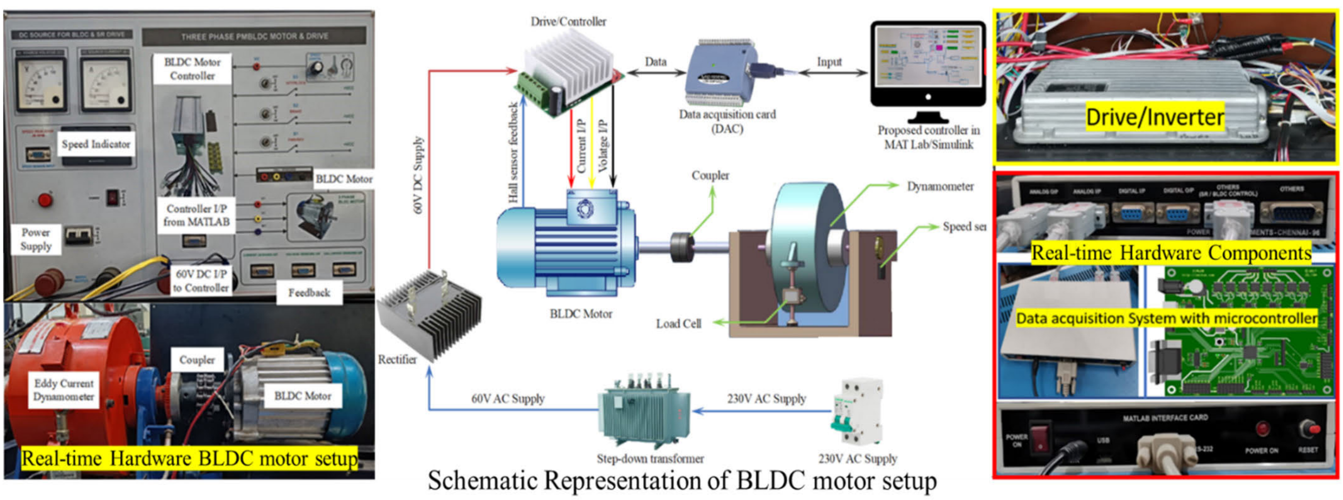
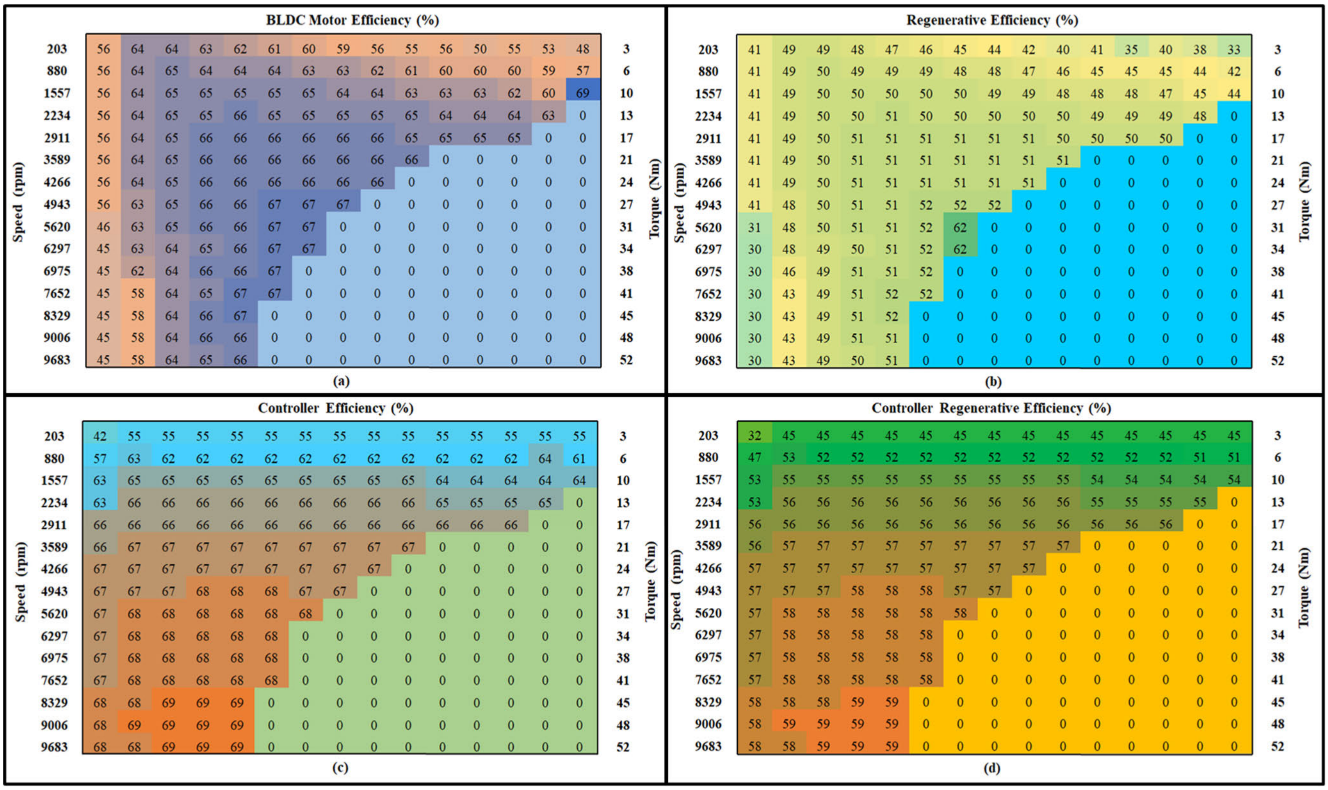
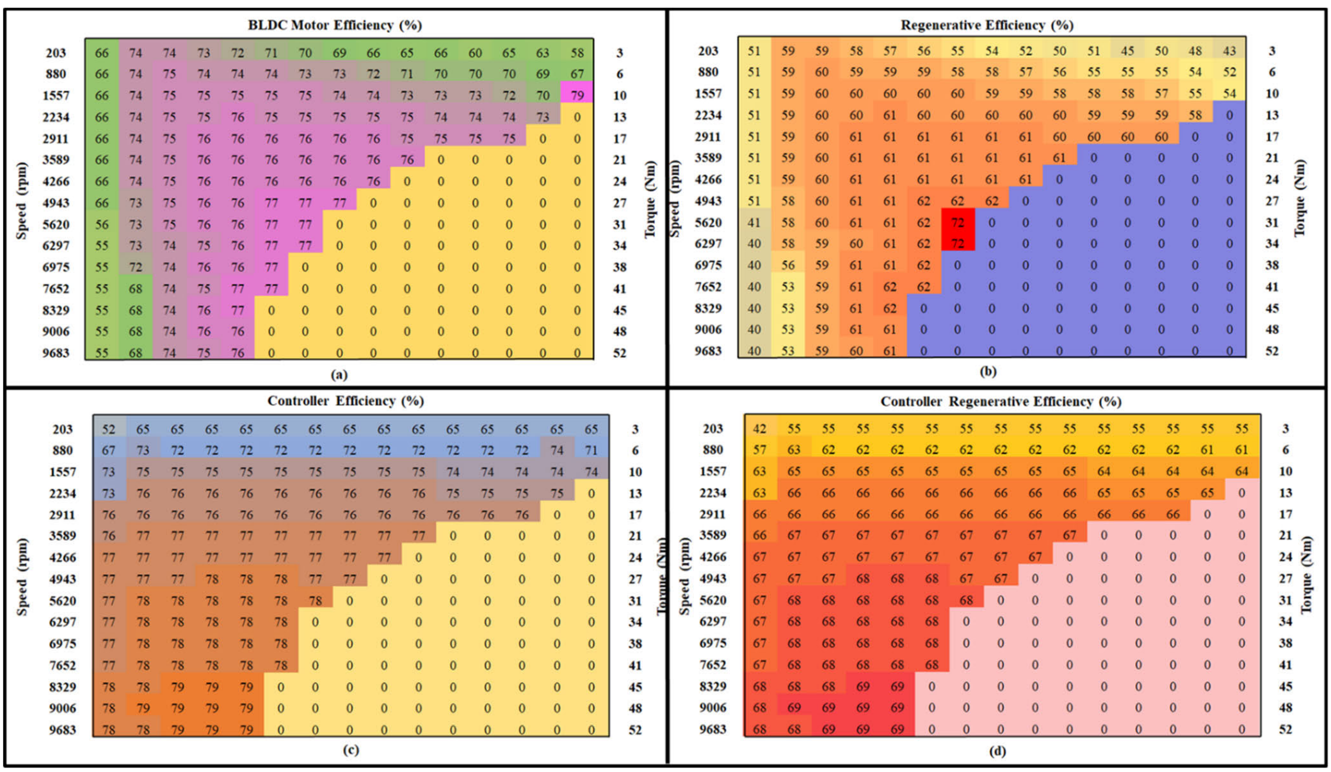


FIGURE 6. Experimental setup for BLDC motor and controller efficiency map development with different strategies.

various road conditions such as urban, rural, and highway. This research discusses the real-time DC design and development process as well as route selection, trip timing and experimental methodology. The selection of a driving route is the first and most important procedure in the development of a driving cycle [30], [36]. Based on the knowledge of local road and traffic conditions, the driving route is chosen in Vellore, India as shown in Fig 9. The selected driving route

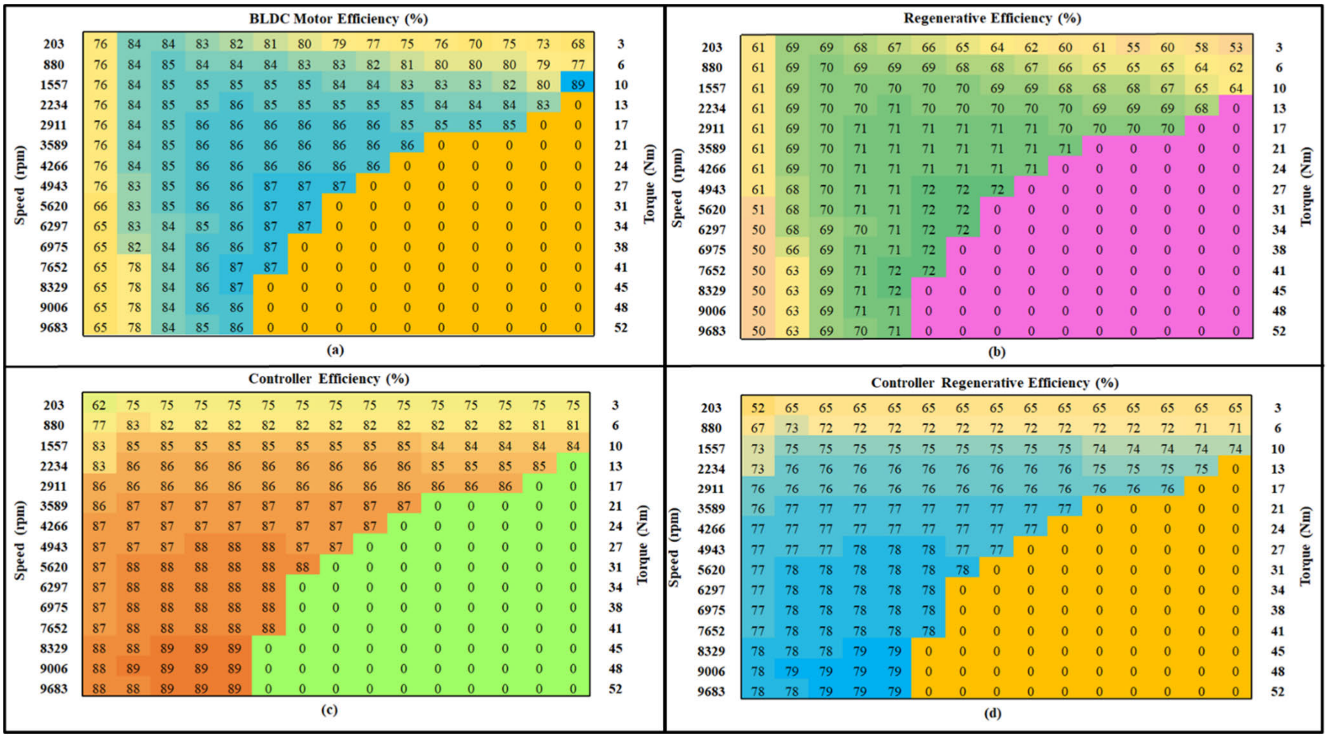


(a)

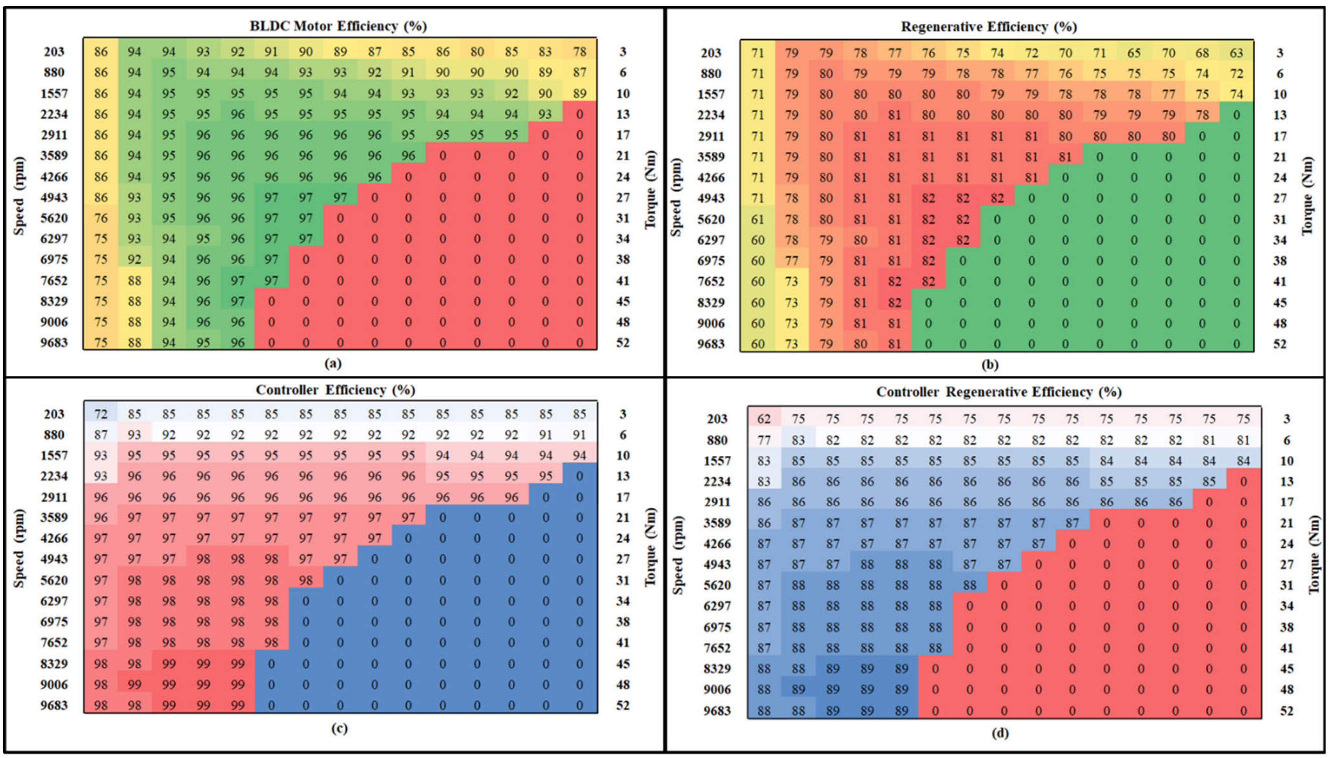


(b)

FIGURE 7. (a): BLDC motor and controller efficiency maps for PID controller under real-time conditions. (b): BLDC motor and controller efficiency maps for fuzzy logic controller under real-time conditions.



(c)



(d)

FIGURE 7. *(Continued.)* (c): BLDC motor and controller efficiency maps for hybrid controller under real-time conditions. (d): BLDC Motor and Controller Efficiency maps for adaptive supervisory self-learning controller under real-time conditions.

includes all three different type roads conditions, including rural, highway, and urban. The overall length of the driving route is approximately 33.45 km. Further, the electric two-wheeler is employed to develop a real-time driving cycle

TABLE 2. Technical specifications of BLDC motor used in EVs.

SNO	Parameter	Value	Units
1	Rated DC Voltage	90	V
2	Rated Speed	10000	RPM
3	Rated power	4500	W
4	Rated current	90	A
5	Motor Phases	3	-
6	Stator phase resistance	2.875	Ohm
7	Stator phase inductance	0.0085	H
8	Rotor moment of Inertia	0.08	Kgm^2
9	Friction coefficient	0.045	Nms
10	Back EMF coefficient	1.3	V/rad/Sec

TABLE 3. Range of the operating parameters under different dynamic conditions.

Parameter	Range	Units
Motor speed	250-9500	rpm
Motor Load	3-52	Nm
Controller	0-90	A
Signal	0-5	V
Dyno Load	0-75	Nm
DAQ	STM 32	-

under various road conditions. The selected vehicle specifications are stated in Table 1. The selected EV is equipped with a microcontroller and mobile phone GPS. The data obtained from the microcontroller includes real-time vehicle speed and performance parameters of battery and motor under different real-time conditions. Along with that, the data obtained from the mobile GPS such as vehicle speed, and position of vehicle with X, Y and Z direction in the predefined driving route. The aforementioned acquired data are stored in the microcontroller memory during driving journey and EOT stored data is transfer to workstation for the performance analysis. Subsequently, based on the acquired data, a real-time DC is developed with several driving routes such as urban, rural, and highway. The profile of the developed real-time driving cycle is shown in Fig 10. Further, the developed real-time driving cycle is integrated with the EV simulation model to estimate performance parameters such as power, C-rate, EC, battery discharge behavior, regeneration efficiency, and so on. Finally, this study combines real-time DC and efficiency maps with an EV simulation model to investigate the performance of the motor and battery under real-time driving conditions.

VII. RESULT AND DISCUSSION

This study incorporates real-time DC and various energy management controller efficiency maps into an EV simulation model in order to verify the effectiveness of the vehicle. In this section, under real-time operating conditions, the EV's numerous performance characteristics, such as motor power, battery power, battery current, C-rate, EC and regeneration efficiency are analyzed and compared with different energy management controllers. As well, to understand the variations and limitations of the EVs under real-time operating conditions, it is necessary to analyze the parameters associated with battery and motor performance.

A. MOTOR POWER

The motor power is influenced by the desired speed and torque of the EVs under various driving conditions. In this section four different types of energy management controllers are used to analyse the motor power fluctuations under real-time conditions. Figure 11 depicts the fluctuations in motor power using various energy management controllers such as PID, intelligent, hybrid, and ASSC during various driving conditions such as urban, rural, and highway. From the figure, the average motor power of the PID, intelligent, hybrid and supervisory controllers with different driving conditions are 5.8, 4.2, 3.1 and 2.2 kW respectively. From the results, the supervisory controller exhibits minimal power variation than the PID, intelligent and hybrid controllers. Also, the motor power of conventional controllers reaches its optimum under diverse road conditions as a result of the absence of real-time parameter adjustment. So, the supervisory controller will minimize the EC and improve the driving range of Evs under various road conditions. Further, the maximal motor power of the PID, intelligent, hybrid and supervisory controllers with different road (urban, rural and highway) conditions are 11.2, 9.1, 7.3 and 6.9 kW respectively. Hence, the conventional controllers such as PID, intelligent, and hybrid exhibit greater motor power fluctuations than the proposed supervisory controllers under diverse driving routes. With a conventional controller, battery discharge rate and energy consumption increase due to significant changes in motor power, and driving range decreases. likewise, the self-learning capabilities of the proposed controller effectively mitigated the real-time power variation of the motor. Eventually, the proposed supervisory controller provides optimal performance outcomes in terms of energy consumption, battery discharge rate, and regeneration efficiency under real-time driving conditions.

B. BATTERY POWER

The maximum velocity of an EVs is described as the quantity of power produced by the battery at a specific time period

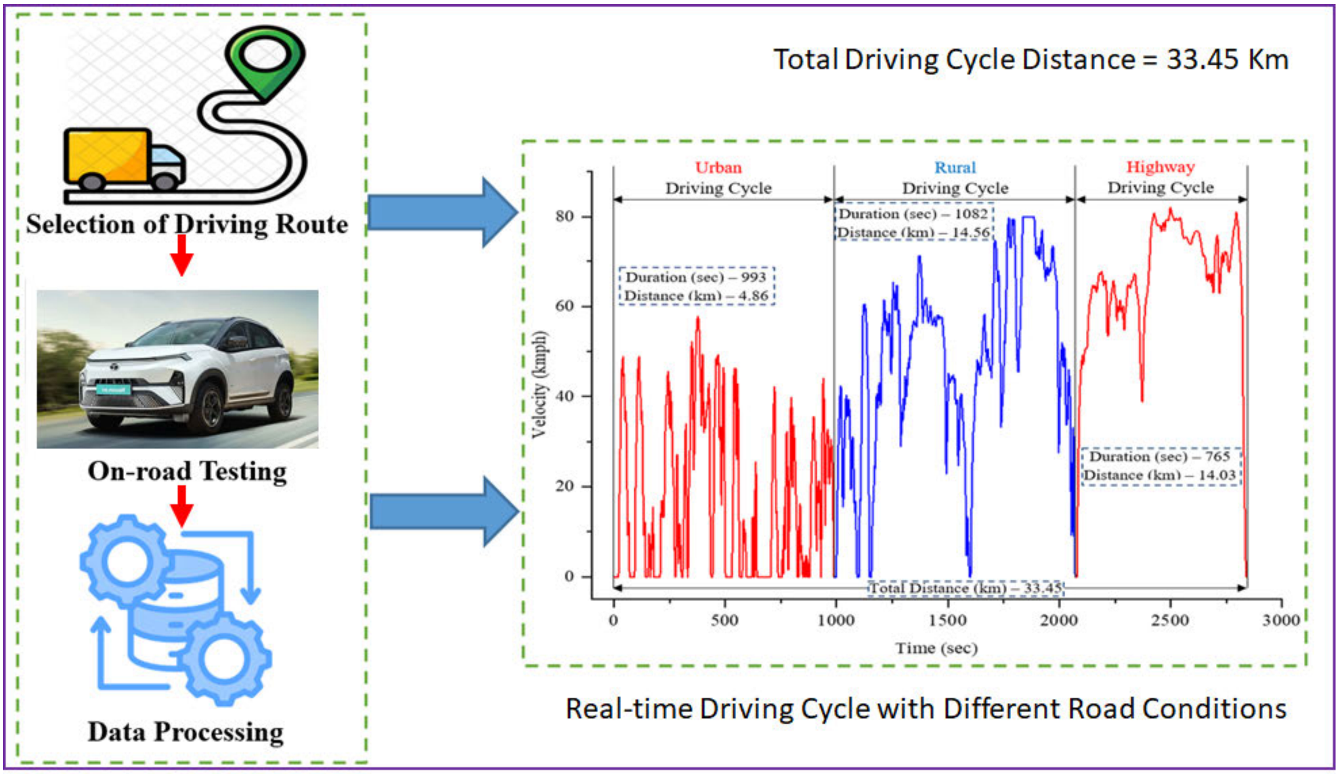


FIGURE 8. Methodology for development of real-time driving cycle under different road conditions.

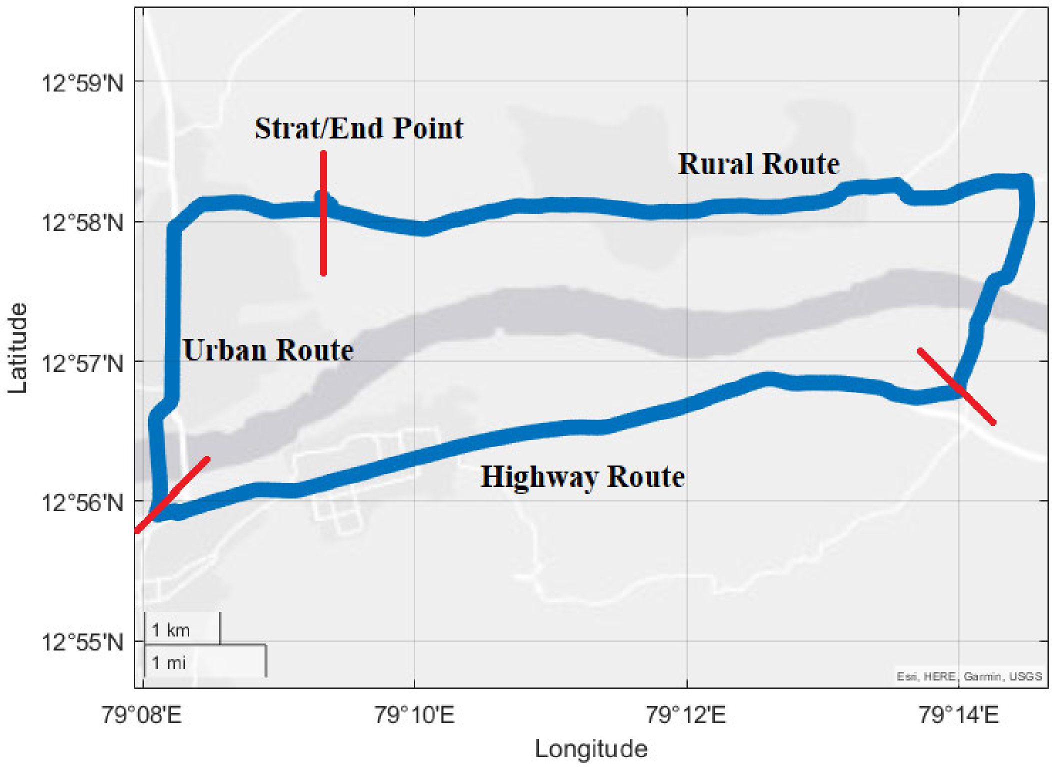


FIGURE 9. Selected driving route for development of real-time driving cycle under urban rural and highway conditions.

during propulsion. The battery power is varied based on the discharge rate and temperature under different dynamic conditions. Figure 12 represents the fluctuations in battery power using various energy management controllers such as

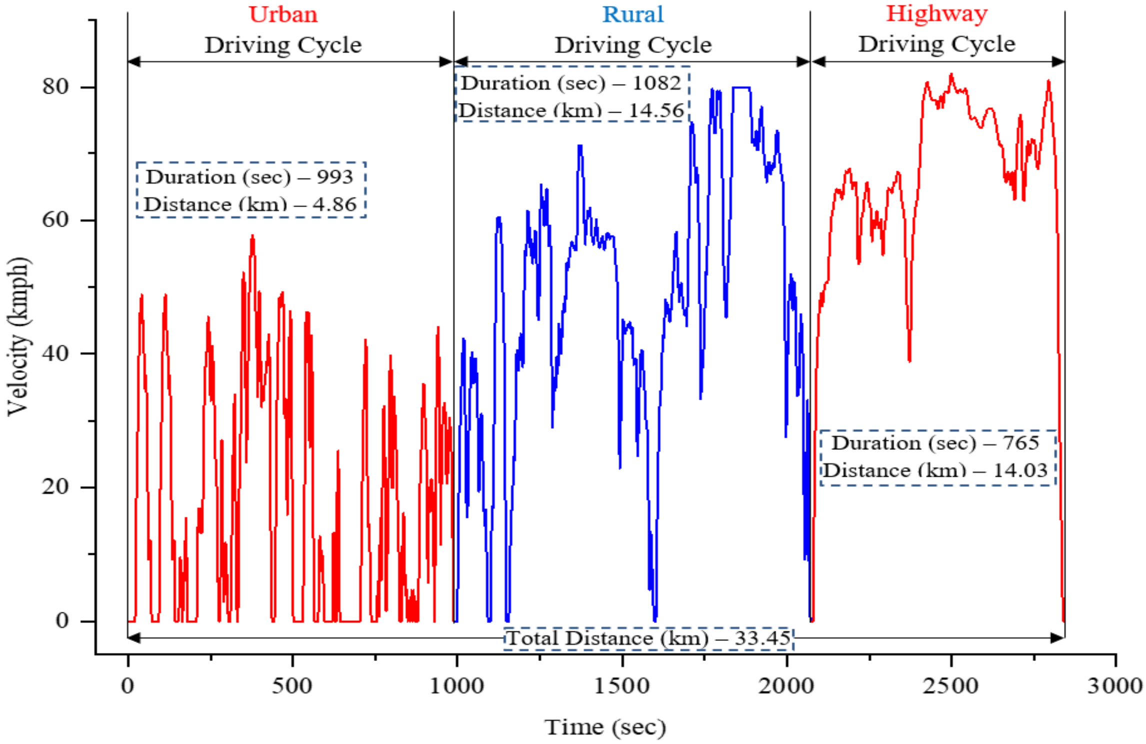


FIGURE 10. Real-time driving cycle profile under different road conditions.

PID, intelligent, hybrid, and ASSC during various driving conditions such as urban, rural, and highway. According to the graph, the proposed supervisory controller exhibits less battery power fluctuations under urban, rural and highway road conditions than other conventional controllers. The average battery power of various energy management controllers (PID, intelligent, hybrid and ASSC) with urban, rural and highway conditions are 7.5, 5.7, 3.7 and 2.1 kW respectively. Due to the maximum battery powers of the conventional controllers, the battery discharge behavior will be affected under real-time driving situations. As a result, the vehicle energy consumption will increase and its operational range will reduce. In this instance, Due to the minimum volatility in battery power, the suggested supervisory controller will help to reduce EC and increase driving range under various driving conditions. Further, the maximum battery powers of the PID, intelligent, hybrid, and supervisory controllers in urban, rural, and highway conditions are 16.3, 11.8, 8.3, and 7.2 kW, respectively. The PID controller has the highest battery power variations; as a result of this fluctuation, the battery discharge rate and EC rise, and the vehicle performance decreases. As well, the intelligent and hybrid controllers reveal more battery power deviations than the supervisory controller under various driving conditions. The proposed supervisory controller gives acceptable results than the other conventional controllers under different driving routes. As a result, the proposed controller will aid in reducing battery power deviation and thus enhance the EC and driving range of EVs under a variety of real-time driving conditions.

C. BATTERY CURRENT

The magnitude and direction of battery current in EVs are varying based on the accelerator and brake pedal position. Figure 13 represents the fluctuations in battery current using various energy management controllers such as PID, intelligent, hybrid, and ASSC during various driving routes such as urban, rural, and highway. According to the graph, the average battery current of various energy management controllers in urban, rural, and highway conditions is 147, 97, 78, and 55 A, respectively. Due to the high non-linear behaviour of EVs under real-time road conditions, traditional controllers (PID, intelligent, and hybrid) display greater battery current than the suggested supervisory controller. The calibration and tuning of real-time parameters with traditional controllers are challenging due to the strong nonlinearity behaviour of EV under real-time conditions. However, Due to its adaptive self-learning capabilities, this suggested supervisory controller would efficiently minimize average battery current fluctuations under real-time driving conditions. As a result, it is used to reduce energy consumption while increasing driving range under various road conditions. Further, in urban, rural, and highway situations, the maximum battery current aeration of PID, intelligent, hybrid, and supervisory controllers is 319.6, 232.5, 176.8, and 139 A, respectively. The higher battery current observed in PID, intelligent, and hybrid controllers can be attributed to the absence of real-time parameter adjustment. Because of that, the battery SOC will discharge extremely rapidly, the EC will increase, and the EV's performance will degrade under various driving

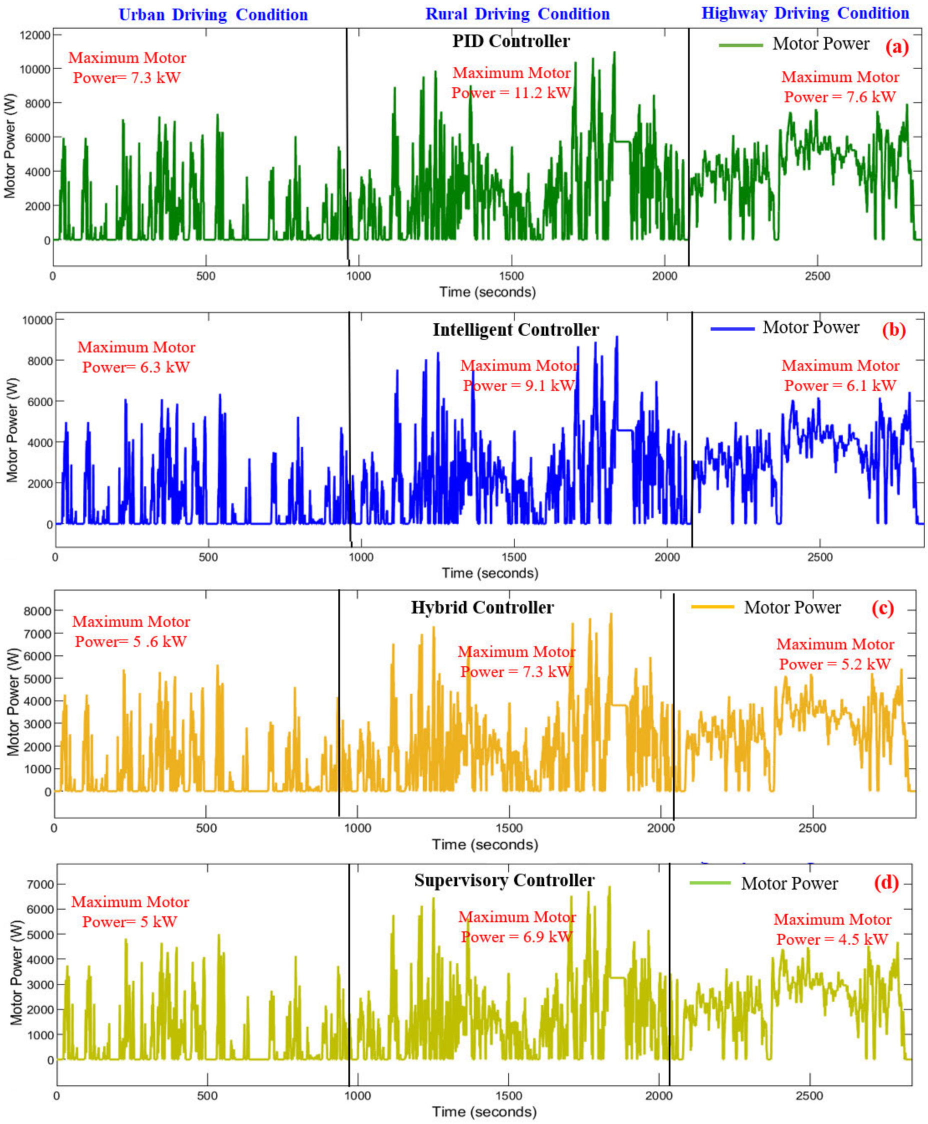


FIGURE 11. Variations in motor power with different energy management controllers under varied driving conditions.

conditions. Although, the proposed supervisory controller depicts minimal variation in battery current across urban, rural, and highway conditions. Accordingly, it is utilized to enhance the battery discharge rate under various driving conditions, as well as to reduce EC and increase operating range. Simultaneously, the proposed supervisory controller enhances battery power, current, SOC, EC, driving range, and regenerative efficiency under a variety of real-time conditions in comparison to other conventional controllers.

D. BATTERY DISCHARGE C-RATE

The C-rate is affected by the battery discharge rate under various real-time driving circumstances. Figure 14 represents the variations in C-rate using various energy management controllers such as PID, intelligent, hybrid, and ASSC during various driving routes such as urban, rural, and highway. According to the graph, the maximum and average C-rates of PID, intelligent, hybrid, and supervisory controllers are 4.47, 3.5, 2.48, 1.95, and 1.9, 1.4, 0.9, 0.4, respectively. The traditional controllers demonstrate a higher C-rate in urban, rural, and highway driving conditions compared to the proposed supervisory controller. Due to the higher C-rate of conventional controller, the battery discharge characteristics will deteriorate under real-time driving conditions. Also, a greater C-rate diminishes battery life and reduces battery discharge efficiency in urban, rural, and highway circumstances. Moreover, the higher C-rate will increase the temperature and discharge rate of battery, due to this reason the battery losses more energy under different driving route. This will result in an increase in energy consumption and a decrease in driving range. However, compared to other conventional energy management controllers, the suggested supervisory controller

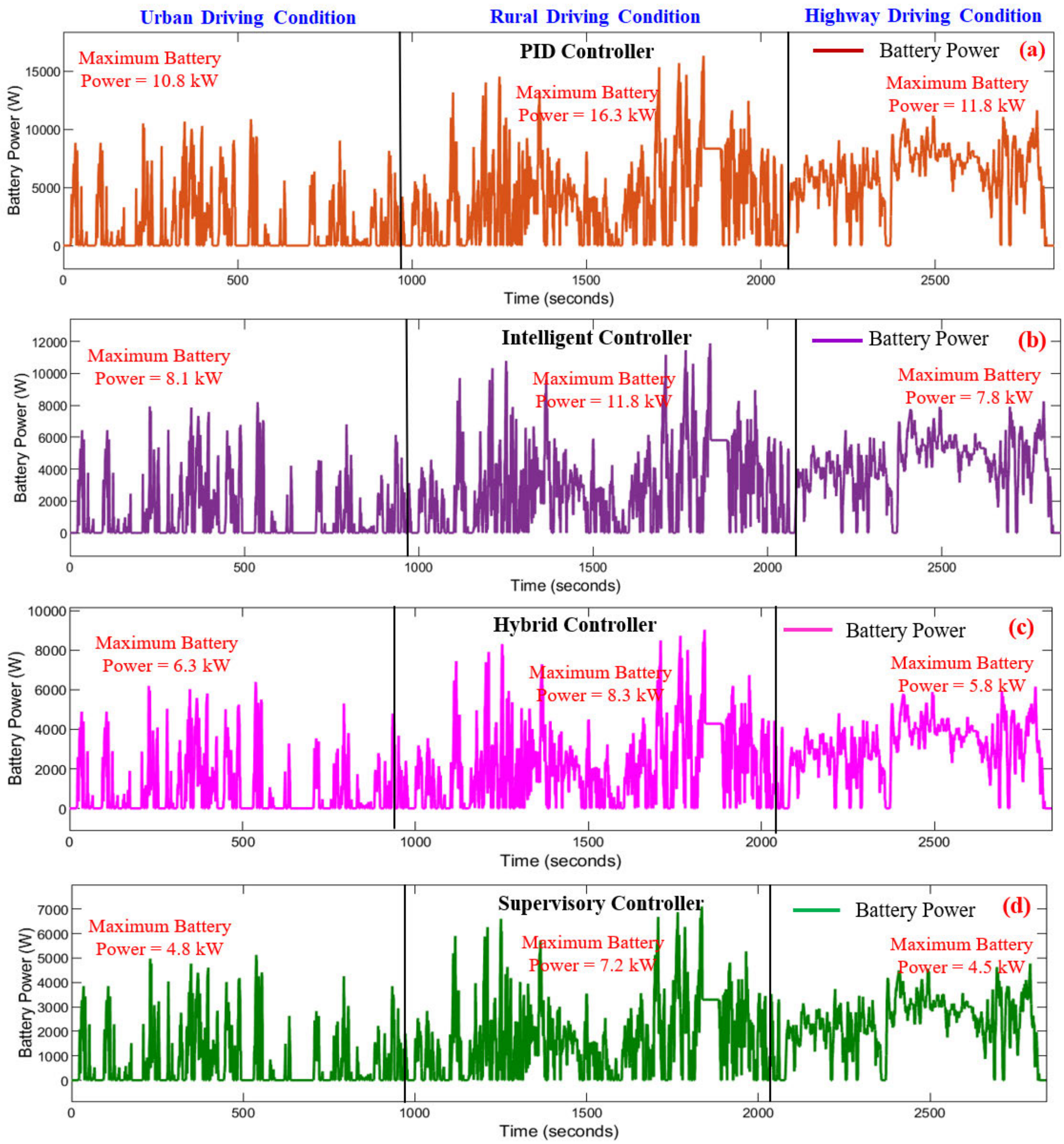


FIGURE 12. Variations in battery power with different energy management controllers under varied driving conditions.

demonstrates lower C-rate for urban, rural, and highway driving circumstances. Due to adaptive self-learning capabilities, the proposed controller can tune the various control parameters in real-time. So, it can easily control the non-linear behaviour systems (EVs) under different dynamic conditions. In this context, Therefore, the supervisory controller will enhance the battery life and discharge rate under real-time operating conditions. As well, it will extend the operational range of EVs in urban, rural, and highway environments while decreasing their energy consumption. Eventually, it is evident that the supervisory controller exhibits optimal performance than other energy management controllers in terms of C-rate, power, EC, performance, range, recovery energy, etc under different driving conditions.

E. STATE OF CHARGE

Battery SOC acts as a direct indicator of the total available energy in the battery during the trips which is a key factor to evaluate the remaining driving range of EVs. Fig 15(a) represents the individual SOC variations of various energy management controllers with urban, rural and highway driving conditions. The end-of-trip (EOT) SOC of a PID controller in urban, rural, and highway environments is 89.3, 56.7, and 21.5%, respectively. Next, the EOT for intelligent and hybrid controllers under urban, rural and highway conditions are 92.2, 69.3, 44.9 and 94.1, 77.1 59.1% respectively. Further, 95.3, 82.2 and 68.4 % are the end-of-trip SOC of proposed supervisory controller under urban, rural and highway driving conditions. According to the results,

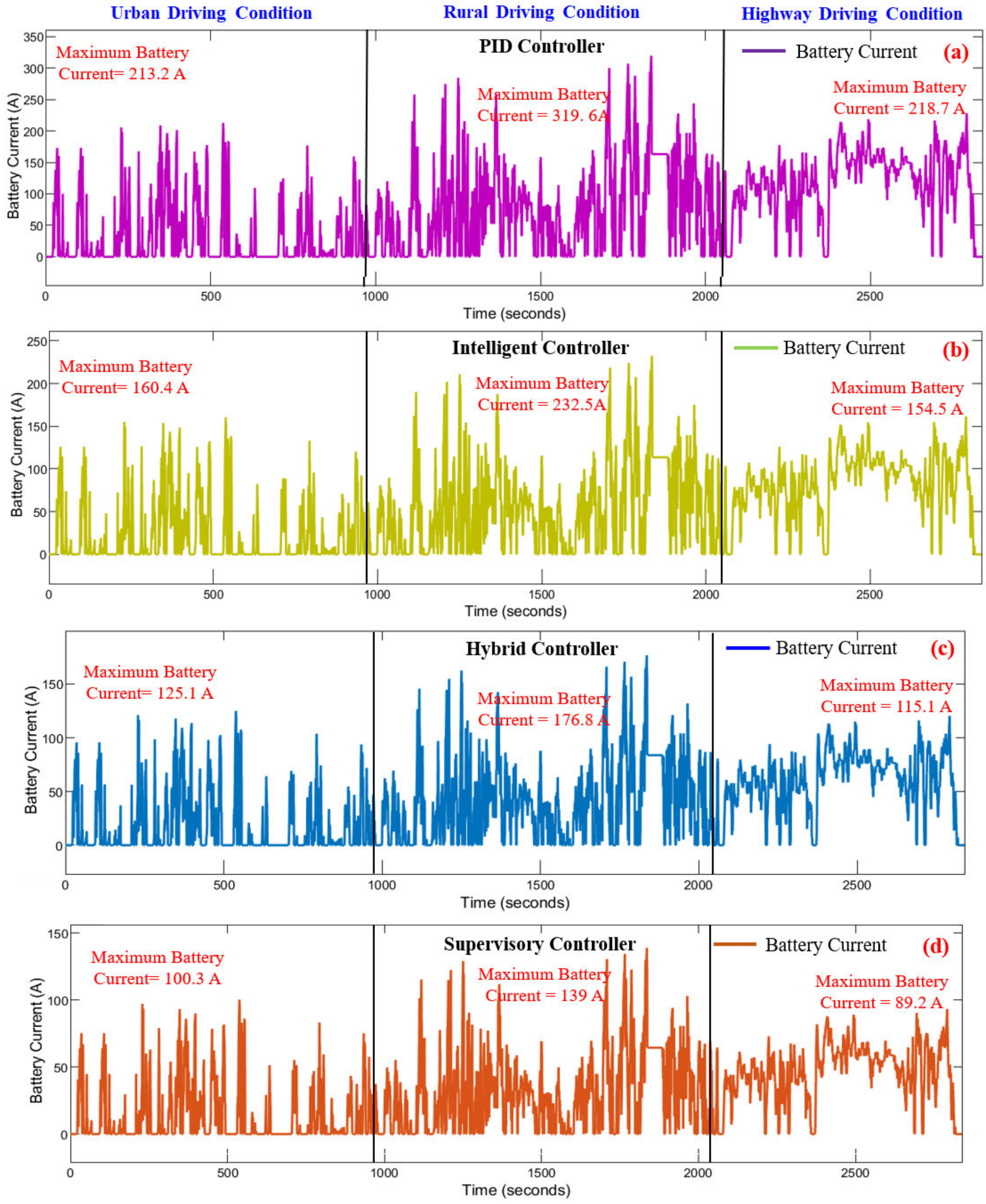


FIGURE 13. Variations in battery current with different energy management controllers under varied driving conditions.

EOT SOC for urban driving conditions with various energy management controllers is 89.3, 92.2, 94.1, and 95.3%. The supervisory self-learning controller has the lowest SOC drop (95.3%) compared to the other controllers. Due to high non-linear behavior of EV in real-time, the traditional controllers are fails to maintain desired SOC level under different road conditions. So, the recommend supervisory controller is appropriate for maintaining the acceptable levels of SOC in urban conditions, while also lowering EC and increasing driving range. Further, EOT SOC levels for rural driving conditions with various energy management controllers is 56.7, 69.3, 77.1 and 82.2%. Due to its self-learning capabilities, the supervisory controller maintains a lower SOC drop in rural driving conditions than other conventional controllers. The PID (56.7%), intelligent (69.3%) and hybrid (77.1%) controllers have more SOC drop, because of this battery

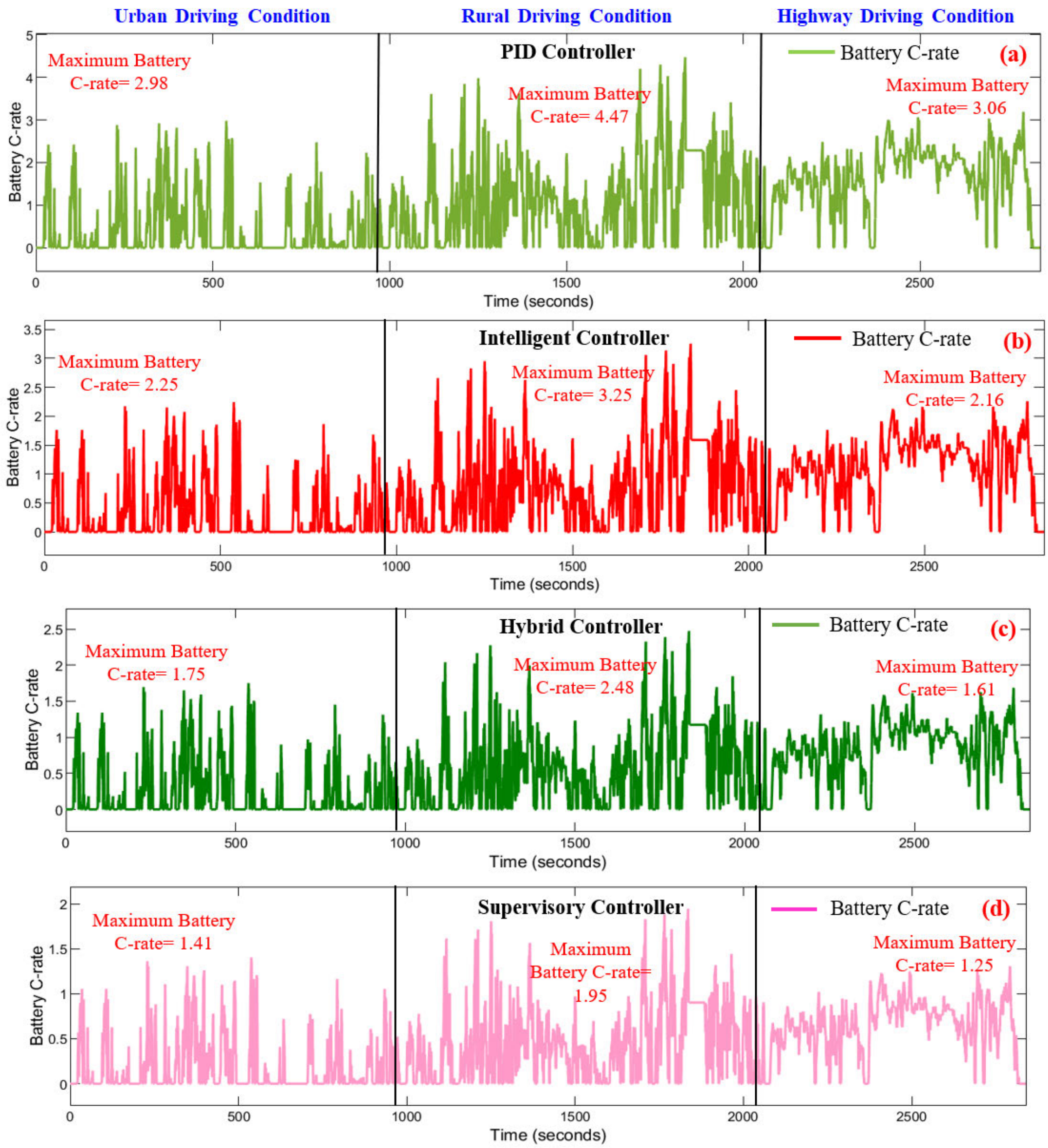
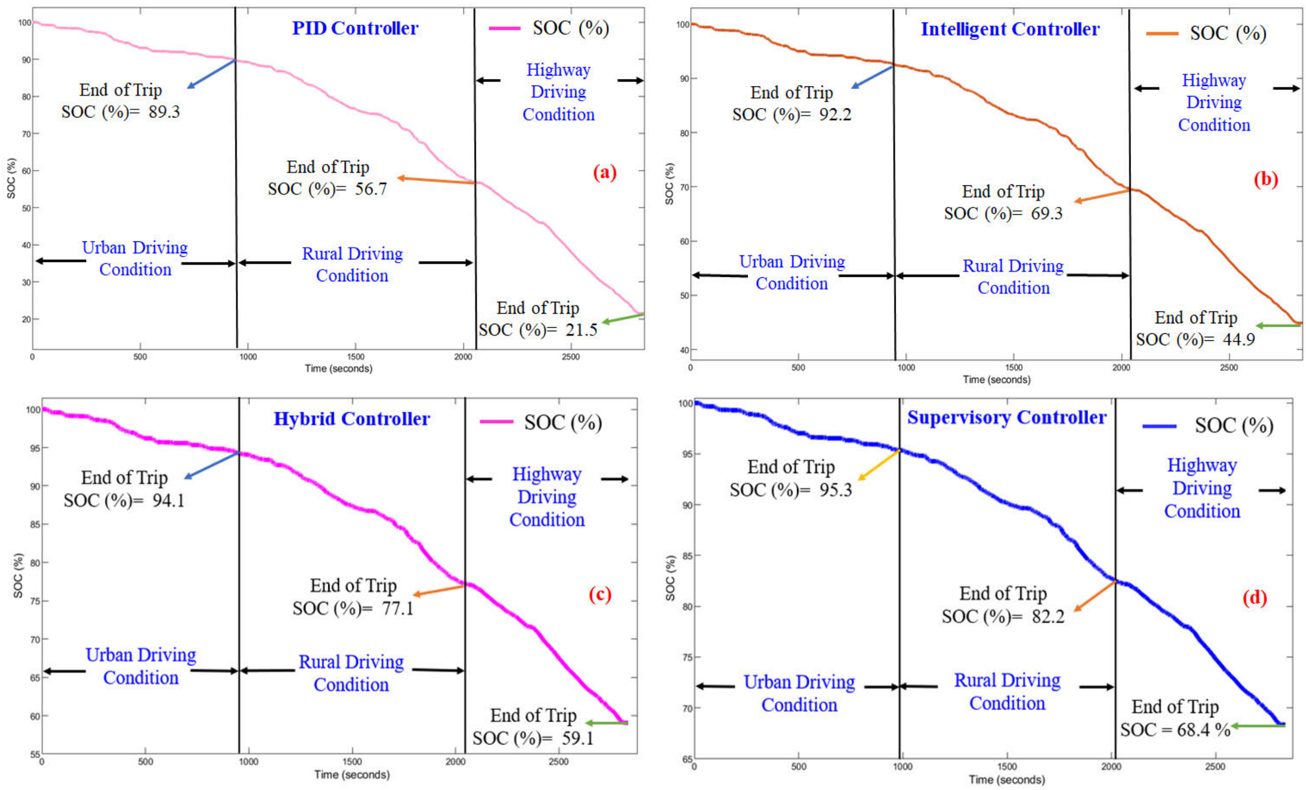


FIGURE 14. Variations in C-rate5 with different energy management controllers under varied driving conditions.

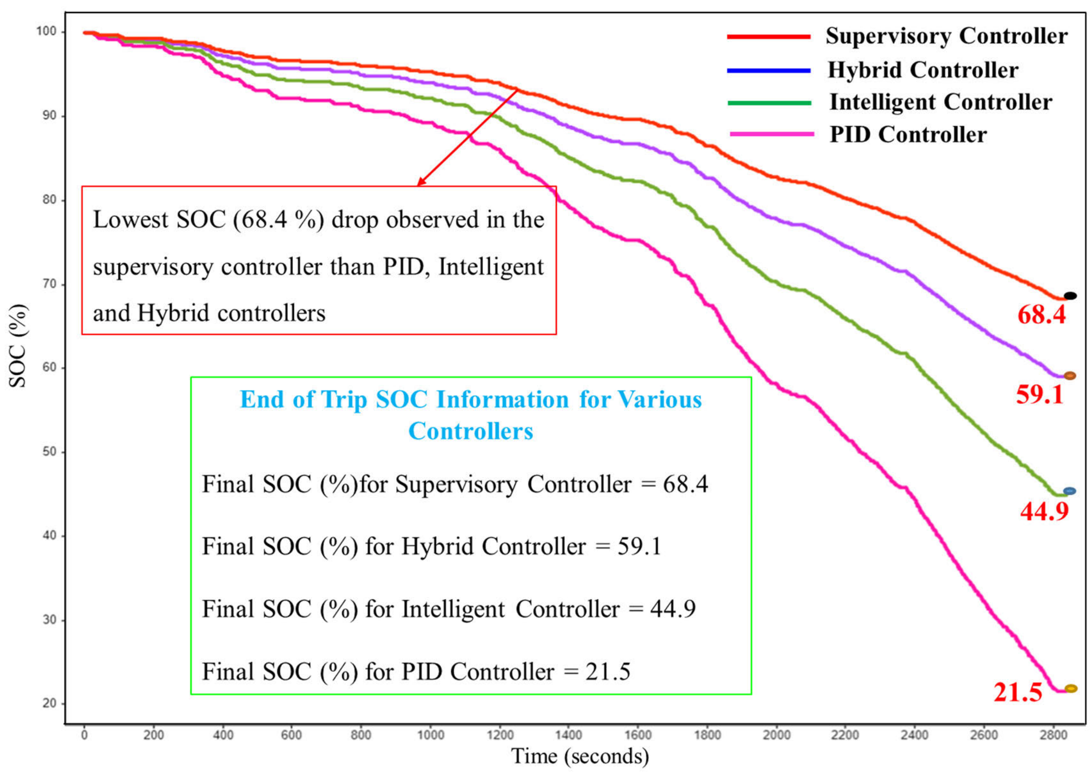
discharge rate will increase and it will improve the EC and decrease the driving range of the vehicle. Moreover, the final or highway EOT SOC of the various energy management controllers are presented in Fig 15 (b). From the figure, the final SOC drops of PID, intelligent, hybrid and supervisory controllers are 21.5, 44.9, 59.1 and 68.4% respectively. At the EOT (including urban, rural and highway), the conventional controller's (PID, intelligent and hybrid) trip SOC is drops more than the supervisory self-learning controller. Therefore, the suggested supervisory controller is intended to reduce EC under various driving conditions by increasing the operational range of EVs. Finally, the efficient energy management controller (PID, intelligent, hybrid and supervisory strategy) will improve the performance of the EVs in terms of SOC, EC, recover energy, etc under real-time driving conditions.

F. ENERGY CONSUMPTION AND REGENERATIVE EFFICIENCY

The total driving range of EVs is directly correlated with the amount of energy consumed and recovered during acceleration and barking, which is primarily depending on the atmospheric conditions and characteristics of road segments, vehicle physical parameters, speed and acceleration. Figure 16 depicts the total energy consumption per km and regeneration efficiency for various EMCs in real-time. The total energy consumption of PID, intelligent, hybrid



(a)



(b)

FIGURE 15. (a): Individual SOC variations of various energy management controllers with urban, rural and highway driving conditions. (b): Final SOC variations with different energy management controllers.

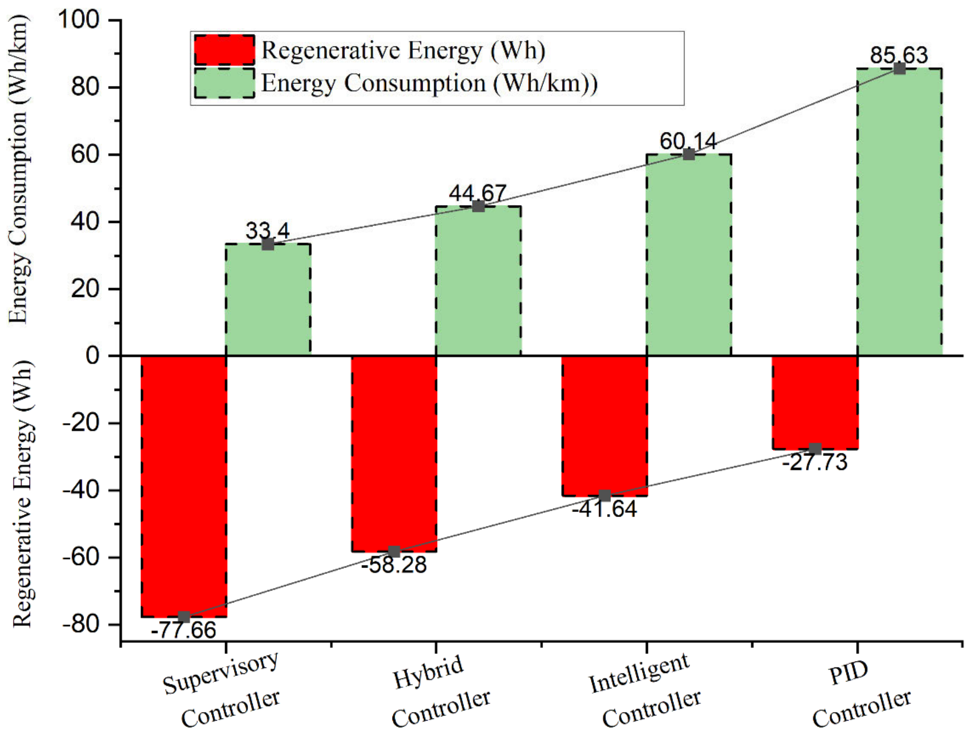


FIGURE 16. Different energy management controllers energy consumption and regenerative efficiency.

TABLE 4. Output parameters of EV with different energy management controllers under real-time driving conditions.

SNO	Parameters	Maximum Value with different Conditions												Average Value with Different Conditions			
		PID Controller			Intelligent Controller			Hybrid Controller			Supervisory Controller						
		Urban	Rural	Highway	Urban	Rural	Highway	Urban	Rural	Highway	Urban	Rural	Highway	PID	FLC	Hybrid	ASSC
1	Motor Power (kW)	7.3	11.2	7.6	6.3	9.1	6.1	5.6	7.3	5.2	5	6.9	4.5	5.8	4.2	3.1	2.2
2	Battery Power (kW)	10.8	16.3	11.8	8.1	11.8	7.8	6.3	8.3	5.8	4.8	7.2	4.5	7.5	5.7	3.7	2.1
3	Battery Current (A)	213.2	319.6	218.7	160.4	232.5	154.5	125.1	176.8	115.1	100.3	139	89.2	147	97	78	55
4	C-rate	2.98	4.47	3.06	2.25	3.25	2.16	1.75	2.48	1.61	1.41	1.95	1.25	1.9	1.4	0.9	0.5
5	SOC (%)	89.3	56.7	21.5	92.2	69.3	44.9	94.1	77.1	59.1	95.3	82.2	68.4	-	-	-	-
6	E/Km (Wh/Km)	85.63			60.14			44.67			33.4			-	-	-	-
7	Regen Efficiency (%)	-27.73			-41.64			-58.28			-77.66			-	-	-	-

TABLE 5. Comparison of current study EV performance results with previous literatures.

SNO	Parameters	Vehicle Type	Distance (km)	Test Conditions	Literature Results				Ref	Current Study Results			
					PID	FLC	Hybrid	ASSC		PID	FLC	Hybrid	ASSC
1	E/km (Wh/Km)	Electric 2-Wheeler	20	Different road conditions	95.7	-	66.5	-	[6-9]	85.63	60.14	44.67	33.4
2	End of Trio SOC (%)	Electric Car	15.7	Different road conditions	11.5	22.3	35.8	44.5	[11-13]	21.5	44.9	59.1	68.4
3	Regen Efficiency (%)	Electric 2-Wheeler	25.6	Different road conditions	-11.8	-22.5	-32.5	-	[[14,15]	-27.73	-41.64	-58.28	-77.66
4	Driving Range (Km)	Electric Car	22.3	Different road conditions	34.5	44.5	62.5	-	[16-18]	55.5	68.3	88.4	105.6
5	Battery Discharge Rate	Electric Car	12.7	Different road conditions	High	High	-	-	[20-23]	High	High	Medium	Low

and supervisory controllers are 85.63, 60.14, 44.67 and 33.41Wh/km under different driving conditions. The supervisory controller shows minimum EC (33.41 Wh/km) than other convention controllers, due to its self-tuning capability

TABLE 6. Advantages and disadvantages of different proposed control approach's.

SNO	Controller Type	Advantages	Disadvantages	Ref
1	PID Controller	• Simple • Provides decent stability • Easy to tune the parameters	• Derivative noise amplifications • Complex for non-linear systems	[6-10]
2	Intelligent Controller	• High precision • Rapid operation • Easy to implement for nonlinear systems	• Lack of real-time response • Instability to tune the fuzzy rules and MF parameters. • Low speed and long run time of the systems	[12-15]
3	Hybrid Controller	• Easy to implement • Fast response • Low computation time	• No extra filtering effects • Lack of robustness • Limited operational range	[16-18]
4	Supervisory Controller	• High filtering effect • High Performance in real-time • Fast response and accurate	• Complex to design • prior knowledge of initial conditions • Large number of datasets are required	[19-23]

it will tune and optimize the control parameters in real-time conditions. Due to non-linear behaviour of EVs, the conventional controllers are fails to tune and optimize control parameters in real-time, so the overall EC will increase, resulting in a reduction in the driving range of the vehicle. Therefore, with the minimum EC (33.41 Wh/km) of proposed controller, the driving range of EV will increase under different dynamic road conditions. Further, Fig 16 shows the regenerative efficiencies of PID, intelligent, hybrid and supervisory controllers are -27.73, -41.64, -58.28 and -77.66 Wh respectively. From the results, the supervisory controller (-77.66 Wh) recuperates the most regenerative energy compared to other conventional controllers. Moreover, the hybrid controller (-58.28 Wh) also recovers significant amount of energy than the PID (-27.73 Wh) and intelligent controllers (-41.64 Wh). Nevertheless, the conventional controllers recover a minimal regenerative energy than proposed controller under various real-time driving conditions. Undoubtedly, the maximum recovery rate will enhance the driving range of electric vehicles. Finally, according to an analysis of a variety of performance characteristics pertaining to various EMCs (PID, intelligent, hybrid and ASSC) under diverse road conditions (urban, rural and highway), an effective energy management controller improves the vehicle's power, efficiency, SOC, energy consumption, regenerative efficiency, etc.

VIII. CONCLUSION

The main objective of this research is to develop an effective energy management controller for the energy optimization of electric vehicles under various real-time driving conditions. This research develops different EMCs such PID, intelligent, hybrid and supervisory strategy to improve the performance of EVs under real-time driving conditions. Also, this study combines many unique methodologies to develop an EV model, efficiency maps, and a real-time DC. In this instance, a mathematical model of an EV with BLDC motor is developed using MATLAB/Simulink. Further, using a novel experimental technique, the efficiency maps of the motor and controller for various EMCs are developed. Then, the developed efficiency maps are incorporated into model-in-loop (MIL)-based EV test platform to analyze the performance of various EMCs. In addition, to validate the EV model, a real time DC has been developed for different types of road conditions, including urban, rural, and highway. Subsequently, the developed DC is associated with a MIL-based EV test platform for real-time examination of energy consumption and battery discharge behavior. Finally, the EV model is simulated with various EMC efficiency maps and real-time DC to analyze motor power, battery power, C-rate, EC, SOC, regenerative efficiency, etc. The validation and other interpretation outcomes of this study endeavor are summarized below.

- To perform the EV simulation, the various energy management controller efficiency maps are successfully developed under real-time condition. As well, to validate the EV model the real-time driving cycle is developed for all types of road conditions, including urban, rural, and highway. In addition
- Based on the motor and battery performance characteristics, the supervisory controller exhibits less variation than other conventional controllers in urban, rural, and highway driving conditions, as shown in Table 5.
- The current study's findings are compared to previous literature using several EV performance parameters under real-time driving scenarios. The current study results show that several energy management controllers (PID, FLC, Hybrid, and ASSC) outperform earlier literatures in terms of E/km, EOT-SOC, regeneration efficiency, driving range, and battery depletion rate under various real-time dynamic situations. The current study has lower EC (33.4 Wh/km), lower SOC drop (68.4%), restored peak regeneration efficiency (77.66%), and a longer driving range (105.6 km) than previous literature evaluations, as shown in Table (6). Table 7 also summarizes the benefits and drawbacks of various energy management control systems. Based on broad findings, the current study results show that EV performance and driving range may be improved under real-time driving situations.
- The proposed supervisory self-learning controller exhibits minimal EC (33.4 Wh/km) than the PID (85.63 Wh/km), intelligent (60.14 Wh/km) and hybrid (44.67 Wh/Km) controller under different real-time operating conditions. So, it can improve the battery utilization behaviour and operating range of EV under dynamic conditions.
- The end-of-trip SOC drop of the proposed supervisory controller (68.4%) is lower than PID (21.5%), intelligent (44.9%) and hybrid (59.1) controller under different road conditions. Hence, it can enhance the battery efficiency and improve the performance of EV under real-time conditions.
- The regenerative efficiency of the PID, intelligent, hybrid and supervisory controllers are of the PID, intelligent, hybrid and supervisory controllers are -27.73, -41.64, -58.2 and -77.6 Wh under different road conditions. It can be observed that the proposed supervisory controller recovered more energy than the other conventional controllers. Thus, it can improve the battery consumption behaviour and driving range under real-time conditions.

Through the proposed adaptive supervisory self-learning controller, the present research enhances performance of EV under real-time driving conditions. Also, it minimizes the EC and improve the driving range under different road conditions. However, the proposed controller is extremely reliant on training information, and this data invariably affects the controller's performance. This could potentially be a limitation of the suggested controller. To address this, advanced controllers like the Multi Adaptive Neuro Fuzzy Inference System (MANFIS) or specialized optimization techniques could be utilized to train the data to achieve stable and effective performance of the proposed controller, which deserves further investigation.

ACKNOWLEDGMENT

The authors wish to acknowledge the Management of the Vellore Institute of Technology, Vellore, for the resources and amenities provided during the implementation of this work.

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PEMMAREDDY SAITEJA received the M.Tech. degree in mechanical engineering from Jawaharlal Nehru Technological University Anantapur. He is currently pursuing the Ph.D. degree with Vellore Institute of Technology (VIT), Vellore, Tamil Nadu, with a focus on control system development for electric motors used in electric vehicles. His research interests include energy management systems, noise and vibration analysis, and control in electric motors.

BRAGADESHWARAN ASHOK received the Ph.D. degree from the School of Mechanical Engineering, Vellore Institute of Technology (VIT), Vellore, in 2017. He is currently an Associate Professor with the Department of Automotive Technology, School of Mechanical Engineering, VIT. His research interests include automotive engineering, electric and hybrid vehicle powertrain calibration, IC engines, and automotive electronics. His research work is aimed toward the motor control algorithm development for electric vehicle applications. He has been awarded as "Top 2% Scientist in the world" by a study conducted by researchers at Stanford University.

BYRON MASON received the B.Eng. degree in mechanical engineering and the Ph.D. degree in powertrain calibration and control from the University of Bradford, Bradford, U.K., in 2005 and 2009, respectively. He is currently a Senior Lecturer in intelligent powertrain systems with the Department of Aeronautical and Automotive Engineering, Loughborough University, Loughborough, U.K.

P. SURESH KUMAR received the master's degree from the National Institute of Technology, Trichy, and the Ph.D. degree in design of control systems from Indian Institute of Space Science and Technology (IIST-ISRO). He is currently an Assistant Professor with the Autonomous Vehicles Research Laboratory, Automotive Research Centre (ARC), Vellore Institute of Technology (VIT) Vellore. With a strong background in modeling and control design, he has published in renowned scientific journals and presented his research at international conferences. His expertise lies mainly in autonomous aerial, ground vehicles, and electric vehicles. He actively engages in interdisciplinary collaborations, in cutting-edge research projects.