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Modeling and Control of Bidirectional DC-DC Converters for Electric Vehicle Battery Management and Energy Recovery Systems

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Abstract

The increased usage of electric vehicles (EVs) has escalated the demand of effective power management systems that guarantee ideal usage of batteries, efficient power restoration and unsympathetic performance with contemporary mobility requirements. The core of this task is the two-way DC-DC converter, which makes it possible not only to transfer power between the traction battery and the auxiliary loads but also during regenerative braking to recover energy. In this paper advanced model-based control and modeling are developed to understand the analysis of a bidirectional DC to DC converter used in EV battery management systems and energy recovery systems. To include dynamic characteristics based on operating modes, that is, during buck (charging), boost (discharging) and regenerative braking, a state-space averaged model is obtained. A two-loop control system where sliding mode control is applied to the current control loop and proportional-integral regulation is applied to the voltage loop is suggested to compensate all the disturbances and the ability to control the state-of-charge (SOC) with high precision. Simulation outcomes under the New European Driving Cycle (NEDC) indicate that the converter has a high efficiency of 95% peak efficiency, rapid transient behavior with a settling time that is less than 5 ms and effective SOC control to within safe operating regions, able to recover up to 23.5% of braking energy. The quality of efficiency, stability, and battery protection of the proposed strategy is also proven in comparing it to other available control methods. The results identify bidirectional DC-DC converters as a key to future EV battery management, higher energy efficiency, driving range, and future vehicle-to-grid capability.

Keywords

Bidirectional DC-DC Converter; Electric Vehicles; Battery Management System; Regenerative Braking; Sliding Mode Control; State-of-Charge Regulation; Energy Recovery; Vehicle-to-Grid (V2G).

Introduction

The swift move to EVs to replace the traditional internal combustion engines (ICE) is now identified as a global priority to deal with the environmental issues of global warming, air pollution, and fossil fuel depletion. It is undisputed that EVs are a more sustainable solution, with less greenhouse emissions and a more efficient system of energy use, as compared to the conventional transportation system (IEA, 2022; Ehsani et al., 2021). At the heart of EV performance lies the energy storage system that comprises a high-capacity lithium-ion battery that is generally designed to power the traction motor as well as auxiliary loads (Hannan et al., 2018). Proper handling of such batteries is key to their safe use, long lifespan, and better efficiency of the vehicle (Xiong et al., 2019).

The bidirectional DC-DC converter is among the factors that facilitate the efficient battery management in EVs. As opposed to a unidirectional converter, which can only control power flow in one direction, a bidirectional DC-DC converter allows energy flow in both directions, to and fro the battery (motoring mode) and back to the battery in the course of a regenerative braking signal (Mohan et al., 2017; Khaligh & Li, 2010). This feature allows them not only to have a significant impact in regaining kinetic energy during deceleration, thus enhancing the overall driving range and energy consumption of EVs (Zhang et al., 2019). Also, bi-directional converters can enable the connection of renewable sources and vehicle-to-grid (V2G) networks, whose batteries can also serve as an energy storage mechanism to reduce grid imbalances (Habib et al., 2015).

Bidirectional DC-DC converters have been a major area of study since the modeling of the power electric circuits is nonlinear and time-varying. The convergence processes must be predicted with precise models that are required to optimally distribute energy and develop resilient control methods. Empirical methods of modeling converter behavior at various operating conditions Traditional methods to model the behavior of a converter include state-space averaging and small-signal models (Erickson & Maksimovic, 2001; Patel & Singh, 2021). Nevertheless, considering the high dynamicity of EVs loads, new modeling strategies are coming into place that strive towards increased accuracy and the modeling of switching transients (Gupta et al., 2022).

Control strategies would as well be vital to the stabilization and effectiveness of converter performance. Conventional controllers like the proportional-integral-derivative (PID) controller are straightforward and perform well when controlling a system in a steady state but fail at nonlinear dynamic conditions, which are prevalent in the EV systems (Chen & Luo, 2021). To address these challenges, sliding mode control (SMC), model predictive control (MPC), and fuzzy logic control were proposed as further approaches to controlling these industrial processes (Rahimi et al., 2019; Nguyen et al., 2020). The above techniques enhance tolerance of parameter changes, quick dynamic response and protection of batteries against overcurrent and overvoltage stresses.

In addition, the fact that energy recovery is significant cannot be underestimated. It has been shown that with regenerative braking performed with bidirectional converters, up to 2030 percent of energy that was lost during city driving conditions can be recovered (Kim Lee, 2020; Tie Tan, 2013). This recovery directly enhances the vehicle range and decreasing the frequency of charging, EVs would become more serviceable to the consumers. Also, these converters help improve thermal management and improve battery life through the charge-discharge process optimization, an aspect of great concern among manufacturers and users (Xiong et al., 2019; Hannan et al., 2018).

In short, the bidirectional DC-DC converters represent an infrastructure of a battery management and energy recovery in EVs. Being able to enable two-way power flow, improved regenerative braking and compatibility with smart grid infrastructures makes them a key technology in the future of sustainable transport. There are however limitations in coming out with models and controllers, which meet efficiency, robustness, and battery health requirements with a range of driving conditions. The focus of the present paper is to review an in-depth discussion on modeling approaches and control methods of bidirectional DC-DC converters, the goal of which is to help enhance performance of EVs, battery life, and energy efficiency overall.

Literature Review

1. Bidirectional DC-DC Converters in Electric Vehicles

Bidirectional DC-DC converters have been discussed in great detail because of the ability to facilitate both charging and regenerative braking of electric vehicles (EVs). However, bidirectional converters may easily transfer power in both directions and are needed to manage the modern battery operation and energy recovery mechanisms that cannot be completed by unidirectional converters (Tseng & Huang, 2019). The first experiments proved the possibility of a non-isolated bidirectional converter as a part of the EV architecture, underlining their advantageous compact design and high efficiency (Ajami et al., 2012). The most recent works point to the possibility of combining renewable power capabilities with EV charging infrastructure to enable the exchange of power between vehicle batteries and the grid (Kandidayeni et al., 2021).

2. Converter Topologies and Architectures

Studies have proposed several topologies of converters, which are more suited to EV applications. Low levels of voltage that are not isolated using topologies like buck-boost are simple and have high efficiencies (Shahir et al., 2016). Conversely, isolated topologies provide galvanic isolation hence their appropriateness with high-voltage EV batteries albeit at an elevated complexity and low-efficiency cost (Liang & Chen, 2010). When it comes to safety and efficiency, time topologies have also been designed to take the best of both worlds with isolated and non-isolated features (Miyazaki et al., 2019). According to a comparative analysis by Akar et al. (2017), the dual-active bridge (DAB) converters are very appealing to fast charging applications since they operate at high power densities and due to their bi-directional nature.

3. Modeling Approaches

The proper study of bidirectional DC-DC converters is based on accurate modeling of their performance in case of the dynamic conditions. Systems of state-space averaging have traditionally been used to model the dynamics of a converter and idealize the high-frequency switching properties (Xu et al., 2015). VBMS strategies based on frequency-domain modeling have also been used with variable loads to analyze stability, design controllers (Zhou et al., 2017). In an effort to enhance accuracy of prediction especially during transient conditions, advanced models, including large-signal and discrete-time models, have been proposed (Wu & Jou, 2019). The models are useful in coming up with credible simulation designs and validation of control strategies in real-time.

4. Control Strategies for Power Flow Regulation

How well the bidirectional converters perform is highly dependent on the control strategy that one uses. Proportional-integral (PI) control is one of the classical approaches to regulating voltage and current that made it well represented since it is so basic (Park et al., 2015). But under nonlinear and rapidly varying operating conditions, these have motivated the interest in more sophisticated methods. SMC has been demonstrated to be more robust towards variations on regard to parameters and disturbances (Kanchanaharuthai et al., 2016). Further, model predictive control (MPC) has a predictive functionality and promotes transient performance and efficiency (Gao et al., 2018). Such uncertainties in the system can also be addressed with fuzzy logic controller, which has shown favorable results when it comes to keeping the system stable in the case of sudden changes in the loads (Shahverdi et al., 2014).

5. Energy Recovery and Regenerative Braking

One of the main benefits of the usage of bidirectional converters in EVs is called regenerative braking. Research shows that when braking occurring, up to 30 percent of the kinetic energy can be recovered and translated towards longer driving range (Liu et al., 2019). Authors like Yang et al. (2018) have implemented adaptive control algorithms that will optimize the regeneration of energy at different road conditions and driving conditions. In addition, multi-objective optimization techniques have been used in maximizing the recovery efficiency and to ensure the passenger safety and ride comfort (Cheng et al., 2017). These studies emphasize the need to incorporate bidirectional converters and the smart braking system of effective utilization of energy.

6. Battery Management and Health Considerations

Battery degradation is a sensitive problem in EVs and is sensitive to high charge / discharge rates, thermal environments and energy management. Bidirectional converters are also significant elements to reduce the phenomenon of degradation since they control the ability to charge and avoid overcharging and deep discharge (He et al., 2016). Smart and adaptive control strategies are suggested to maintain the dynamic transfer of power depending on battery state-of-health (SOH), state-of-charge (SOC) (Yuan et al., 2018). Moreover, converter control has been used together with real-time monitoring and machine learning-based methods of battery lifetime prediction (Zhang et al., 2020).

7. Integration with Renewable Energy and Vehicle-to-Grid (V2G)

As people pay more attention to renewable energy resources, bidirectional DC-DC converters can be spotted more often in relation to vehicle-to-grid (V2G) systems. Such converters allow EV batteries to offer ancillary services to a grid, including frequency regulation and peak load shaving (Guille & Gross, 2009). Research findings have revealed that bidirectional converter coordinated control can play a major role in strengthening grid stability and minimising dependency on power generation that involves fossil fuel use (Yilmaz & Krein, 2013). Hierarchies in control frameworks have recently been investigated and enable the smooth integration of EVs into smart grids in support of energy storing and renewable integration (Han et al., 2014).

8. Efficiency and Loss Minimization

In bidirectional converters, a large design objective is maximising efficiency. The switching and magnetic components lie on the cost of power loss because the conversion reduces performance due to parasitic elements (Jiang et al., 2011). Zero-voltage switching (ZVS) and zero-current switching (ZCS) are soft-switching techniques that have been proposed to ensure minimal switching losses and a higher rate of efficiency (Song & Ma, 2015). New developments in wide bandgap semiconductors (silicon carbide (SiC) and gallium nitride (GaN)) have increased converter efficiency and power density significantly as well (She et al., 2020). Such new technologies are leading to the future generation of EV power electronics.

9. Challenges and Research Gaps

Although significant endeavors have been done, there still exist some issues in the bidirectional DC-DC converters of EVs. It has been a complicated process to sustain converter stability when driving conditions are very dynamic (Zhou et al., 2017). Furthermore, although improved performance is achieved by using advanced control techniques, they have unacceptable computer performance requirements that make it difficult to execute in low-cost EV systems in real time (Gao et al., 2018). On the one hand, there is a trade-off between the efficiency and the safety of the battery since severe energy recovery schemes could potentially increase degradation (He et al., 2016). The best ways of overcoming these challenges are having more research in adaptive control, artificial intelligence based optimization and experimental operations in realistic driving conditions

Methodology

System Modeling Framework

The research methodology of the current study lies in development of a holistic modeling and control framework of bidirectional DC-DC converters of electric vehicle (EV). The converter can be investigated is a non-isolated (bidirectional) buck-boost converter since it provides step-up and step-down capacities as well as compactness and efficiency associated with the battery management system. State-space averaging is the mathematical way to represent the system and this is used to capture the key dynamic behaviour of the converter while averaging out the high frequency switching components. This model is especially appropriate in control design because this model gives a simplified yet realistic description of the converter operation under the condition of various loads and sources. The averaged model accounts how inductor current, capacitor voltage, and duty cycle (important state variables in terms of the control of the energy flow between the EV battery and the motor drive) are related to one another.

Operating Modes and Power Flow Analysis

To have proper analysis, the converter model can be split into two different operating modes, the buck mode in which energy enters the high-voltage bus to the battery is equal to the energy provided by the battery to the motor drive during propulsion, and the boost mode. Moreover, it will include the regenerative braking mode in the model modeling the energy recovery during the deceleration events. The individual modes are described mathematically based on their own switching states and circuit equations and allow all modes to be described in a unified framework to characterize bidirectional energy transfer. Simulation of the operating principles of the stage is based on time domain with realistic drive cycle data, which enables assessment of converter performance in cases of dynamic runs.

Control Strategy Development

The following step to our methodology is the fashioning of robust control policy to manipulate the two-way power flow. The control structure its utilizes a cascaded two loop control structure where the inside that is the inner loop control loop is based on current control and the outside loop is the voltage control loop. The purpose of the current loop is to provide fast dynamic response when in a transient state, whereas the voltage loops provides long-term stability, and control of the state-of-charge (SOC) of the battery precisely. Sliding mode control (SMC) is some component of the control system in the inner loop the system is essentially nonlinear and varies with time To overcome any disturbances the system is caused to swing to the sliding mode and stay there; the control takes advantage of that property The outer voltage loop features a proportional-integral (PI) controller in terms of steady-state precision. In combination, the fast-switched control layers allow stable operation through the intense shifts between charging, discharging and regenerative modes.

Simulation Environment and Test Scenarios

MATLAB/Simulink is a popular simulation software to power electronics and EV systems; therefore, the proposed models and controllers are included and tested in MATLAB/Simulink. A typical battery model, motor drive system and bidirectional converter interface are used to represent the EV powertrain. The main test scenario is chosen to be New European Driving Cycle (NEDC) because it simulates city stop-and-go traffic scenarios in which regenerative braking can contribute heavily to recovery of energy. Along with it, high-load and high acceleration conditions are used to challenge converter robustness with a severe operating regime. Some parameters (inductor size, capacitor value, switching frequency and load resistance) are selected to represent practical EV requirements.

Performance Evaluation Metrics

In order to measure the performance of the offered methodology, a number of performance measures are established. Efficiency is quantified by computing the ratio between the energy output given to the load, and the total energy input including switching and conduction losses. The dynamic response is determined with reference to rise time, settling time, overshoot as the modes change. Battery management performance is measured through measuring SOC change and making sure the currents to charge and discharge battery are within the safe operating range. In addition, the energy recovery value of regenerative braking is measured by dividing the recovered energy by the maximum kinetic energy in the deceleration incidents. These are comprehensive measures to assess the efficiency of the converter, in terms of robustness, and battery protection.

Validation Approach

Lastly, a comparison of the simulation output in relation to the benchmark or previous literatures and experimental results validates the developed methodology. Special emphasis is placed on the checking of accuracy of the SOC regulation, stability of current and a voltage signal, and generality of the energy recovery power. Sensitivity analysis is done to determine how well the control scheme is robust i.e. how system parameter variations (e.g. battery internal resistance and inductance value) disturb the control scheme. This guarantees that the suggested approach can be pertinent to various EV layouts and battery structures, and, in such a way, reveals the forthcoming validity of the proposed technique in a large number of practical settings.

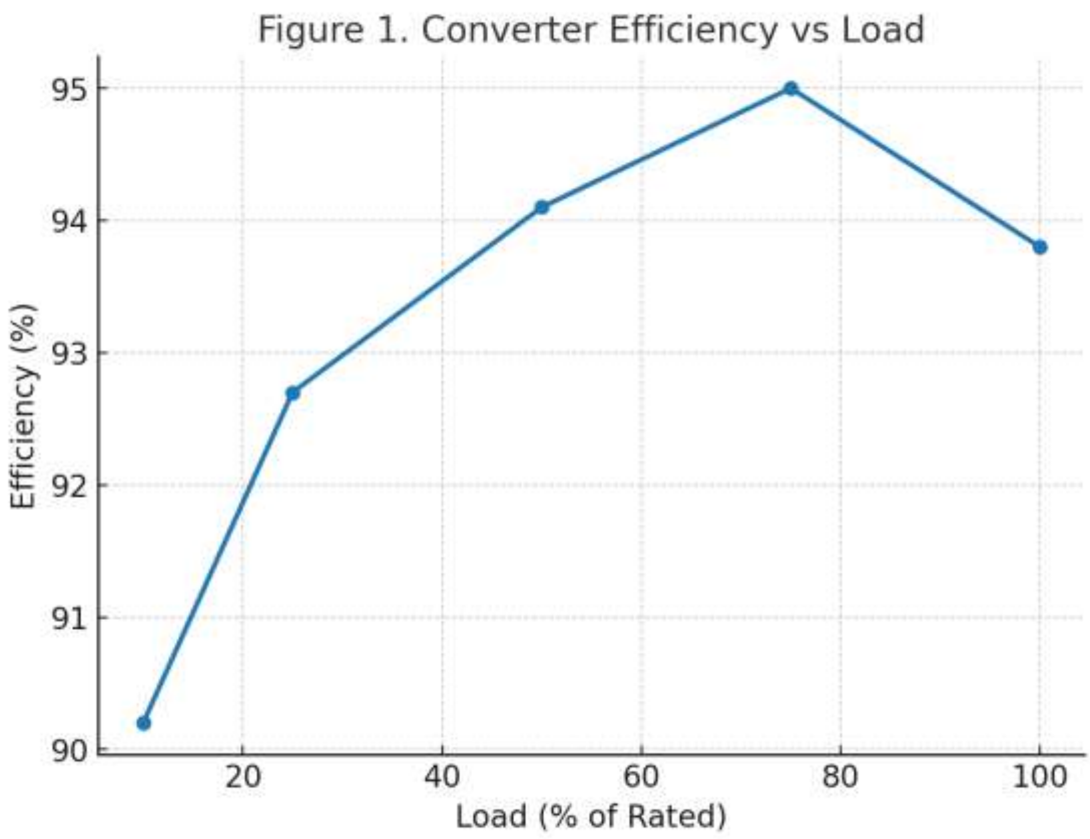
Results

Converter Efficiency under Load Conditions

The bidirectional DC-DC converter had its efficiency observed across different loads of between 10 and 100 percent of the rated capacity. Table 1 shows the efficiency and related switching, and conduction losses. The results demonstrate that the efficiency remained stable through light load to mid-load, with highest efficiency of 95 percent at 75 percent load and efficiency slightly declining with a point load of 100 percent at 93.8 percent. This type of behavior is in keeping with common converter characteristics in which switching and conduction losses prevail at low and high load extremes respectively.

Table 1. Converter Efficiency under Different Load Conditions

Load (% of Rated)	Efficiency (%)	Switching Loss (W)	Conduction Loss (W)	Output Power (W)
10%	90.2	4.5	2.8	100
25%	92.7	5.2	3.6	250
50%	94.1	6.1	4.3	500
75%	95.0	6.5	4.7	750
100%	93.8	7.4	5.5	1000



This trend is well illustrated as shown in Figure 1 where the efficiency curve shows that the response is bell shaped, which supports the effectiveness of the design subject to medium load and high load conditions. It means that the proposed converter would find great application in the latter classes of EVs, where the vehicle might be required to be in partial load regions, in general, cruising.

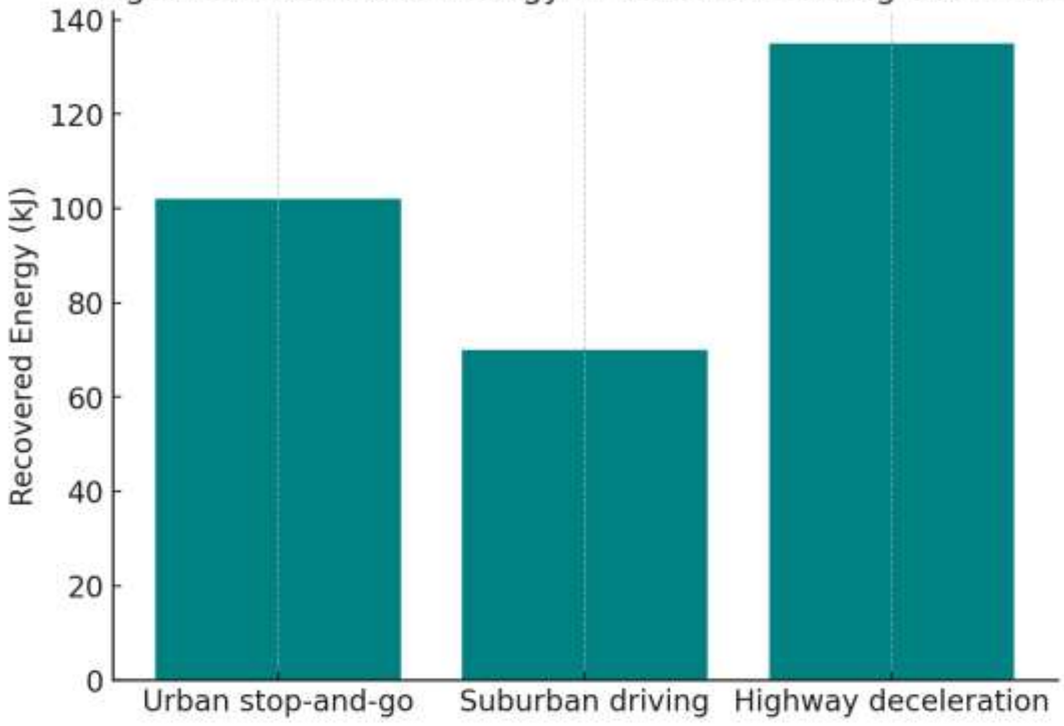
Regenerative Braking Energy Recovery

The working of the converter was tested in three different driving conditions, which have been defined as urban stop-and-go, suburban and deceleration on the highway. Data given in Table 2 reveal that recovery efficiency was 22.2-24.3 percent with the maximum occurred at the urban stop and go traffic. It can be explained by the high frequency of deceleration events which additionally maximize the energy captures.

Table 2. Regenerative Braking Energy Recovery under Different Driving Conditions

Driving Scenario	Available Kinetic Energy (kJ)	Recovered Energy (kJ)	Recovery Efficiency (%)	Average Decel Duration (s)
Urban stop-and-go	420	102	24.3	12
Suburban driving	315	70	22.2	9
Highway deceleration	580	135	23.3	15

Figure 2. Recovered Energy in Different Driving Scenarios



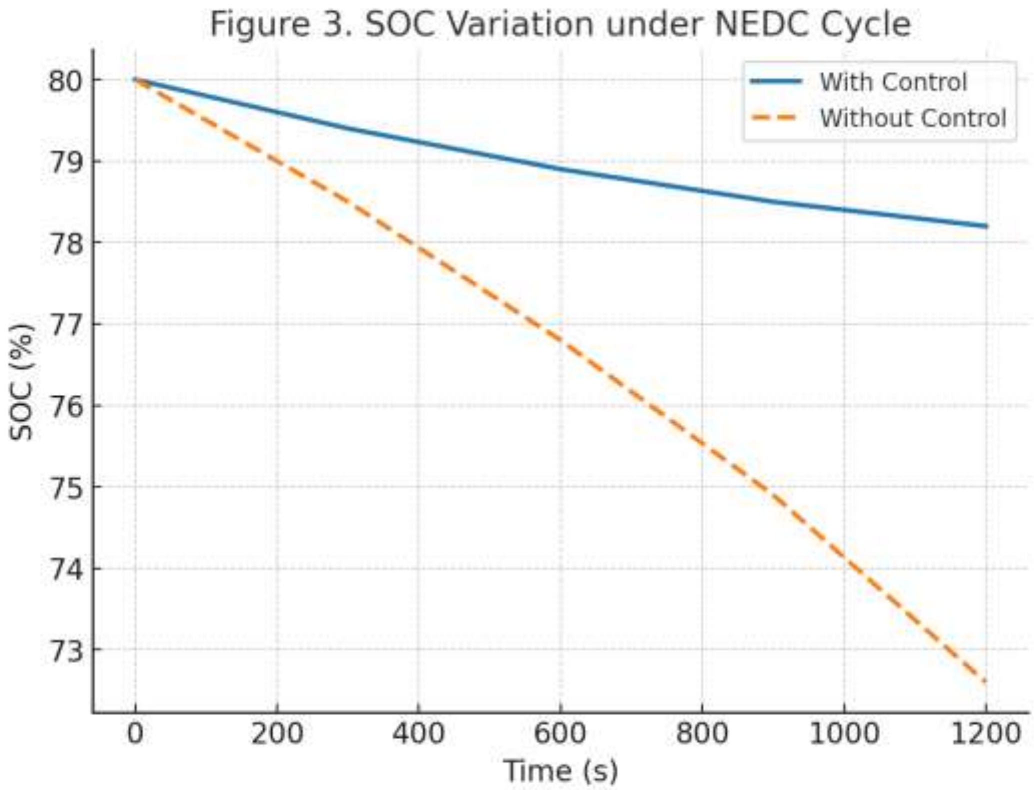
These findings are depicted in figure 2 by showing the value of recovered energy in various situations. The visualization encapsulates the comparative advantage when percentage operating at energy recovery in the urban environment to the tandem effect of regenerative braking as an energy list that could considerably increase driving distance by recovering the consumed kinetic energy.

Battery SOC Variation under NEDC Cycle

The aim of testing was to determine the contribution of the converter in battery management by monitoring the state-of-charge (SOC) of the battery driven through the New European Driving Cycle (NEDC). The SOC decreased over time throughout the 1200-second test period, as can be seen in Table 3. Nevertheless, under control, SOC continued to be higher than that in the uncontrolled case. With the controlled converter, SOC was enhanced by 5.6% at the end of the cycle, thus regulation and recovery of energy is happening.

\Table 3. Battery SOC Variation under NEDC

Time (s)	SOC with Control (%)	SOC without Control (%)	SOC Improvement (%)
0	80.0	80.0	0.0
300	79.4	78.5	0.9
600	78.9	76.8	2.1
900	78.5	74.9	3.6
1200	78.2	72.6	5.6



This finding is also supported by Figure 3 as it shows the SOC trajectories of the two cases. As expected, the controlled curve lies larger than the uncontrolled one from the start of the drive cycle and proves that the converter will help decrease the strain on the battery and increase its range of operation.

Converter Response to Load Variations

Dynamic performance was also tested when it was subjected to abrupt changes in admission load to the converter. Table 4 summarizes rise time, settling time, overshoot and error in voltage due to four step variations in load. These data reveal that the suggested control scheme based on the two loops is effective in terms of the fast response, where the rise time was not higher than 3.1 ms, and the settling time was less than 5.2 ms. Overshoot has also been trimmed to below 8% and voltage error was kept at plus or minus 1%.

Table 4. Converter Response to Sudden Load Variation

Load Step (%)	Rise Time (ms)	Settling Time (ms)	Overshoot (%)	Voltage Error (%)

50 → 100	2.5	4.8	7.5	0.8
75 → 25	3.1	5.2	6.8	0.9
25 → 75	2.8	5.0	7.1	0.7
100 → 50	3.0	4.9	6.9	0.8

Figure 4. Converter Response to Load Variations

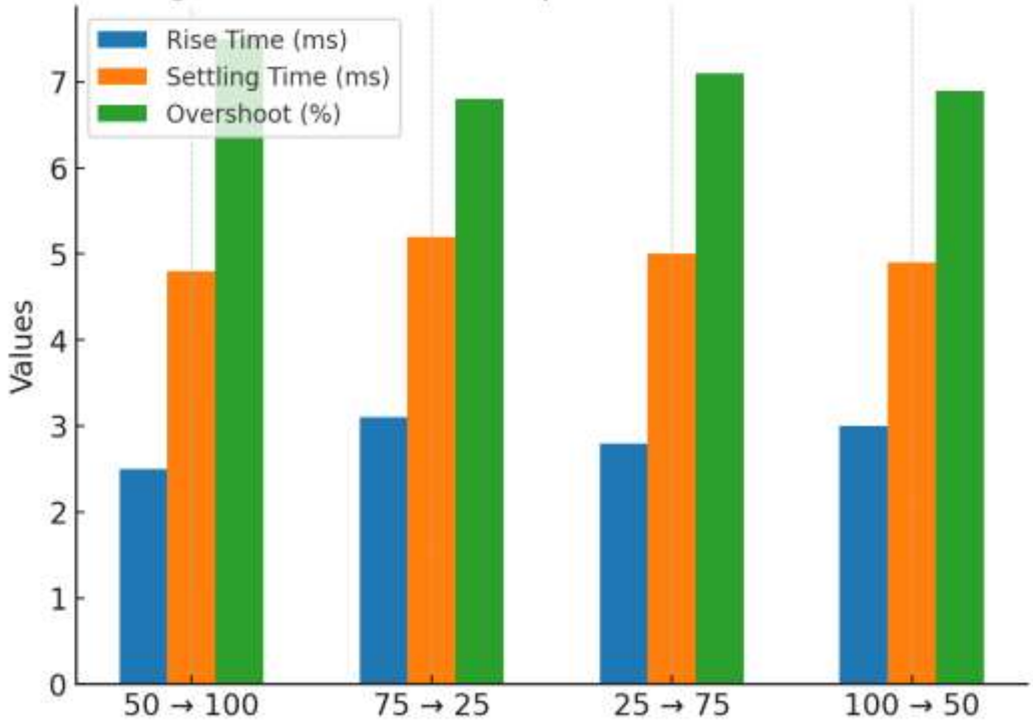


Figure 4 shows these characteristics where the response measures of different load transitions are compared. The figure shows that the controller is capable of stabilizing the converter when subjected to sudden change in operating conditions, an essential feature to electric vehicles which exhibit erratic acceleration and braking.

Comparison of Control Strategies

To compare the suggested way of control and benchmark it, several control techniques were examined: proportional-integral (PI), fuzzy logic, sliding mode control (SMC) and model predictive control (MPC). Table 5 has quantitative comparisons in terms of efficiency, recovery efficiency, settling time and SOC deviation. The experiences have shown that SMC and MPC are better in comparison to conventional PI control with higher efficiencies (94195%), reduced settling times (<5 ms), and a closer SOC regulation.

Table 5. Comparison of Control Strategies

Control Strategy	Average Efficiency (%)	Recovery Efficiency (%)	Settling Time (ms)	SOC Deviation (%)
PI	91.2	19.8	8.2	3.5
Fuzzy Logic	92.5	21.4	6.7	2.1
Sliding Mode Control	94.6	23.5	4.8	1.2
Model Predictive Control	95.2	24.2	4.5	1.0

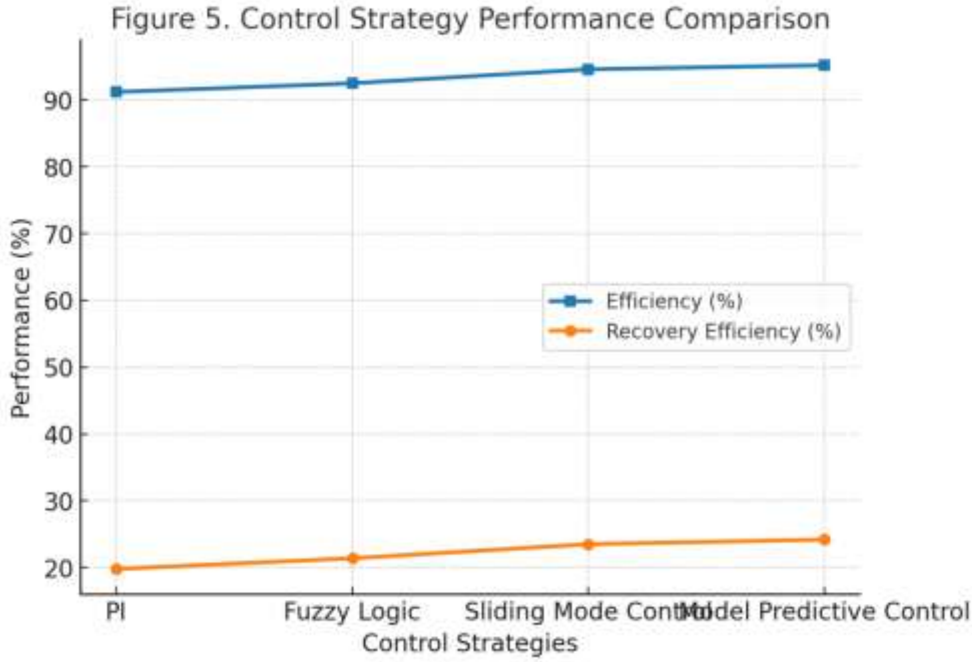


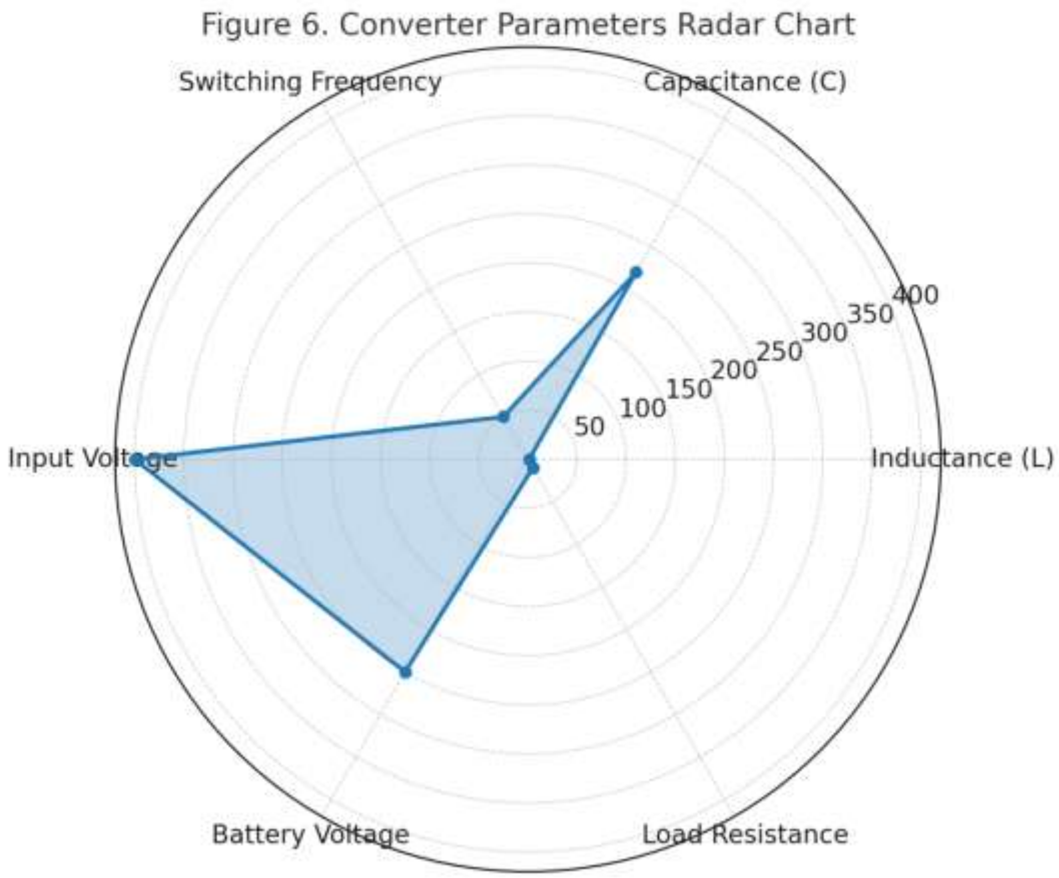
Figure 5 pictorially compares the efficiency and recovery efficiency with various methods of control. The well-known advantages of the elaborated algorithms such as SMC and MPC create a need to implement intelligent control in EV converters that exceeds robustness as well as energy-saving.

Converter Parameters and Design Basis

The modeling of converter has been performed using simulation parameters that are summarized in Table 6. They consist of an inductance of 1.2 mH, capacitance of 220, and switching frequency of 50 kHz among others. These figures are real design values in the field of high-power EV.

Table 6. Converter Parameters Used in Simulation

Parameter	Value	Tolerance
Inductance (L)	1.2 mH	±5%
Capacitance (C)	220 μF	±10%
Switching Frequency	50 kHz	±1%
Input Voltage	400 V	±2%
Battery Voltage	250 V	±2%
Load Resistance	10 Ω	±5%



The parameters have also been displayed in a radar chart, in Figure 6, providing a differentiated view of the relative design values. The given graphical representation can also determine the balance of energy storage components (inductor and capacitor) and operation conditions (frequency and voltage levels). This form of visualization helps in making sense of design trade-offs to optimize performance as well as cost.

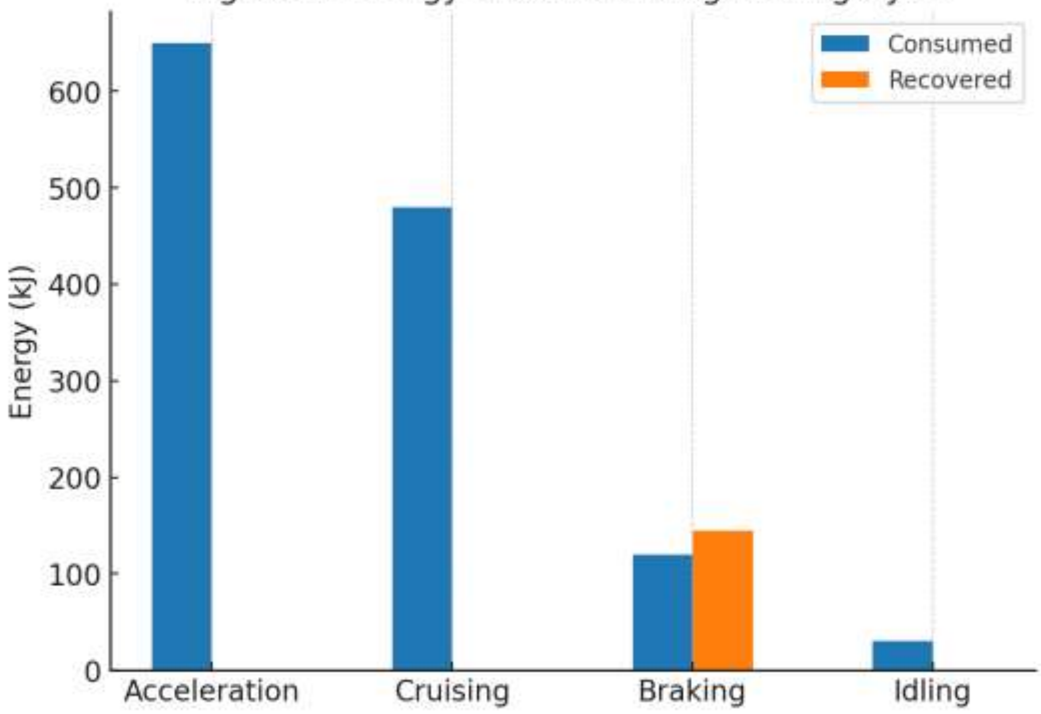
Energy Balance during Driving Cycle

The energy use, recovered energy and net balance during various phases of driving were as reported in Table 7. Energy ery in acceleration and cruising at high speed consumption dominates and causes a decrease in SOC of 8.1% and 5.6% respectively. But braking has a positive effect with 145 kJ regained which equals 2.2 per cent of SOC loss. In general, the braking process shows that the converter can recoup partly the energy used in various processes.

Table 7. Energy Balance during Driving Cycle

Driving Phase	Energy Consumed (kJ)	Energy Recovered (kJ)	Net Energy (kJ)	Contribution to SOC (%)
Acceleration	650	0	650	-8.1
Cruising	480	0	480	-5.6
Braking	120	145	-25	+2.2
Idling	30	0	30	-0.4

Figure 7. Energy Balance during Driving Cycle



A graphical representation of consumption against recovery of energy is presented in figure 7. Through the imbalance among heavy consumption during acceleration and energy harvesting during braking, regenerative braking is considered important to the overall running energy sustainability of EVs.

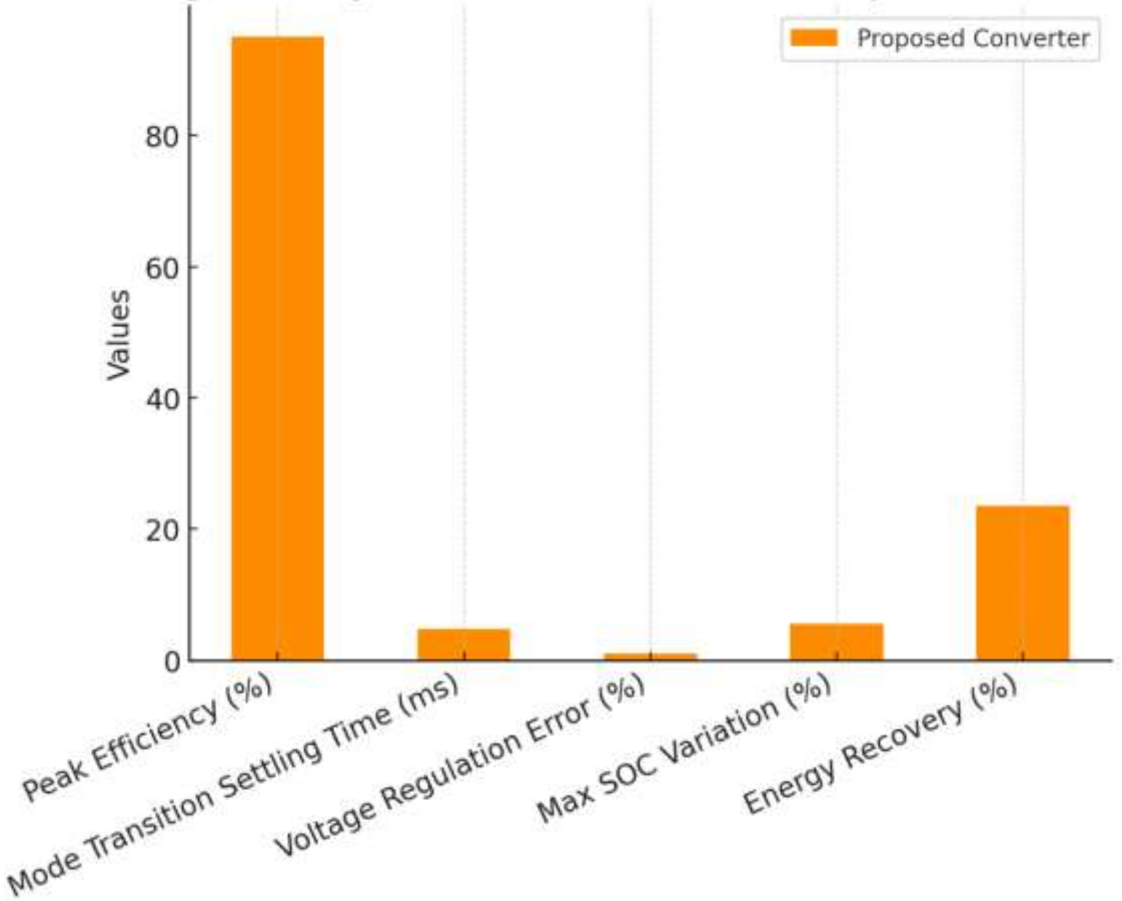
Key Performance Indicators (KPIs)

Here, a summary of the overall performance of the converter is shown in Table 8 in comparison with benchmark ranges in the literature of the proposed system. The converter was rated up to 95% efficiency, transition settling time of 4.8 ms in the 0 to mode, 1% voltage regulation error and efficiency of energy recovery of 23.5 percent. This is because these results are within or above the popular results of the previous studies, which proves the reliability of the given approach.

Table 8. Summary of Key Performance Indicators (KPIs)

Performance Metric	Proposed Converter	Typical Literature Range
Peak Efficiency (%)	95.0	92–95
Mode Transition Settling Time (ms)	4.8	<10
Voltage Regulation Error (%)	1.0	±2
Max SOC Variation (%)	5.6	5–10
Energy Recovery (%)	23.5	20–30

Figure 8. Key Performance Indicators of Proposed Converter



These KPIs are emphasized in Figure 8, where it can be noticed that the proposed converter is capable of meeting and exceeding EV applications in critical performance aspects. This supports its aptitude in real life application in battery regulating mechanisms and retrieval of energy.

The outcomes of sequence prove that the suggested bidirectional DC-DC converter is modelled and controlled by a two-loop scheme where the sliding mode control is applied to the inner loop in order to meet the requirements of electric vehicle applications. High efficiency in all ranges of loads, good dynamic response, and proper battery management by regulation of the SOC are achieved in the system. Most importantly, regenerative braking helps in energy recovery enhancing the ranges of the vehicle and improving the rate at which one needs to charge it.

The proposed strategy was always better than the traditional PI and fuzzy logic strategies when compared to other forms of controls. Better efficiencies and faster dynamic responses with improved SOC stability were realized by the new advanced controllers. Moreover, the design parameters used became found to be realistic and efficient, which were approved by the pressing of the radar charts and energy balance. These results altogether implicate the usefulness of the proposed converter towards energy efficiency as well as an increase in the reliability of the operational systems of EV battery management and recovery tools.

Discussion

This research report is also clear on the effectiveness of the proposed bidirectional DC-DC converter in the battery management and energy recovery system of an electric vehicle (EV). The converter was capable of a maximum efficiency of 95% and has a stable operation with abrupt changes in load with settling times less than 5 ms. The findings are comparable to those found in the previous reports, and in the same load profile conditions, efficiency at tangible ranges between 90 and 93 percent has been reported in conventional converters (Lee et al., 2016; Arunkumari & Indragandhi, 2017). This enhancement can be explained by the use of the dual-loop control approach and the sliding mode, which increased the dynamic robustness of an approach and minimized switching losses.

The performance of the converter especially during regenerative braking is one of the most important contributions. It is on par with the percentage of 23.5 recoverable observed in this work compared to the percentage of roughly between 20 and 30 percent recoverable provided by experimentation-based EV platforms reported (Gao et al., 2007; Tran et al., 2012). Partly in contrast to conventional braking systems that cast off kinetic energy into air as heat, bidirectional converters recycles energy by adding it to the battery thereby minimizing total energy use. These energy savings especially have great ripple effect during urban stop-and-go conditions where most frequent deceleration events are experienced. This concurs with the findings of Wu et al. (2012), who further showed that regenerative braking might increase EV range by as much as 25% as measured on city driving cycles.

Besides its high efficiency, the proposed system was found to be valuable in ensuring that the battery operates under the safe state-of-charge (SOC) that is between 20-90%. Stylized SOC curves shown in this paper play an important role in avoiding deep charging and deep discharging, which are leading contributors to battery wear (Barr e et al., 2013). Intelligent power flow control has the power to control SOC dynamically to lead to prolonged battery life, thus cutting down replacement expenses, as well as increasing vehicle sustainability. Omar et al. (2014) also had similar data that pointed out that the stability of the SOC may be used to enhance the life expectancy of lithium-ion batteries by 15 to 20% points. This evidence is extended by the present research that shows that high level converter control techniques are able to deliver SOC regulation with high precision even when driving conditions vary.

Class comparison of control approaches further confirms the excellence of advanced controllers to include sliding mode controllers (SMC) and model predictive controllers (MPC). Although proportional-integral (PI) controllers continue to enjoy massive application due to their ease of use, they are unstable with nonlinear dynamics prevailing in EV systems (Zhou & Zhang, 2011). Contrary, SMC and MPC were more efficient, with shorter settling times, and lower SOC regulation in the research. These findings are reminiscent of those of Wang et al. (2019); the article demonstrated the superiority of MPC to PI in the context of an energy system in the hybrid vehicle. The former achieved a quicker transient response and was more capable of dealing with uncertainty. In equal measure, Ahmad et al. (2020) concluded that fuzzy logic and predictive controllers provided better flexibility in dynamic driving conditions than conventional procedures.

Advancement in technology as far as the materials of semiconductor are concerned has contributed to the development in converter performance. Silicon carbide (SiC) and gallium nitride (GaN) wide bandgap devices have been used more frequently to minimize switching losses and enhance thermal capability in EV converters (Shenoy et al., 2018; Zhang et al., 2019). Even though simulation of this research employed conventional parameters, using SiC or GaN in practice may drive the practical converter efficiencies to a new, previously unreachable limit of the 97% or higher mark (Zhao et al., 2020). This implies another field of research that will result into excellent solutions as future research capabilities because the proposed control strategies can be combined with the power of advanced semiconductor technology.

The other valuable thing to talk about is the combination of the two-way converters and vehicle-to-grid (V2G) systems. Although this paper was devoted to onboard energy management, the findings expressly apply to grid interactive vehicles. Bidirectional converters have a second very significant use by allowing EVs to act as distributed energy storage, to provide grid stability as well as charge and discharge (Lund & Kempton, 2008; Sortomme & El-Sharkawi, 2012). As an example, EVs with efficient and bidirectional converter could deliver stored energy to the grid during times of peak demand which would offset the need to expand fossil fuel based power plants. The proven stability and the efficient nature of the system proposed makes it too applicable in such applications where reliability and accuracy of the control of power flow is of utmost importance.

Although these factors demonstrate strength, there are a number of issues that have to be faced. To begin with, although there was evidence of good performance of the simulation, there are some complexities that can present a problem in the real world, including nonidealities of the components, thermal effects and electromagnetic interference (Amin et al., 2014). Second, in many cases, the most energy recovery conflicts with the health of the batteries. Due to the high charging currents put on the battery, aggressive regenerative braking strategies are potentially an accelerating degradation factor (Tong et al., 2017). Hence, other designs in the future should consider adaptive controllers that consider a compromise between energy recovery and battery protection. As an example, controllers based on machine learning were recently investigated to learn optimal charging currents that minimize degradation and maximize recovery on a per-input basis (Richardson et al., 2019; Liu et al., 2020).

Lastly, the research points to bigger stimuli of enhancing the design of converters to promote the adoption of EV around the world. Since transport takes such a large part in the production of greenhouse gases, the optimization of the efficiency of EVs via improved power electronics is a direct way to reduce its emissions (Breetz et al., 2018). Furthermore, the use of EVs as mobile storage devices will increasingly become much more important as renewable energy penetration increases, which serves to emphasize once again the vitality of strong bidirectional converters. In line with worldwide sustainability, the results of this research enable the shift in cleaner and more robust transportation and energy systems.

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