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Integrating Fuzzy Logic and Brute Force Algorithm in Optimizing Energy Management Systems for Battery Electric Vehicles

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ABSTRACT

The limited driving range of BEVs is the main challenge in developing zero-emission Battery Electric Vehicles (BEVs) to replace traditional fuel-based vehicles. This limitation necessitates an increase in battery energy while balancing the power supply and consumption requirements for the vehicle's motor and auxiliaries, such as the Heating, Ventilation, and Air Conditioning (HVAC) system. This research proposes a solution to achieve more efficient control of HVAC consumption by integrating fuzzy logic techniques with brute-force algorithms to optimize the Energy Management System (EMS) in BEVs. The model was based on actual parameters, implemented using MATLAB-Simulink and ADVISOR software, and configured using a backward-facing design incorporating the technical specifications of a Malaysian electric car, the PROTON IRIZ. An optimal solution was proposed based on the Satisfaction Ratio (SR) and State of Charge (SoC) metrics to achieve the best system optimization. The results demonstrate that the optimized fuzzy EMS improved power consumption by 23.2% to 26.6% compared to a basic fuzzy EMS. The proposed solution significantly improves the driving range of BEVs.

Keywords: Battery electric vehicle, brute-force algorithm, energy management system, fuzzy logic, satisfaction ratio, state of charge

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INTRODUCTION

An Electric Vehicle (EV) is a car that uses a minimum of one electric-powered motor rather than the traditional combustion engine. It is a second-hand innovation since this idea has existed since the mid-1800s.

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Although the enthusiasm for this technology was strong during the 20th century, the demand for longer-range vehicles, the lower cost of gas, the invention of the power starter in standard cars, and the beginning of the mass development of internal burning EVs have reduced the attention on EVs until the start of the 21st century (Termiz, 2015).

The environmental issues caused by traditional transportation and increasing oil prices have revived the passion for power vehicles in recent years (Eberle & von Helmolt, 2010; Termiz, 2015). Due to pollution caused by conventional vehicles, fume emissions and the scarcity of fossil fuels, there has been much interest in the work on sustainable transportation, such as Hybrid Electric Vehicles (HEVs) (Han et al., 2018; Zhang et al., 2017) and Plug-in Hybrid Electric Vehicles (PHEVs) (Hassanzadeh & Rahmani, 2022) that can reduce the carbon impacts but are unable to remove them completely. A BEV is powered entirely on electric electricity, normally a huge electric motor and a huge battery pack, consisting of a DC-DC converter and transmission, driving cycle, and longitudinal vehicle dynamic model. Pure electric motor vehicle is a type of EV that makes use of chemical power saved in rechargeable battery packs. BEVs use electric motors and motor operators instead of internal combustion engines (ICEs) for power.

BEVs present an eco-friendly solution with exceptional drivetrain performance and energy efficiency, and the trade-off is the restricted driving range attributed to limitations in battery capacity and volume. The situation becomes more intricate with the rise in power requirements and the inclusion of multiple electrical loads due to the electrification of transportation. For BEVs that rely solely on batteries as their energy storage and need to cater to numerous loads, the challenge lies in alleviating range anxiety by devising stringent control rules and a management strategy that can effectively extend the driving range (Dou et al., 2021; Hu et al., 2020; Mohd, 2020).

An Energy Management System (EMS) is a computer-supported device utilized by drivers of electrical frameworks to manage and optimize the efficiency of transmission systems. The EMS needs to be maximized to enhance its performance and battery efficiency, as well as to increase the travel distance for Battery Electric Vehicles (BEVs) and maintain driver confidence. To improve the performance of the EMS, artificial intelligence (AI) techniques have been rapidly evolving, particularly in the field of EMS (Hussain et al., 2019; Górriz et al., 2020; Pan et al., 2021; Mohd, 2020). Their revolutionary applications provide efficient control strategies that increase the capabilities, efficiency, and accuracy of EMS, as well as reduce EVs' energy consumption. Hence comes the need for AI approaches in energy management to provide a battery power supply that fulfills power consumption for motors and auxiliaries such as heating, ventilation, and air conditioning systems (HVAC). Applying EMS is one of the AI approaches that can reallocate the electrical power flow inside the HVAC system to boost power efficiency and obtain optimum effectiveness. Therefore, this research is focused on the energy consumption of BEVs by developing optimization algorithms based on fuzzy logic techniques to apply the best solution in EMS. Such innovative AI solutions can enhance the efficiency of smart EMS in BEVs as the future sustainable transportation.

The main aim of this study was to develop an optimal fuzzy logic control system algorithm for the energy management of an autonomous EV system. Thus, the proposed system employed an algorithm based on the optimal-fuzzy method. The structure and parameters of optimal-fuzzy were tuned using a brute-force heuristic algorithm as the optimization method. The brute force algorithm has been successfully used as an optimization technique in other applications, and it is the best learning method based on a set of small number of inputs and outputs (Pham & Månsson, 2018). However, no previous studies have used brute force with fuzzy logic techniques to find the best solution or set a strategy EMS for BEVs. Therefore, the brute-force algorithm has been chosen to integrate with the fuzzy controller because the algorithm is the best optimization for the system when involving a small number of inputs-outputs, and also, the system is not working continuously. This technique finds the best solution from a wide range of measures, where the decision is based on two or more variables. Hence, the optimized controller would be able to provide an appropriate energy supply to each auxiliary EV component, along with a significant improvement in its travel range.

METHODS

This simulation-based study was conducted to develop improvements for the existing system using experimental simulation. Several computerized tools were used to simulate the desired system. Among the numerous vehicle modeling and analysis platforms, MATLAB/Simulink, integrating the ADVISOR library, is the most widely used platform in academic studies of mechanical engineering simulations (Tammi et al., 2018). Therefore, in this study, the simulations were based on the ADVISOR library integrated within the MATLAB/Simulink system.

The main aim of this study was to develop an optimal fuzzy logic control system for the energy management of an autonomous EV system. Thus, the proposed system employed an algorithm based on the optimal-fuzzy method. The structure and parameters of optimal-fuzzy were tuned using a brute-force heuristic algorithm as the optimization method. Hence, the optimized controller would be able to provide an appropriate energy supply to each auxiliary EV component, along with a significant improvement in its travel range.

Design of Battery Electric Vehicle Basic System

The simulation model comprises five key components that work together to provide a comprehensive view of the electric vehicle's performance, as shown in Figure 1. These components are:

1. The driving cycle represents the pattern of acceleration and deceleration of the vehicle over time. It is an important input for the simulation as it determines the power required from the electric motor and the energy required from the battery.
2. The electric motor model models the behavior of the electric motor in response to the power demand from the driving cycle. It takes into account the motor efficiency, torque-speed characteristics, and other parameters.
3. The transmission model models the behavior of the transmission system that delivers the power from the electric motor to the wheels. It takes into account the gear ratios and the efficiency of the transmission system.
4. The battery charge controller model with the DC-DC converter models the behavior of the battery charge controller and the DC-DC converter that regulates the voltage and current flow between the battery and the electric motor.
5. The longitudinal vehicle dynamics model models the behavior of the vehicle in terms of its acceleration, speed, and distance traveled, taking into account the driving cycle, electric motor model, transmission model, and battery charge controller model.

The simulation employs a backward-facing model, which forecasts the vehicle's behavior by considering the input driving cycle and the behavior of its components. The model operates without the need for a driver, requiring the user to only input the driving pattern or velocity profile.

It is essential to have comprehensive knowledge of all relevant technical specifications to ensure the accurate utilization and optimization of the batteries. Therefore, in selecting

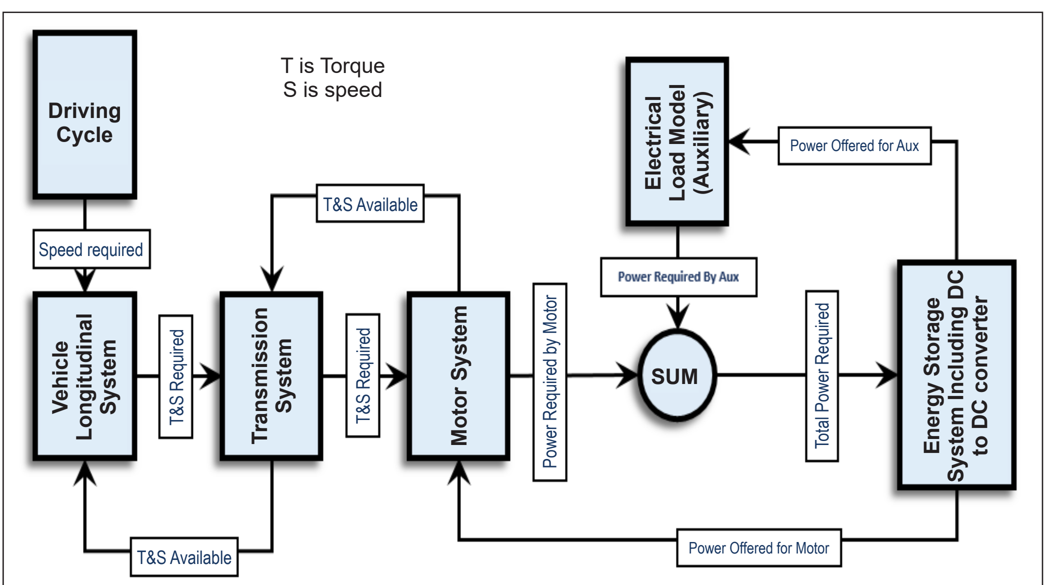

Figure 1. Block diagram of BEV system components based on a backward-facing model

the most suitable battery for the modeled EV, the technical specifications of the LG-PROTON IRIZ BEV were utilized (Table 1).

Table 1
Technical specification for LG-PROTON IRIZ BEV

Drivetrain Parameters	
Drive System	Front-wheel drive
Curb Weight	918 kg
Adds wright (Cargo)	56 kg
Gross Weight	1516 kg
Wheel/Axe	Front Wheel Drive 195/55R15 (Standard)
Accessories	Variable ACC_Small_Car
Powertrain	EV – Manual – PTC_EV
Rated Voltage	330 V
Rated Capacity	39.6 kWh, 120 Ah
Rated Lifetime	10 years \ 160,000 km
Motor Type	PMAC (YASA-400)
Max Output	116 kW
Max Torque	360 Nm
Transmission	Single Speed 3.37:1
Normal Voltage	330 V
Total Cells	360 Cells
Total Weight	540 kg

Auxiliary Electric Load Model

Valentina et al. (2014) stated that the major challenges with EVs are the driving range and battery lifetime. The performance and efficiency of EVs need to be optimized, and consumption needs to be reduced to mitigate these problems. In order to achieve these objectives and to insert the configurable subsystems of this study, the Auxiliary Electric Load Model was added to the basic BEV model. The following Equation 1 provides an example of the typical auxiliary load:

$$\mathrm{AUX} = \mathrm{HVAC} + \mathrm{HS} + \mathrm{SS} + \mathrm{CS} + \mathrm{SN} \tag{1}$$

where AUX = auxiliary load; HVAC = heat, ventilation, and air conditioning; HS = heated seats; SS = sound system; CS = camera system; and SN = satellite navigation.

This study considered the Heating, Ventilation, and Air Conditioning (HVAC) system and Heated Seat (HS) because EVs have the largest auxiliary power loads. As part of the auxiliary components of cars nowadays, the HVAC and HS units may significantly deplete the energy from the battery, depending on the vehicle's settings. If heated seats are used, as required in some European countries, energy depletion would increase even more.

The auxiliary loads in EVs, such as heating, air conditioner, sound system, and satellite navigation, use electrical energy from batteries, reducing the vehicle's driving range. Some of these loads are considered very important. Controlling the auxiliary loads can improve the total fuel consumption without decreasing the energy consumption of the auxiliary system.

Design of BEV with Optimal Fuzzy Logic Energy Management System

In this study, a designed fuzzy logic strategy was integrated into the EMS to improve battery power capacity utilization. The EMS system is characterized by a simple black box design and features SoC and Speed inputs. Additionally, it had three outputs, namely Heated Seats (HS), Front HVAC, and Rear HVAC, as illustrated in Figure 2.

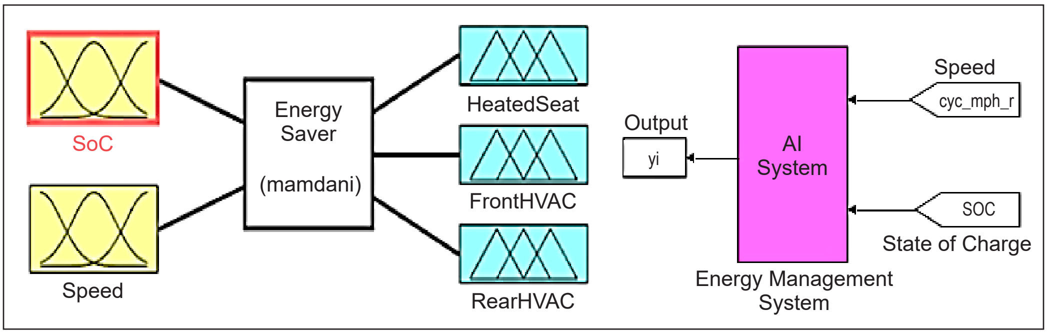

Figure 2. EMS with the fuzzy logic controller

In order to achieve optimal load consumption for the desired HVAC components, the controller was driven by the following two inputs:

- The SoC represents the remaining capacity of the power storage system, scaled as a percentage fraction ranging from 0 to 100. This input is important because it helps the controller determine how much energy is available for use by the HVAC components. By monitoring the SoC, the controller can adjust the load consumption of the HVAC components to ensure that they are not consuming more energy than is available in the power storage system.
- The speed of the vehicle is also an important input for the controller because it helps to determine the energy requirements of the HVAC components. As the speed of the vehicle increases, the energy requirements of the HVAC components also increase. Therefore, by monitoring the speed of the vehicle, the controller can adjust the load consumption of the HVAC components to ensure that they are not consuming more energy than is required for the given speed.

By combining the SoC and Speed inputs, the controller can adjust the HVAC load consumption in real-time to ensure maximum efficiency while maintaining the occupants' comfort. This approach helps to reduce energy consumption and extend the range of electric vehicles, leading to lower operating costs and a more sustainable mode of transportation. Based on the desired HVAC components provided, the output required would be three separate values, each representing the power consumption of the individual components. The three components are:

- Front HVAC: The main HVAC system facilitates the driver and is measured in watts. The power consumption of this component is assumed to be a fixed load of 1,000 watts.
- Rear HVAC: It is also the main HVAC system that facilitates the passengers instead of the driver. Similar to the front HVAC, the power consumption of this component is assumed to be a fixed load of 1,000 watts.
- Heated Seat (HS): This component represents the auxiliary seat heating in modern

vehicles and is used to facilitate the driver. The power consumption of this component is also assumed to be a fixed load of 1,000 watts.

Therefore, to provide the required output, the power consumption of each of these components needs to be calculated and expressed in watts. It is important to note that these power consumption values are based on assumptions, and actual power consumption may vary based on factors such as vehicle make and model, environmental conditions, and usage patterns. Each input and output variable has three linguistic levels, low, medium, and high, represented as membership functions. This study used a triangular shape encoded by three points (Le, He, and Re). The fuzzy logic rules were designed to depend on these values. The values calculated using the fuzzy logic for the standards of the inputs and outputs are listed in Table 2.

The rules were set based on real situations by considering different levels of real speed inside cities, highways, and mixed situations. The rules have also considered real SoCs at different levels. Moreover, the rules also considered the largest auxiliary power load in electric vehicles (EVs): the HVAC system and HS. The following rules of the fuzzy logic strategy, as produced by the software, were implemented:

1. If {(SoC is high)} and (Speed is low)} then {(HS is high) and (Front HVAC is high) and (Rear HVAC is high)}
2. If {(SoC is high)} and (Speed is medium) then {(HS is high) and (Front HVAC is high) and (Rear HVAC is high)}
3. If {(SoC is high)} and (Speed is high) then {(HS is medium) and (Front HVAC is medium) and (Rear HVAC is medium)}
4. If {(SoC is medium)} and (Speed is low) then {(HS is medium) and (Front HVAC is medium) and (Rear HVAC is medium)}
5. If {(SoC is medium)} and (Speed is medium) then {(HS is medium) and (Fr0ntHVAC is medium) and (Rear HVAC is medium)}

Table 2
Inputs and outputs for the membership functions

Input		Output		
SoC Status	**Speed Status**	**HS**	**Front HVAC**	**Rear HVAC**
High	Low	High	High	High
High	Medium	High	High	High
High	High	Medium	Medium	Medium
Medium	Low	Medium	Medium	Medium
Medium	Medium	Medium	Medium	Medium
Medium	High	Low	Low	Low
Low	Low	Low	Low	Low
Low	Medium	Low	Low	Low
Low	High	Low	Low	Low

6. If {(SoC is medium)} and (Speed is high) then {(HS is low) and (Front HVAC is low) and (Rear HVAC is low)
7. If {(SoC is low)} and (Speed is low) then {(HS is low) and (Front HVAC is low) and (Rear HVAC is low)}
8. If {(SoC is low)} and (Speed is medium) then {(HS is low) and (Front HVAC is low) and (Rear HVAC is low)}
9. If {(SoC is low)} and (Speed is high) then {(HS is low) and (Front HVAC is low) and (Rear HVAC is low)}

The goal of conducting optimization was to reduce energy consumption and extend the SoC range. Figure 3 shows the block functional design of the proposed system. This solution was based on the brute force function, which used the optimization algorithm to find the best solution from a wide range of measures. In this case, the decision can be made based on two or more conflicting measures, the SoC and the Satisfaction Ratio (SR).

The fuzzy system was built to preserve the energy level for longer. This aim was achieved by limiting the consumption of energy based on the current level of SoC and speed, which is supposed to consume more energy in an EV. However, there is an implicit relationship between the fuzzy system and the SR. More specifically, the positioning of the edges of the membership function in the fuzzy was vital in changing both SR and SoC. Therefore, the fuzzy logic was added with an optimization algorithm that simultaneously optimizes both measures. The optimization of two variables can be done by finding the Pareto front.

Figure 4 shows the flowchart of the fuzzy controller during the brute force mode. The idea was that the system would try different configurations of membership functions. The SR was memorized for every configuration, and the system continued to change the configuration with every new SoC cycle until it ended with all possible configurations. The system used the brute force algorithm from the memorized SR scores to find the optimal value sent to the controller to recalibrate the membership function. The brute-force algorithm was working offline to choose the best solutions for the membership function based on historically memorized scores of SoC and SR. Thus, this step needed to be done just once at the beginning.

Brute force is a searching algorithm for all possible solutions in the solution space. The brute force approach is to divide the solution space into small partitions. The solution space was defined by nine variables (Equation 2) because the study involves three variables, each with three membership functions. For every variable, one point needed to be changed. Table 3 shows the logic of the solution, in which every alternative solution is a function of these variables.

$$\text{Any solution } X = [x_1\ x_2\ x_3\ x_4\ x_5\ x_6\ x_7\ x_8\ x_9] \in [0\ 1]^9 \tag{2}$$

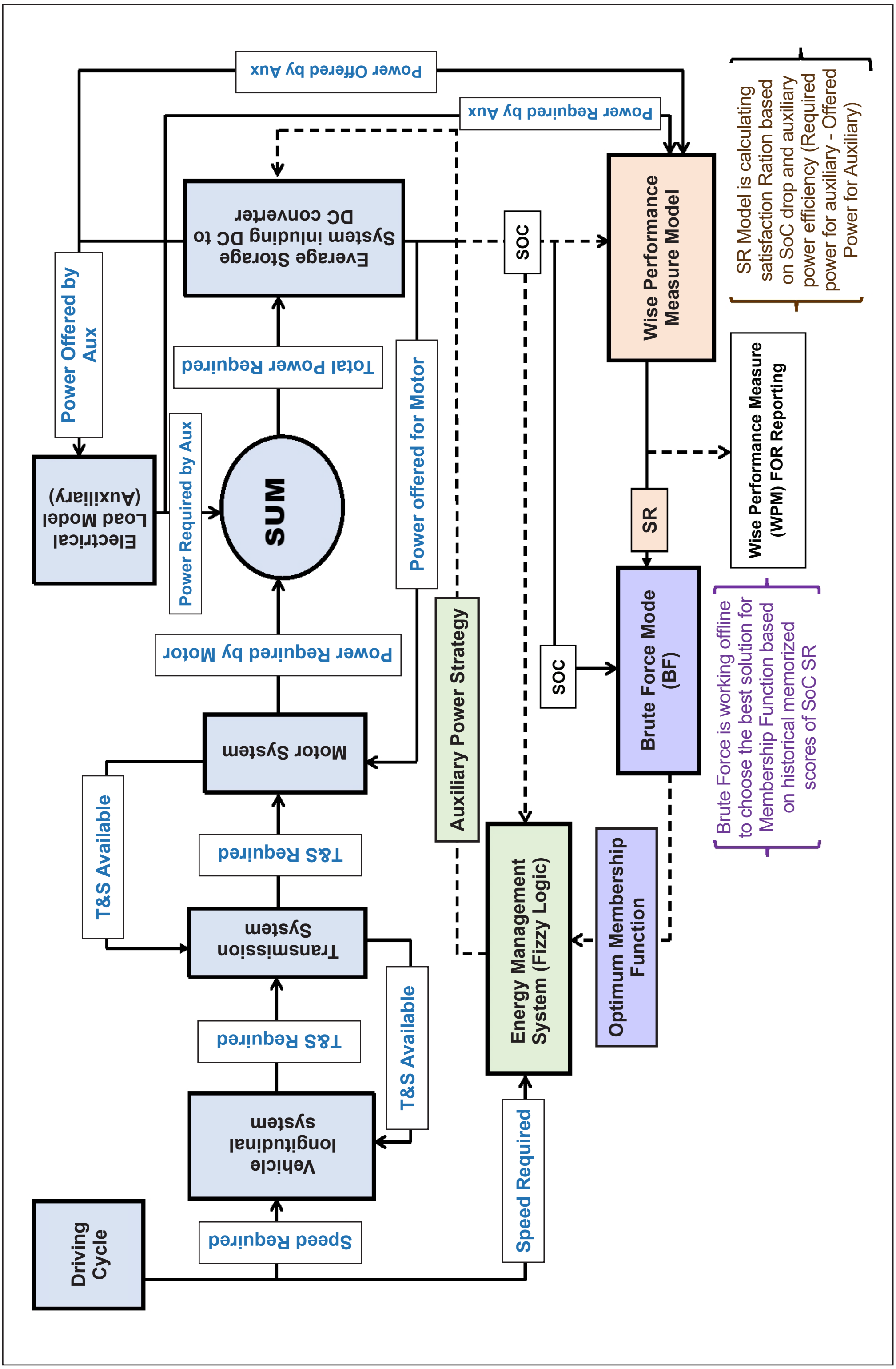

Figure 3. Design of the BEV with optimal fuzzy system

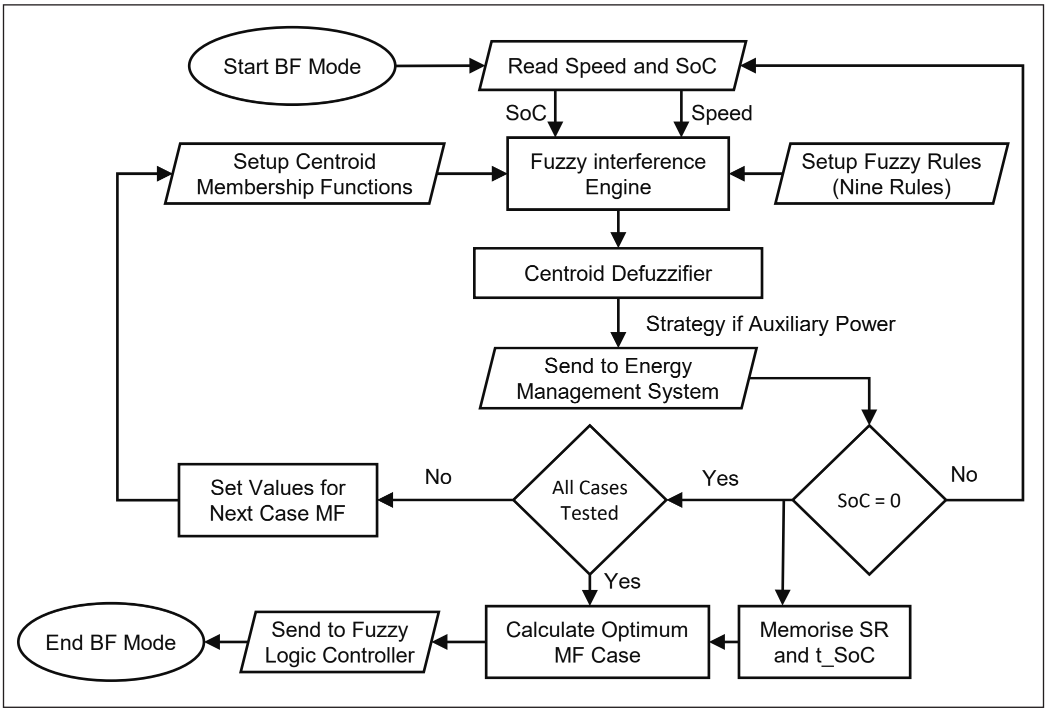

Figure 4. Optimal fuzzy logic flowchart

Table 3
Logic for the solutions in the brute force algorithm

Solution	Dimension	Meaning
X	1 × 9	The solution defined the points as 1, 2, and 3 for every variable (two inputs and one output), which meant there were nine points in total

The process of the brute force logic solution is described as follows:

- The brute force is supposed to generate all possible X values and call the solution decoder.
- The search gave every value of x_i one of four possible values (0, 0.3, 0.6, or 0.9), which meant the size of the solution space was 262,144 (four values × nine membership functions).
- The set of all possible cases was labeled as *X*. Each solution consisted of two objective values: the first one was the time when SoC was zero, and the second one was SR. However, these two solutions were the opposite because the maximization of one will minimize the other when the objective was to maximize both, as shown in the example solution in Figure 5.
- The results became the final set of non-dominated solutions, known as the Pareto front.

Figure 5 shows one sample solution among the 262,144 solutions obtained. Higher satisfaction was shown to be equivalent to lower SoC and vice versa. The nature of the problem was to achieve multi-objective optimization, with conflict between the two objectives. The optimization solution that met certain required modes was extracted from the brute force results: maximum SoC was more economical, while maximum SR was more comfortable. The relationship between the SoC and the SR was conflicting. Consequently, the solutions were also conflicted because maximizing one, minimizes the other.

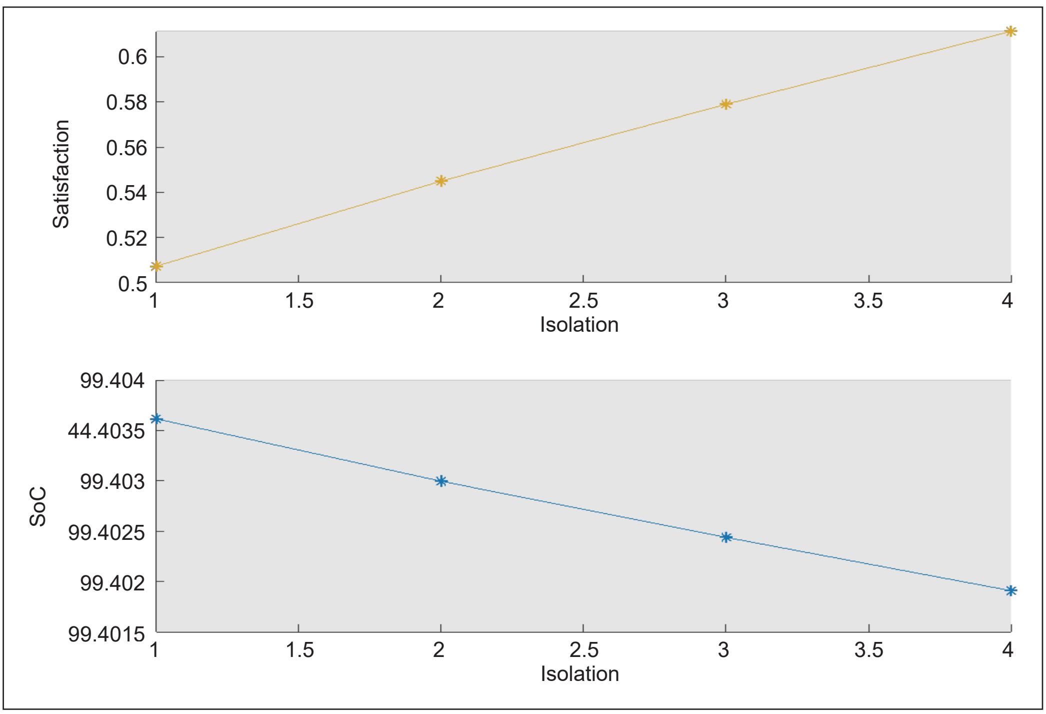

Figure 5. A subset of the solutions to show the conflicting nature between SR and SoC (one sample solution out of 262,144 solutions)

Evaluation Performances of Energy Management System

This research aims to provide a solution to improve the driving range of EVs by keeping an acceptable level of comfort for the driving experience. The SoC refers to the energy stored in a battery or other power source at a given time. The efficiency of the SoC of the battery can be determined using the calculated current. The model used Coulombic Efficiency (CE) and optimal capability values, which are functions of temperature, to calculate the recurring battery ability in systems of ampere-hours (Ah). SoC estimation can be made using the following Equation 3:

$$\mathrm{SoC} = \frac{(\mathrm{Ah}_{mx\ capacity} - \mathrm{Ah}_{used\ capacity})}{\mathrm{Ah}_{mx\ capacity}} \tag{3}$$

where SoC is the State of Charge, $Ah_{mx\ capacity}$ is the maximum power of the battery in ampere-hours, and $Ah_{used\ capacity}$ is the used power in ampere-hours.

The drain of the State of Charge (dSoC) refers to the rate at which energy is depleted from the battery or power source. A higher drain rate in electric vehicles or other battery-powered systems can lead to reduced efficiency and shorter driving ranges, as the battery would need to be recharged more frequently. Therefore, a threshold value of 0.005 (0.5%) suggests that the researchers were concerned about the efficiency of the system and were likely investigating the power consumption and efficiency of an electric vehicle or a similar system. The fact that the study was interested in understanding the impact of different driving conditions further supports the idea that the researchers were investigating the power consumption and efficiency of an electric vehicle. Different driving conditions, such as varying speeds and terrains, can have a significant impact on the power consumption and efficiency of an electric vehicle, so studying these factors can help to optimize the design and performance of such systems.

The driving cycle(speed) is a collection of information embodying the speed of a vehicle versus time. Different nations and companies have created driving cycles to assess the functionality of cars in several ways, for instance, gas usage and pollution discharges for all auto types inside or even outside urban areas (highways). A driving cycle holds regular records offered in ADVISOR and is managed as a 2-D research table listed through Speed and Time. The driving cycles are used to test the gas economic condition and efficiency of vehicles. Moreover, the speed range of driving cycles amounted to scores from 0 to max speed in km/h based on the type of driving cycles (Giakoumis, 2017).

In this research, the thresholds for SR were set at 50%, depending on the weather in Malaysia. For example, when the weather is very hot, the driver would not use all electrical accessories, such as the heated seats. Moreover, if the driver is in a country with cold weather, the driver would not use the air conditioner. Thus, the SR is a flexible value that can be increased or decreased depending on the situation. The SR is presented in Equation 4:

$$\text{SR} = 1 - \frac{\overline{|y_{id} - y_i|}}{y_{id}} \tag{4}$$

where y_{id} denotes the desired load from the user, y_i denotes the actual load from the controller, and $\overline{|y_{id} - y_i|}$ denotes the absolute value of the mean of the difference between the desired and the actual energy.

Wise Performance Measurement (WPM)

The study also introduces a new metric called the Wise Performance Measure (WPM) to balance the energy requirements of SoC and auxiliaries. It is accomplished by setting threshold levels for SoC drop and SR and then tracking any breaches of these thresholds at regular intervals.

The new measure aims to evaluate two aspects of EV driving. The first aspect was to save the energy of the battery while driving, and the second was to satisfy the driver's desire for energy for the usage of accessories. Thus, the new measure was developed as a combination of both SoC and SR while driving. The standard of WPM was developed based on the SoC and SR; thus, the lower the value of WPM, the better. The new measure can be calculated as follows, and as shown in Figure 6:

1. The whole-time interval of the drive is divided into sub-intervals, ΔT, where each sub-interval expresses a part of the time that requires a lower level of SoC saving and SR
2. An accumulator of A = 0 was initiated, with A denoting the WPM
3. Each ΔT would find a two-time series of $\frac{dSoC}{dt}$, and the second was SR

- Compared $\frac{dSoC}{dt}$ with a threshold, T_{SoC}, where the value of $\frac{dSoC}{dt}$ has to be higher than T_{SoC}
  - $\frac{dSoC}{dt} > T_{SoC}$, if the condition is not applied, then A = A + 1; otherwise, A is kept without a change
- Compared SR with a threshold, T_{SR}, where the value of SR has to be higher than T_{SR}
  - SR > T_{SR}, if the condition is not applied, then A = A + 1; otherwise, A is kept without a change

4. At the end of the experiment, the value of A would indicate how many times the condition was not applied. Thus, the goal would be to minimize A. The improved performance would be equivalent to a lower value of A.

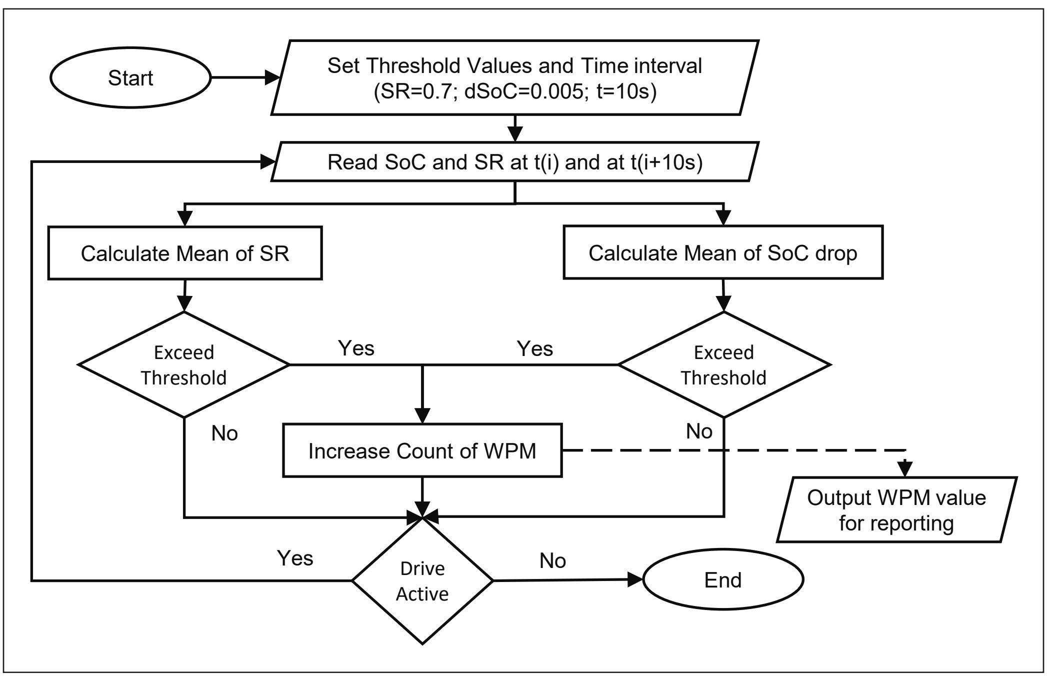

Figure 6. WPM calculator flowchart

As shown in Equation 4, this study selected $T_{SR} = 0.5$, which means that the SR has to be at least 50%. Two experiments were conducted to calculate T_{SoC}: (1) without a load and (2) with a full load. The entire SoC was recorded for both experiments. Subsequently, this study identified the threshold as a new time series that indicates a 50% slope between SoC1 and SoC2. Based on this observation, the drain of the SoC must remain below the threshold value of 0.005 (0.5%) at any time interval. In this research, the threshold for draining the SoC (dSoC) was set at 0.5%, depending on the changes in driving cycle time. All parameters were measured at different stages. The SoC and speed (driving cycle) were measured during the developmental stage of the Fuzzy Logic Controller (FLC), as they were inputs for the FLC. The SR and WPM were measured during the developmental stage of the Brute Force (BF) method. The SR was one of the inputs for BF and one of the outputs for WPM.

RESULTS AND DISCUSSION

The optimal fuzzy controller of this study is an adaptive version of the traditional fuzzy logic by integrating another technique to reconfigure the fuzzy membership function based on calculating the different SRs and SoC in different conditions and then deciding the best configuration. The simulation is based on three driving cycles: The New European Driving Cycle (NEDC), the Urban Dynamometer Driving Schedule (UDDS) and the Japanese 10-15 Mode Driving Cycle (Japan 10-15).

Based on the results presented in Figure 7, it can be concluded that the model using a fuzzy logic controller and optimization by brute-force algorithm for the NEDC with a maximum accumulative load of 3000W for the HVAC system has a better range than the other models. The achieved SoC of 25605 seconds corresponds to a full trip distance of 238.9 km, which is better than the range achieved by the basic model with a load for the NEDC, which is about 193.9 km, and the basic fuzzy logic model, which is about 216.6 km as shown in Table 4.

Moreover, the 100% range for NEDC is also 238.9 km, while the 80% range is 191.1 km. It indicates that the proposed model can achieve a longer range, which can benefit electric vehicles in terms of usability and practicality. In summary, the model with a fuzzy logic controller and optimization by brute-force algorithm for the NEDC with a maximum accumulative load of 3000W for the HVAC system has shown to be more effective in terms of range performance and can be a useful tool for improving the overall performance of electric vehicles.

In Figure 8, the actual SR achieved by the model using FLC and optimization by brute force is higher than the assumed limit, indicating that the driver is more satisfied with the driving range provided by the model. The dSoC is relatively low, indicating that the battery performs efficiently during the driving cycle. Overall, these results suggest that the model

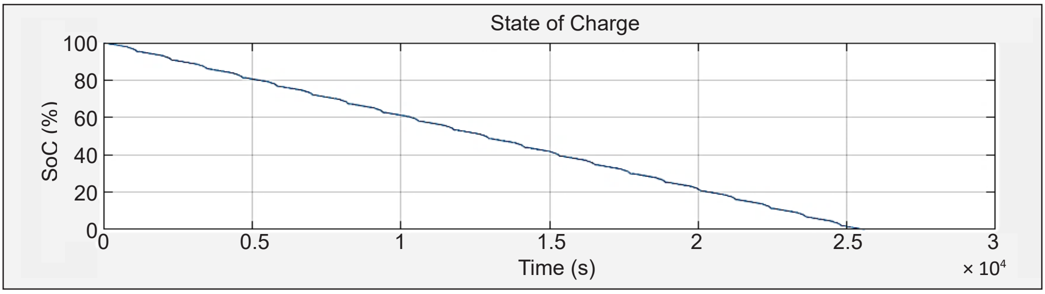

Figure 7. SoC for BEV using NDEC

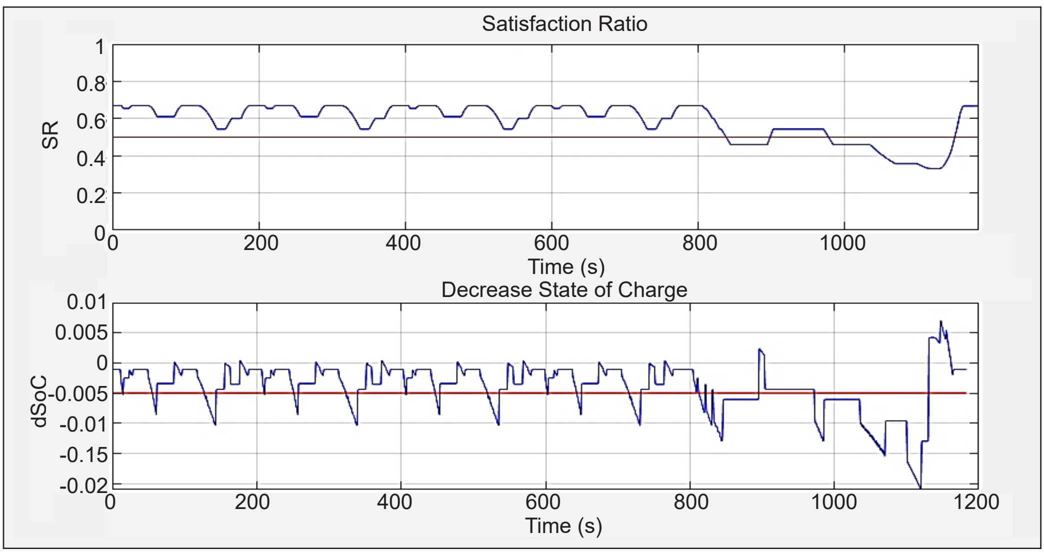

Figure 8. SR and dSoC for BEV using NDEC

using FLC and optimization by brute-force algorithm effectively improves both battery range and driver satisfaction.

Based on the results presented in Figures 9 and 10, it can be concluded that the BEV model using FLC and optimization by brute-force algorithm for the UDDS with a load has a better range compared to the basic model with load and the basic fuzzy model with load. The achieved SoC of 26058 seconds corresponds to 247.5 km for the full trip, which is better than the range achieved by the basic model with a load of about 200 km and the basic fuzzy model with a load of about 223 km, as shown in Table 4. Additionally, dSoC is relatively low and maintained in the threshold range. It indicates that the battery is performing efficiently and is able to maintain a stable state of charge throughout the cycle.

It is important to note that the distance traveled may vary depending on various factors, such as driving conditions, terrain, and temperature. The study also shows that the 100% range for the UDDS is 247.5 km, and the 80% range for UDDS is 198 km. The results

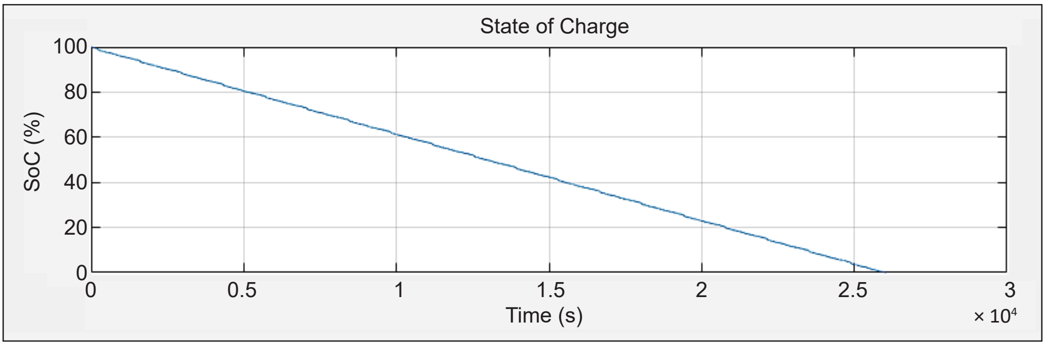

Figure 9. SoC for BEV using UDDS

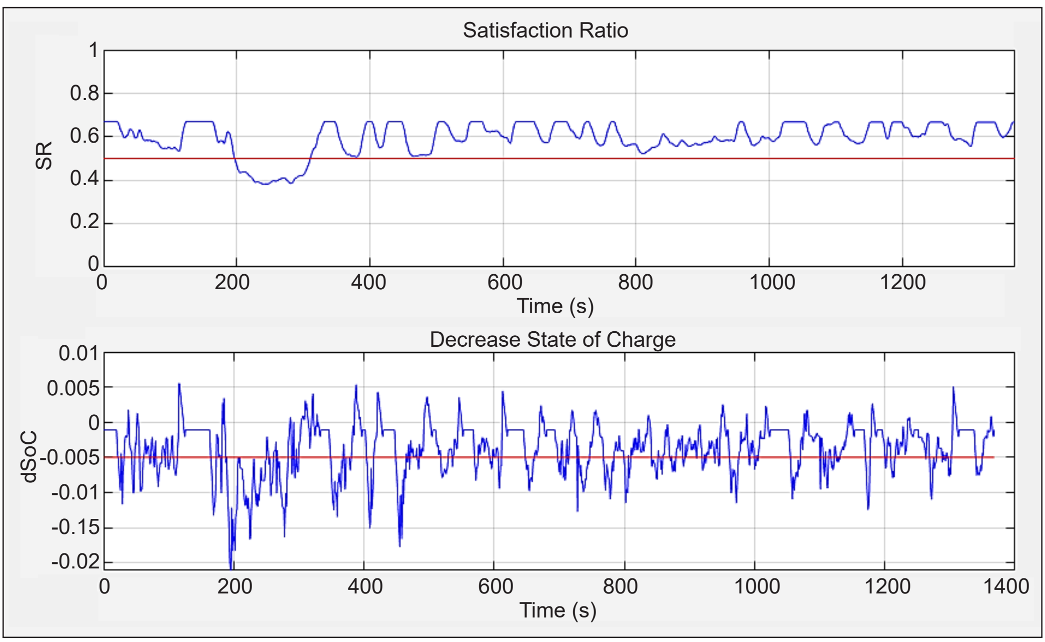

Figure 10. SR and dSoC for BEV using UDDS

show that the FLC and optimization by brute-force algorithm could potentially improve the range of the BEV model, which could be valuable information for developing more efficient and effective electric vehicles.

Figures 11 and 12 show the results of the BEV model using FLC and optimization by brute-force algorithm for the Japan 10-15 driving cycle mode with a load of about 3000 W for the HVAC system. The study reports that the SoC lasted for 32574 seconds, equivalent to 205.3 km for the full trip. A low and stable dSoC during a driving cycle is a positive sign for battery performance. It is important for the reliability and longevity of the battery, as well as for the performance of the vehicle that relies on it for power. A low and stable dSoC is a good indicator of efficient battery performance.

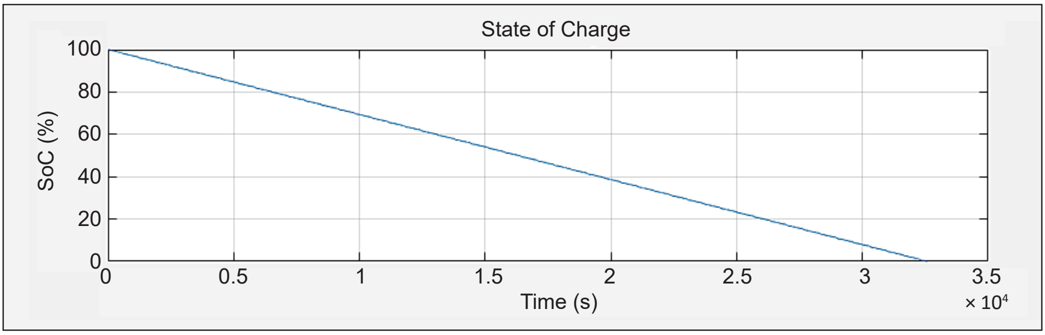

Figure 11. SoC for BEV using Japan 10-15

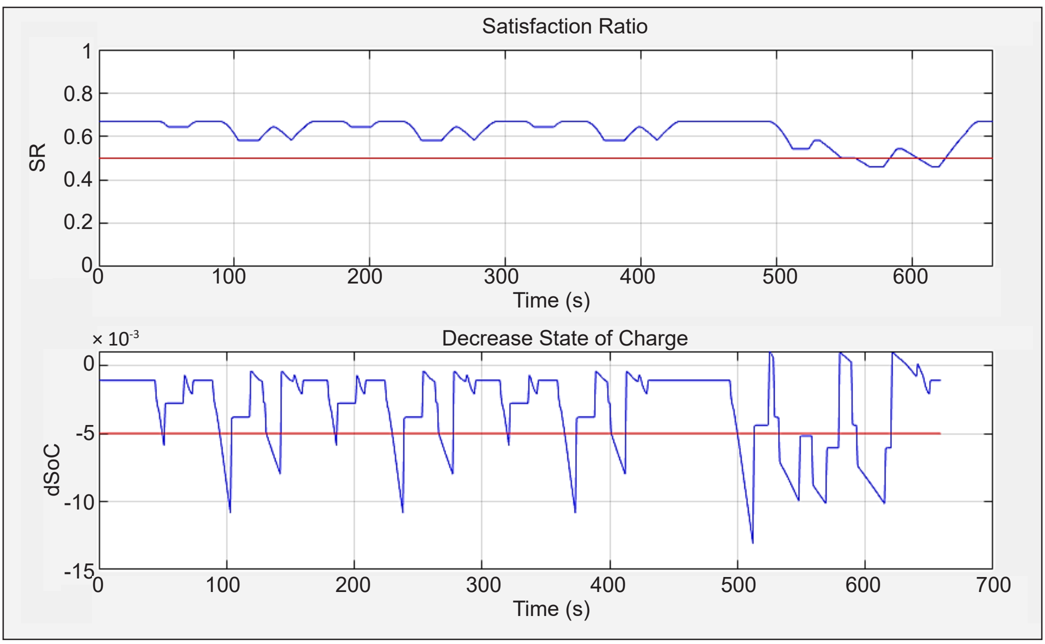

Figure 12. SR and dSoC for BEV using Japan 10-15

Based on the results presented in Table 4, it can be concluded that the model using FLC and optimization by brute-force algorithm for Japan 10-15 with load has a better range compared to the basic model with load for the Japan 10-15 mode and the basic fuzzy model with load for the Japan 10-15 mode. The 100% range for Japan 10-15 mode is reported to be 205.3 km, while the 80% range is 164.3 km. These findings suggest that the optimal model can achieve a longer range of about 205.3 km, which is better than the range achieved by the basic model with load for the Japan 10-15 mode, which is about 162.2 km, and the basic fuzzy model with load, which is about 183.3 km. It indicates that the proposed model can improve the range performance of electric vehicles in Japan's 10-15 mode, which can benefit drivers in Japan. Therefore, using FLC and optimization by brute-force algorithm can be considered a useful approach to improve the range performance of electric vehicles in Japan's 10-15 mode with load.

Overall, the study shows that using a fuzzy logic controller and optimization by brute force can significantly improve the range of battery-powered electric vehicles, as shown in Table 4. The results also suggest that the performance of the EMS can vary depending on the driving cycle used for testing. Implementing the fuzzy logic strategy and optimization demonstrates a clear improvement in power consumption for the HVAC system while preserving power capacity for motor torque and speed. The results show that the basic fuzzy EMS can improve power consumption by 11.7% to 12.4%, and the optimized fuzzy EMS can improve it by 23.2% to 26.6%. The optimal strategy for improving the range of the BEV with an auxiliary load system was the fuzzy logic controller and optimization by brute force, with the highest improvement observed in the NEDC mode. Additionally, the optimal strategy performed better than the basic BEV model with an auxiliary load system in all four driving cycles. These findings can be useful for designing and optimizing EMS for battery electric vehicles, ultimately leading to more efficient and practical electric vehicles.

Table 4
Summary of results for the three EMS model

EMS	Performance	Driving Cycle		
		NEDC	UDDS	Japan 10-15
Basic BEV with HVAC Load	SoC(second)	20774	21060	25726
	Full Trip Distance (km)	193.9	200.0	162.2
	Full Consumption Rate (%)	34.8	36.3	44.2
BEV FL Model with HVAC load	SoC(second)	23214	23515	28925
	Full Trip Distance (km)	216.6	223.0	182.3
	SR (%)	90	90	90
	Fuzzy Enhancement Rate (%)	11.7	11.7	12.4
BEV FL Model + Optimization (brute-force algorithm) with HVAC load	SoC(second)	25605	26058	32574
	Full Trip Distance (km)	238.9	247.5	205.3
	SR (%)	65	65	65
	Optimization Enhancement Rate (%)	23.2	23.7	26.6

COMPARISON OF RESULTS WITH PUBLISHED WORKS

Upon comparing the results of this study with previous studies, it is evident that this study has obtained significant improvements, especially in terms of driving range. Table 5 shows a comparison with the previous work.

The proposed solution can provide better results than most of the previous studies that focused on the EMS system because no previous studies have used the Fuzzy technique with BF in the BEV field and placed emphasis on achieving a balance between two conflicting objectives: reducing power consumption by the HVAC and satisfying the driver. The

Table 5
Comparison between the performance of the proposed solutions and the previous work

Source	Solution/Design	Driving cycle	Results
(Pan et al., 2021)	Fuzzy optimal EMS concerning the equivalent speed (FLC strategy combined with a GA optimal algorithm)	Custom with Slope	- 8.66% improvement in the driving range
(Hu et al., 2019)	generalized regression neural network (GRNN) and Dynamic programming – based energy management strategy (DPEMS) under typical driving	Custom	- 5.65 to 11.04% improvement in range and power-saving
(Masjosthusmann et al., 2012)	Four modular EMS (storage, drivetrain, load, consumption estimation)	Custom	- 15% improvement in range and power saving
Auxiliary power strategy by using a Fuzzy Logic Controller that is based on SoC and speed **(Proposed)**		NDEC UDDC Japan 10-15	- 11.7% - 11.7% - 12.4% Improvement in range and power-saving
Optimal auxiliary power strategy by using Hybrid Design of Fuzzy Logic Controller that is based on SoC and Speed and Brute force algorithm for Optimal FLC **(Proposed)**		NDEC UDDC Japan 10-15	- 23.2% - 23.7% - 26.6% Improvement in range and power-saving

challenge lies in reducing the power supplied to the HVAC system while maintaining driver satisfaction at an appropriate level. While most previous studies concentrated on enhancing power consumption or recharge efficiency, they did not address driver satisfaction.

This study introduces a novel measure called WPM, which establishes a relationship between the SR and the rate of dSoC. The optimal trade-off between these two conflicting measures can be attained using brute force techniques, which have not been utilized in prior studies. The results from the four proposed systems, tested on different driving cycles, clearly demonstrate that implementing fuzzy logic with the BF strategy can enhance the power efficiency of the HVAC system while preserving power capacity for motor torque and speed. However, previous studies did not incorporate the brute force technique with a Fuzzy Logic Controller to identify the best solution or establish a strategy for resetting BF at any point for BEVs. Furthermore, these studies did not propose a measurement technique similar to WPM.

CONCLUSION

This study aims to propose an optimization algorithm that integrates the brute-force technique and the fuzzy logic controller. A basic fuzzy logic controller is designed and integrated into the EMS to achieve this goal; an additional optimization technique is integrated to seek the optimal configuration of the fuzzy logic controller using a brute force algorithm. The fuzzy controller of this study is designed to control the auxiliary load consuming power based on the SoC and speed. The solution is based on the brute force function, the proposed optimization technique to find the best solution from a wide range of measures in which the decision is based on two or more conflicted measures. Brute force is a searching algorithm for all possible solutions in the solution space.

Overall, the study provides valuable insights into the design and optimization of EMS for battery electric vehicles, specifically improving their range. Using fuzzy logic controllers and optimization by brute force is an effective approach for achieving this goal, with significant improvements observed in all driving cycles tested. The study highlights the importance of considering different driving cycles for testing and evaluation, as well as the potential benefits of incorporating auxiliary load systems and optimizing the power consumption of the HVAC system. These findings can inform the development and optimization of EMS for battery electric vehicles, ultimately leading to more efficient and practical electric vehicles.

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