

Dual-battery Control Strategies for Agricultural EV's

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Abstract

Agricultural electric cars present an excellent opportunity for reducing greenhouse gas emissions, increasing energy efficiency and fostering sustainability. Weights that can be expected by Agricultural Electric Vehicles (AEV) depend on various factors including geography, soil type, implement penetration depth and agriculture activities. It is difficult to optimize the use of battery energy. There is unbalanced usage of battery, poor mileage and less operational flexibility in conventional single battery structure due to energy demands. With respect to this problem, this research paper proposes the modeling and analysis of AEV DBEMS. Heuristic rule based control, FLC and RL energy management systems are designed and simulated in MATLAB/Simulink under realistic agricultural load. The system takes into consideration energy allocation, state of charge balancing, switching frequency and energy efficiency. Comparative simulation results show that there is significant state of charge imbalance with little switching in the heuristic control system. The fuzzy logic controller helps to balance the SoC; however, it raises the switching frequency, while the RL controller offers the best performance due to its ability to balance the SoC, reduce unnecessary switching operations and enhance energy efficiency. This technique helps to extend battery life and improve battery adaptability. The results obtained provide evidence for the application of intelligent dual battery energy management systems in future agricultural electric vehicles and precision agriculture adaptive energy management systems.

Keywords: Agricultural Electric Vehicle, Battery State of Charge, Dual-battery Energy Management System, Fuzzy Logic Controller, Heuristic Control, Reinforcement Learning.

Introduction

Electrification, automation and digital agriculture have led to a move toward sustainability and smart farming in the agricultural business. Compared to passenger electric cars, AEVs operate under different loads (1). Due to soil type, slope, crop density, tillage depth and AEV equipment, power requirements vary. This stresses the batteries and causes erratic discharge, rapid deterioration and unreliability. Thus, an intelligent power distribution system that effectively manages power needs is a crucial research problem (2). Due to its versatility, durability and longer battery life, twin battery systems are becoming increasingly common. In DBEMS, two battery packs may coordinate to distribute power dynamically based on vehicle operating parameters and battery status (3). Proper battery pack coordination reduces stress, balances state-of-charge and extends battery life. Dual battery systems' efficiency depends on energy management. Classical rule-based or heuristic controllers are computationally efficient and simple but largely reliant on

predefined operating rules. Fuzzy logic controllers use expert knowledge and nonlinear system behavior to increase controller flexibility, although membership functions are crucial (4). AI advances suggest using Reinforcement Learning (RL) for electric vehicle energy management. RL may learn optimum policies via repeated interactions with its environment without formal modeling of system dynamics, unlike classical control systems. RL is intriguing for agriculture because real-world conditions are unpredictable and cannot be accurately modeled (5). Few studies have examined sophisticated dual-battery management in agricultural electric cars working in actual farming situations, despite substantial research on energy management of passenger electric vehicles (6). Few agricultural studies compare fuzzy logic and reinforcement learning controllers under comparable load settings. MATLAB Simulink is used to develop a dual-battery energy management system using heuristic, fuzzy and reinforcement learning controllers.

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The contributions of this study can be summed up as:

- a) Developing a full Dual-Battery Energy Management System model for agricultural EVs in different field conditions.
- b) Using three methods of energy management: heuristic control, fuzzy logic and reinforcement learning.
- c) Performance evaluation of controllers based on energy management parameters like balancing SoC, switching frequency, energy delivery and battery usage.
- d) The reinforcement learning approach has an edge over others in battery management in dynamic agricultural conditions.
- e) Suggestions for the design of an intelligent battery management system for autonomous agricultural vehicles.

Depending on regeneration conditions and the original machine's economy degraded owing to overcharging, the hybrid turbocharger's energy saving rate may vary between 1% and 5% throughout driving cycles (7). We use RL and velocity predictions to manage a parallel hybrid electric vehicle's (HEV) energy consumption in this work (8). Fog/edge computing and the Internet of Things (IoT) are examined in this paper, along with IoT-related problems (9). The simulation shows that the energy management method increases FCHV fuel economy compared to a reference condition when the driving cycle stays constant and the hybrid power split ratio is optimized (10). With the quantity of information supplied, readers will be ready to improve FLC EMS in hybrid electric and electric automobiles with hybrid energy storage systems (11). DRB-TD3 improves sampling efficiency by improving DRL's TD3 algorithm and leveraging dual replay buffers (12). Fuel consumption and SOC prediction methods are investigated and the forecast horizon size's influence on energy management is compared (13). Historical driving data transition probability is computed using Markov chain and Monte Carlo stochastic prediction (14). EMSs are needed to maximize energy efficiency (15). Making HEV EMSs that improve fuel economy and vehicle performance is hard (16). AI promotes the global energy industry's digital transformation, but adoption barriers hinder cross-border energy supply resilience (17). Agent learning stability is greater in continuous action space than discrete

action space (18). This work proposes series hybrid electric tracked vehicle energy management methods based on reinforcement and deep reinforcement learning (19). New RL algorithm improves power distribution and sparse reward in training (20). DRL is being utilized to build energy management strategies (EMSs) for hybrid electric vehicles (HEVs) (21). This study presents an experience-augmentation-based RL method that optimizes energy allocation and accelerates training (22). Deep reinforcement learning-based EMS may work for hybrid electric automobiles (23). To prevent grid-connected hybrid PV-wind power systems from voltage fluctuations (24). Process battery and SMES-based DVRs adjust for voltage sag (25). Model developed in MATLAB Simulink. We evaluated constant and changing load and irradiance. Results reveal the control method balances PCC voltage, frequency and power (26).

Research Gap

- a) The dynamic operating conditions of agricultural electric vehicles are not suitable for passenger electric car Energy Management Systems (EMS).
- b) Rule-based and heuristic controllers are too rigid for agricultural load variations, wasting batteries and causing SoC imbalance.
- c) Fuzzy logic controllers improve battery balance but need rule tweaking and may increase battery switching frequency.
- d) Most RL-based research focuses on single or hybrid EVs, not farm DBEMS algorithms.
- e) Heuristic, Fuzzy Logic and RL controllers should be compared utilizing agricultural load profiles and performance criteria.
- f) Thus, adaptive energy distribution, SoC balancing, lower switching frequency and improved battery life in agriculture need an intelligent DBEMS.

Research Objectives

The objectives of this study are:

- a) To design and develop an intelligent Dual-Battery Energy Management System (DBEMS) for agricultural electric vehicles.
- b) To implement and compare three control techniques namely Heuristic Control, Fuzzy Logic Control (FLC) and Reinforcement Learning (RL) for battery selection and energy allocation.

- c) To investigate the performance of the controllers using certain performance indicators like State-of-Charge balancing, number of switching, minimum SoC and energy management efficiency.
- d) To find out which of the energy management techniques performs best.

Methodology

System Architecture

The proposed DBEMS aims to intelligently allocate the power requirement of AEV among two parallel lithium-ion batteries. Contrary to traditional energy management system designs where a single battery is used to supply the entire power requirement, the novel architecture enables

flexible power allocation dependent on battery SoC, load demand and the controller's decision (6, 7). The objective is to improve battery utilization, reduce battery degradation, minimize unnecessary switching and ensure continuous energy delivery under highly dynamic agricultural operating conditions. Figure 1 illustrates the architectural design of the suggested DBEMS design for AEVs. The design is made up of two battery packs, a supervisory energy management control unit and the agricultural load. The control unit ensures continuous monitoring of SoC of the battery, load requirements and environmental conditions to determine the most suitable battery and power distribution.

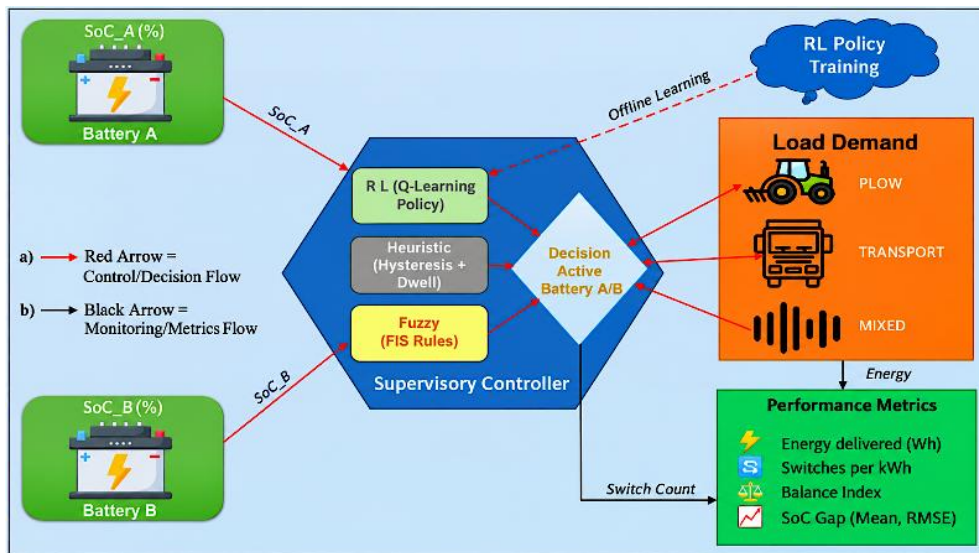


Figure 1: System Model Architecture for the Proposed DBEMS

Note: SoC = State of Charge, RL = Reinforcement Learning, FIS = Fuzzy Inference System, Wh = Watt-hour, RMSE = Root Mean Square Error.

Battery Mathematical Model

Each battery is represented using a first-order equivalent circuit model consisting of an ideal voltage source and an internal resistance.

The terminal voltage is given by Equation [1]:

$$V_t = V_{oc} - IR_{int} \quad [1]$$

The battery SoC is updated using Coulomb counting, as given in Equation [2]:

$$SOC(t) = SOC_0 - \frac{1}{C_n} \int_0^t I(T) dT \quad [2]$$

Where, C_n = Battery Capacity and SOC_0 = initial SoC.

Unlike passenger EVs, agricultural electric vehicles experience continuously varying load conditions due to soil hardness, implement depth, field inclination, payload and wheel slip, as defined in Equations [3-5].

Therefore,

$$P_{load} = P_{traction} + P_{implement} + P_{auxiliary} \quad [3]$$

$$P_{traction} = F_t \vartheta \quad [4]$$

$$F_t = F_r + F_g + F_d \quad [5]$$

The agricultural load profile is generated in MATLAB using time-varying power demand varying between 2–12 kW.

The system consists of two battery packs (Battery A and Battery B) each represented with a nominal capacity of 2 kWh and an initial state-of-charge (SoC) of 100%. Only one of the packs is operative at one time, with the decision being made by the supervisory controller. Three load demand profiles are considered to model realistic conditions:

- Plough Profile**–High and continuous power demands.
- Transport Profile** – Intermittent bursts of load.
- Mixed Profile** – A combination of the plough and transport patterns.

Energy Management Controllers

The proposed Dual-Battery Energy Management System (DBEMS) employs three different supervisory control strategies to determine the optimal battery pack for supplying power to the agricultural electric vehicle under dynamically

varying operating conditions. The controllers continuously monitor the battery State-of-Charge (SoC), instantaneous load demand, battery operating limits and switching history before selecting the most appropriate battery. The supervisory controller becomes the decision-making entity for the DBEMS system proposed in this study (9, 10). In each sample period, the supervisory controller gathers the information from Battery A, Battery B and the load of the vehicle. Depending upon the chosen control method (Heuristic, Fuzzy Logic and Reinforcement Learning), it decides the battery source that must be chosen to power the needed load. Figure 2 illustrates the supervisory energy management system of the Dual-Battery Energy Management System (DBEMS). The system receives input in real time from the agriculture electric vehicle such as the State of Charge (SoC) of batteries, load demands and conditions. After receiving the inputs, the supervisory controller implements the chosen control strategy of Heuristic control, fuzzy logic control, or reinforcement learning.

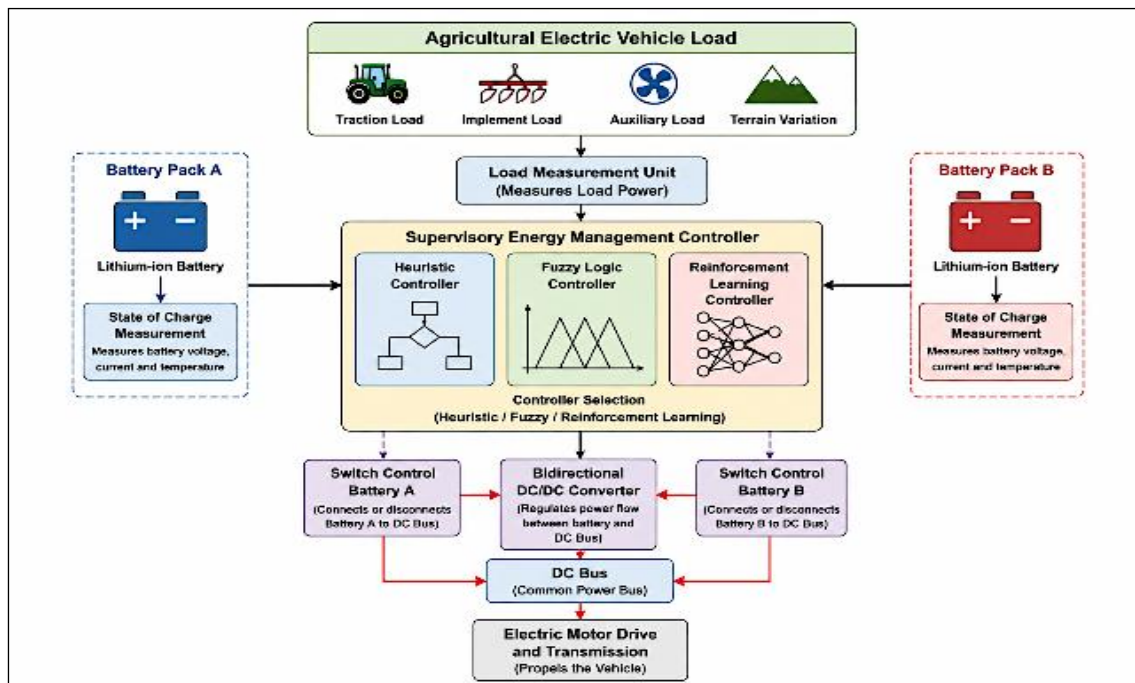


Figure 2: Overall Supervisory Energy Management Framework

Note: SoC = State of Charge, RL = Reinforcement Learning, FIS = Fuzzy Inference System, AEV = Agricultural Electric Vehicle.

Heuristic Controller

Heuristic controller forms the reference scheme for power management. It uses predetermined

criteria for decision-making depending on the battery State of Charge (SoC) and uses hysteresis and minimum dwell time to ensure that no

frequent swapping of batteries occurs. This controller constantly monitors the state of charge in Batteries A and B. The battery that has more energy is chosen, while keeping in mind the minimum acceptable SoC to prevent deep discharging [12].

The decision rules can be listed as below in Equation [6]:

Mathematically,

$$u(k) = \begin{cases} A, & SOC_A > SOC_B + \delta \\ B, & SOC_B > SOC_A + \delta \\ A + B, & |SOC_A - SOC_B| < \delta \end{cases} \quad [6]$$

Where, $u(k)$ represents the switching decision, δ denotes the hysteresis threshold.

The inclusion of hysteresis eliminates frequent oscillations between batteries under small SoC variations.

Fuzzy Logic Controller

To overcome the limitations of fixed rule-based control, a Mamdani-type Fuzzy Logic Controller (FLC) is implemented in the proposed Dual-Battery Energy Management System (DBEMS). The FLC effectively manages the nonlinear and uncertain operating conditions encountered in agricultural electric vehicles by emulating human decision-making through a set of linguistic IF-THEN rules [14, 15]. Compared with heuristic

- If $SOC_A > SOC_B + \Delta SOC$, Battery A supplies the load.
- If $SOC_B > SOC_A + \Delta SOC$, Battery B supplies the load.
- If both batteries possess nearly equal SoC values, the load is shared equally.
- Battery switching is prohibited until the minimum dwell time expires.

control, the fuzzy controller provides smoother battery switching decisions and improved State-of-Charge (SoC) balancing under rapidly varying load conditions.

The fuzzy controller receives the State-of-Charge (SoC) of Battery A (SoC_A), State-of-Charge of Battery B (SoC_B) and the instantaneous load power (P_{load}) as input variables. Based on these inputs, the controller determines the battery power-sharing factor (D_A), where the duty factor of Battery B is calculated as given in Equation [7]:

$$D_B = 1 - D_A \quad [7]$$

Where, D_A = Duty factor of Battery A and D_B = Duty factor of Battery B

The duty factor varies between 0 and 1, representing the proportion of power supplied by Battery A.

Typical fuzzy rules are listed below:

- Rule 1:** IF SoC_A is High AND SoC_B is Low AND P_{load} is High, THEN D_A is High.
- Rule 2:** IF SoC_A is Low AND SoC_B is High AND P_{load} is Medium, THEN D_A is Low.
- Rule 3:** IF SoC_A is Medium AND SoC_B is Medium AND P_{load} is Low, THEN D_A is Medium.

The complete rule base enables smooth transition between battery packs while avoiding abrupt

switching under fluctuating agricultural load conditions. Figure 3 illustrates the architecture of the Fuzzy Logic Controller (FLC), which will be employed in the Dual-Battery Energy Management System (DBEMS) for battery management purposes. The FLC takes battery SoC and the load demands as the input variables and then applies a set of pre-defined linguistic rules to determine which batteries to use and how to distribute the power among them.

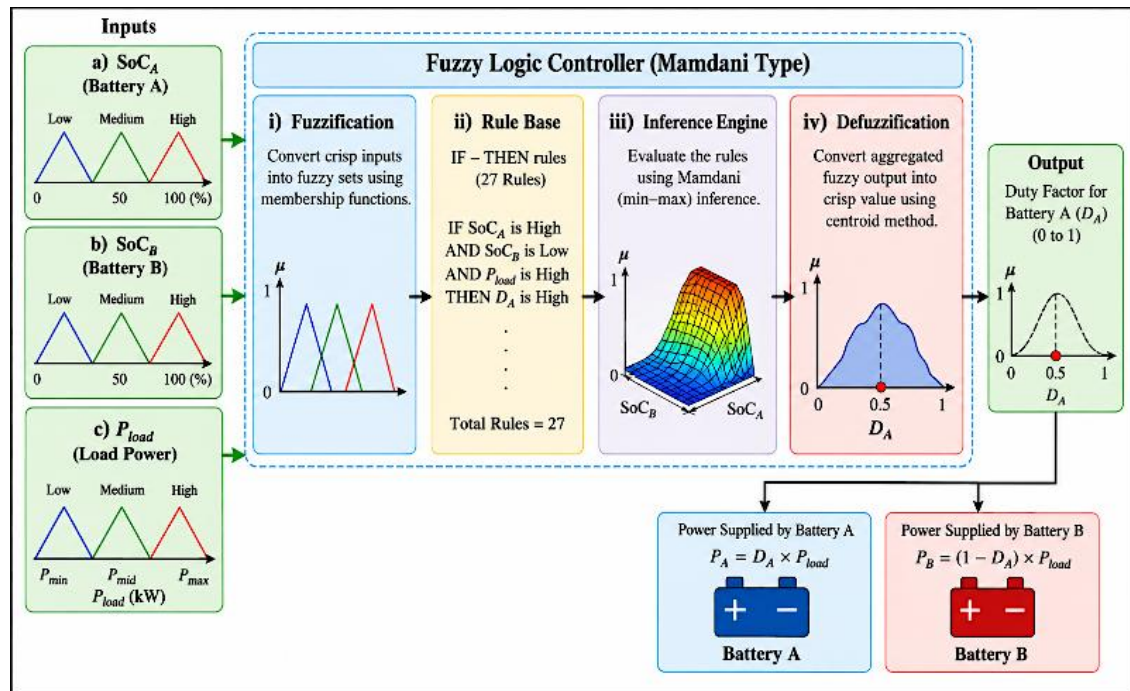


Figure 3: Fuzzy logic Controller for Battery Management

Note: SoC = State of Charge, P_{load} = Load Power, D_A = Duty Factor of Battery A, P_A = Power supplied by Battery A, P_B = Power supplied by Battery B.

Reinforcement Learning Controller

To have a more adaptive and intelligent battery energy management for dynamic operating conditions in agriculture, a Reinforcement Learning (RL) based controller is designed for the Dual Battery Energy Management System (DBEMS) proposed in this research. Unlike heuristic and fuzzy logic-based controllers, the RL-based controller can learn from the operating environment to come up with an optimal policy to use the batteries as time passes. This allows the controller to automatically adapt itself to changes in loads, battery condition and operating scenarios without having any mathematical modeling of the problem and predefined control policies (18, 19). For this purpose, Tabular Q-learning, a model-free reinforcement learning technique has been used due to its simplicity and efficiency in computation along with its ability to be applied to discrete state-

space action space decision-making problems. In this case, the RL agent interacts with the simulated agricultural vehicle model and gets rewarded according to the performance of battery usage, State-of-Charge (SoC) balance, frequency of switching and delivery of energy. The goal of the learning process is to get a maximum total long-term reward by picking the right battery under different conditions. Figure 4 demonstrates the process workflow of the Reinforcement Learning (RL) controller employed in the developed Dual-Battery Energy Management System (DBEMS). The RL controller keeps monitoring the SoC of the batteries, load requirement and system status to decide regarding the best battery selection. As the RL controller receives reward feedback from energy efficiency, SoC balance and switching operations, it develops a control policy accordingly.

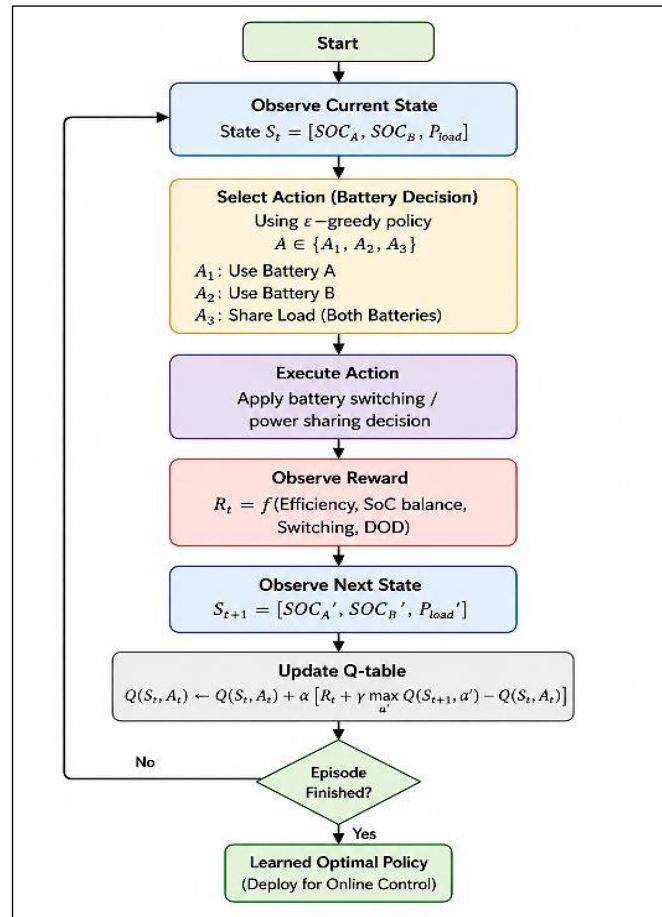


Figure 4: Flowchart of Reinforcement Learning Controller

Note: SoC = State of Charge, P_{load} = Load Power Demand, R_t = Reinforcement Learning, DOD = Depth of Discharge, S_t = Current State, S_{t+1} = Next State, A_1 = Use Battery A, A_2 = Use Battery B, A_3 = Share Load Between Batteries, R_t = Reward at Time Step t , $Q(S_t, A_t)$ = State-Action Value Function, α = Learning Rate, γ = Discount Factor.

Performance Metrics

To ensure a fair comparison, all controllers are evaluated using standard performance metrics:

- Energy Delivered (Wh)** – Total useful energy supplied to the load.
- Switches per kWh** – Normalized switching frequency.
- Balance Index (0–1)** – Reflects the degree to which SoC is balanced between the two packs.
- SoC Gap (Mean and RMSE)** – Computes mean and dynamic gaps between the two SoCs.

These readings cumulatively measure efficiency, stability and battery health so that overall controller performance can be evaluated. Table 1

contains a comparison between the three controllers used in the Dual-Battery Energy Management System (DBEMS): Heuristic Control, Fuzzy Logic Control (FLC) and Reinforcement Learning (RL). The comparison is made based on various parameters such as State of Charge balancing, switching, adaptability, computational complexity and energy management efficiency. This shows the advantages and disadvantages of each controller. It is clear from this table that the controller using reinforcement learning is more efficient than others in terms of providing balanced utilization of batteries, minimum switching and energy efficiency.

Table 1: Comparison of Controllers for the Proposed Dual-battery Energy Management System

Feature	Heuristic Controller	Fuzzy Logic Controller	Reinforcement Learning Controller (Proposed)
Control Strategy	Rule-based decision using predefined SoC thresholds	Knowledge-based fuzzy inference using linguistic rules	Learning-based adaptive decision using Q-learning
Input Variables	State of Charge, threshold values	SoC(A), SoC(B), Load Power	SoC(A), SoC(B), Load Power (State Space)

Decision Method	Fixed IF–THEN rules	Fuzzy rule base with Mamdani inference	Optimal policy learned through interaction with the environment
Adaptability	Low	Medium	High
Requirement of Mathematical Model	No	No	No (Model-Free Learning)
Learning Capability	No	No	Yes
Handling of Nonlinearity	Poor	Good	Excellent
Handling of Dynamic Load Variations	Limited	Good	Excellent
Battery SoC Balancing	Fair	Good	Excellent
Battery Switching Frequency	Low	High	Moderate (Optimized)
Energy Utilization Efficiency	Moderate	Good	Excellent
Battery Life Improvement	Moderate	Good	Excellent
Computational Complexity	Very Low	Medium	High (Training), Low (Testing)
Training Requirement	Not Required	Not Required	Offline Training Required
Real-Time Implementation	Easy	Easy	Suitable after Training
Scalability	Limited	Moderate	High
Robustness to Uncertainty	Low	Moderate	High
Suitability for Agricultural Electric Vehicles	Moderate	Good	Excellent
Major Limitation	Fixed rules cannot adapt to changing operating conditions	Performance depends on membership functions and rule design	Requires sufficient training episodes and reward function tuning
Overall Performance	Baseline Controller	Improved Intelligent Controller	Best Overall Performance

Note: SoC = State of Charge, SoC_A = State of Charge of Battery A, SoC_B = State of Charge of Battery B, RL = Reinforcement Learning, Q-learning = Quality Learning Algorithm, AEV: Agricultural Electric Vehicle.

The Dual Battery Energy Management System (DBEMS) will involve the employment of two batteries linked through a supervisory controller responsible for controlling the distribution of energy according to the demand for energy and the state-of-charge of the batteries. The main aim of the system will be to maximize the efficiency of energy usage in order to achieve maximum battery utilization.

The controller is responsible for monitoring the state-of-charge of the batteries, the demands and the switching process. Based on these parameters, three controllers will be implemented namely; Heuristic Controller, Fuzzy Logic Controller (FLC) and the Reinforcement Learning (RL) controllers. The heuristic controller utilizes pre-established threshold rules while the FLC utilizes decision rules in language form and the RL learns optimal switching rules through interaction with the environment.

The control scheme is designed to accomplish the following four goals:

- Maintain balanced state of charge between the battery banks.
- Avoid unnecessary switching of batteries.
- Increase energy usage efficiency.
- Increase battery life for different agricultural loads.

Experimental Design for Performance Evaluation

In order to make sure that the Dual Battery Energy Management System (DBEMS) is reproducible and systematically evaluated, a well-structured experiment design was designed using MATLAB/Simulink. This experiment examines the performances of three types of controllers for supervisory control, which are Heuristic Control, Fuzzy Logic Control (FLC) and Reinforcement Learning (RL). The three controllers are being tested using same conditions for agricultural

applications. Initially, two batteries will be set with same specifications and State-of-Charge (SoC). After setting up the two batteries, the agricultural load demand is applied to the system. Each controller decides which battery is used for the power allocation. To have a basis for an objective evaluation, all controllers are evaluated based on the same load profile, duration of simulation, battery properties and constraints. There are four main factors that will be used to evaluate the performance of the controllers, which include minimum battery SoC, SoC balancing index, frequency of switching and overall efficiency in terms of energy consumption. This helps in coming up with the best approach for managing the batteries.

Results and Discussion

Dual-Battery Energy Management System (DBEMS) that is suggested in this paper has been tested with respect to the mixed agricultural load profile by applying three different supervisory control techniques namely Heuristic, Fuzzy Logic and Reinforcement Learning (RL). All these

controllers have been simulated in MATLAB/Simulink software under the same operational conditions for proper performance evaluation of the controllers.

Load Tracking and Battery Switching Performance

Figure 5 shows the load demand pattern, battery selection process and respective variations in State of Charge (SoC) for Heuristic Controller. The Heuristic Controller operates through the switching of batteries A and B following the preset threshold criteria. While the switching rate is very low, the variations in the SoC reveal some disparity between the two batteries. In the heuristic control system, there are preset values for SoC limits and dwell times to ensure that unnecessary switching does not take place. Therefore, the total number of switching operations in the entire operation cycle is reduced to only three. Even though this control system is optimal in terms of switching losses and ease of implementation, battery A provides more energy than battery B, which is underused.

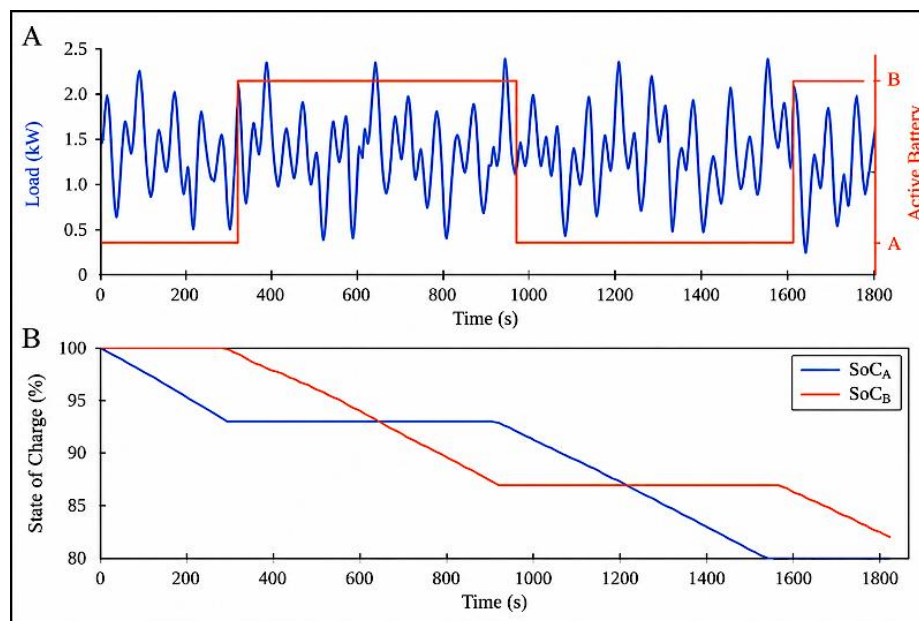


Figure 5: Load-SoC response under Heuristic Controller. (A) Load vs Time, (B) SoC vs Time

Note: SoC = State-of-Charge, SoC_A = State of Charge of Battery A, SoC_B = State of Charge of Battery B.

The controller based on fuzzy logic operates continuously by monitoring changes in the SoC of the batteries and the required load. The controller distributes the load evenly between the batteries and hence helps in balancing the SoC. However, the balancing process involves ten switching operations of the batteries that could cause

increased switching losses. Figure 6 shows the load demand characteristics, the switching pattern of the battery and the variation of the State of Charge (SoC) using the FLC. Power is allocated between Battery A and Battery B through the use of fuzzy inference logic rules depending on the SoC and load demands. As compared to the rule-based

method, FLC performs better in terms of SoC balancing and battery usage. Even if the control system operates at a relatively high frequency of

switching, the system performs well in energy management.

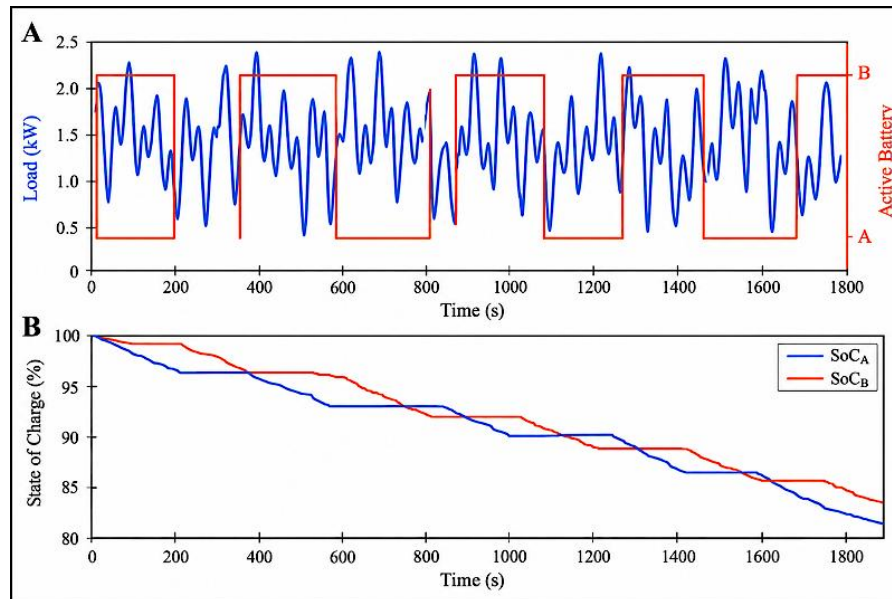


Figure 6: Load-SoC response under Fuzzy Controller. (A) Load vs Time, (B) SoC vs Time

Note: SoC = State-of-Charge, SoC_A = State of Charge of Battery A, SoC_B = State of Charge of Battery B.

The reinforcement learning controller adapts to intelligent switching since the optimal switching of the battery is learned during training. Unlike the heuristic controller, the RL does not over-discharge the batteries; however, it makes fewer switching actions than the reactive strategy. The two batteries have similar discharge profiles for the entire period of operation, implying equal energy use. Figure 7 shows the profile of the demand of load, choice of batteries and changes in

the SoC using the Reinforcement Learning (RL) controller. In the RL controller, the decision for the right battery is taken according to the system state and the reward policy learned by the controller. It has been seen that through this method, there is proper balancing of the battery discharge, reduction in unnecessary switchings and effective SoC management as compared to heuristics and fuzzy logic.

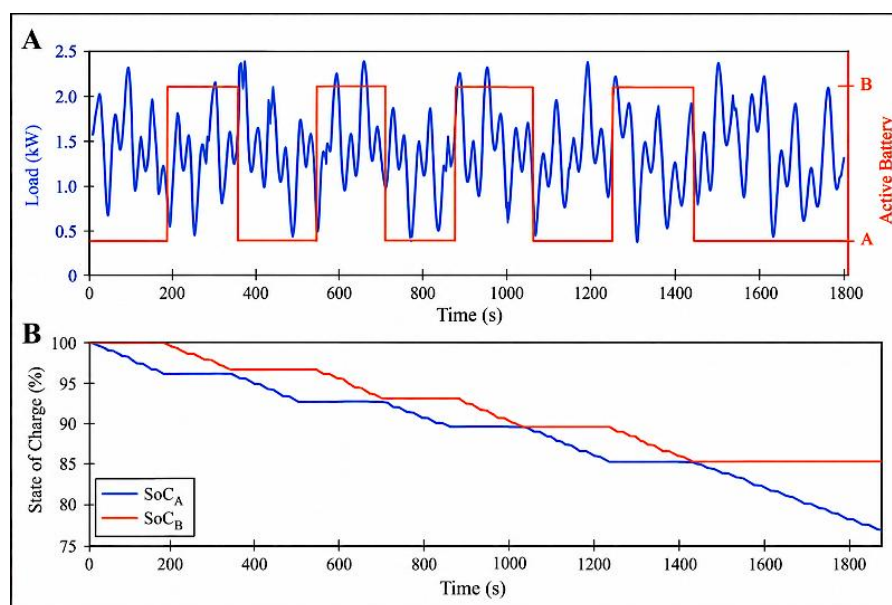


Figure 7: Load-SoC response under R-L Controller. (A) Load vs Time, (B) SoC vs Time

Note: SoC = State-of-Charge, SoC_A = State of Charge of Battery A, SoC_B = State of Charge of Battery B.

Table 2: Comparative Performance of the Proposed Controllers

Performance Metric	Heuristic	Fuzzy Logic	Reinforcement Learning
Energy Delivered by Battery A (Wh)	395.2	382.5	358.6
Energy Delivered by Battery B (Wh)	335.3	348.0	371.9
Total Energy Delivered (Wh)	730.5	730.5	730.5
Number of Switching Events	3	10	10
Switching per kWh	4.11	13.70	13.70
Balance Index	0.965	0.985	0.983
Minimum SoC (%)	80.2	80.9	82.1

Note: SoC = State of Charge, Wh = Watt-hour, kWh = Kilowatt-hour, RL = Reinforcement Learning, BI = Balance Index.

Table 2 presents the comparative performance analysis of the Heuristic, Fuzzy Logic and Reinforcement Learning controllers in terms of the proposed Dual Battery Energy Management System (DBEMS). The comparison takes into consideration the energy distribution to the batteries, the switching frequency, the balance index and the minimum State-of-Charge (SoC). From the comparison, it can be seen that each controller has its own unique features in terms of operation in the suggested Dual-Battery Energy Management System (DBEMS). While all controllers yielded an equal amount of total energy produced of about 730.5 Wh, there were notable differences in the usage of batteries, switching operations and SoC balancing capabilities. The heuristic controller has the least number of switches needed, only three throughout the simulation period. It is beneficial because it leads to decreased switching and processing costs; but it causes the most unequal distribution of energy usage between Battery A and Battery B and thus yields the lowest Balance Index value [0.965]. Recent researches on rule-based battery management systems showed similar shortcomings of this approach due to inability of fixed threshold control strategy to adapt to changing loads and battery state, leading to increased battery wear and inefficiency of the system [4, 12].

The fuzzy logic controller performed best in terms of SoC balancing with a Balance Index of 0.985. This finding validates the effectiveness of using fuzzy inference systems for dealing with nonlinear relations between battery conditions and load demands through fuzzy reasoning rules. Energy management schemes based on the fuzzy approach are effective in battery balancing and energy sharing in electric vehicles. Nevertheless, the higher switching rate of the fuzzy controller will add to the stress and switching losses of the

converters, a problem that has been recognized previously [14-16].

In comparison with other approaches, the RL algorithm demonstrated the most balanced behavior of the system under consideration. While its Balance Index [0.983] is slightly smaller compared to the balance index of the fuzzy controller, the minimal SoC level (82.1%) remains at its maximum value, which means that this system provides better resistance to deep battery discharge. Also, it should be noted that energy consumption from Battery A (358.6 Wh) and Battery B (371.9 Wh) is even, which indicates the ability of RL-based algorithms for adaptive decision making. This statement is confirmed by the results of recent studies that demonstrated that RL-based energy management systems could learn optimal battery utilization strategies without any mathematical model [18, 20, 21].

Moreover, the results suggest that RL is an excellent compromise in the aspect of balancing battery power, energy use and reliability of operations. In recent studies, researchers who studied intelligent energy management of electric cars and smart energy systems observed that RL algorithms performed better than rule-based and fuzzy algorithms while working under highly fluctuating load profile as a result of their capability of learning and adaptation from environmental interaction [22, 23]. This means that the proposed RL-based DBEMS can be a great solution for future agricultural electric cars due to the fact that the load profile changes frequently.

Conclusion

This research introduced a Dual-Battery Energy Management System (DBEMS) for agricultural electric vehicles and compared the efficiency of three kinds of supervisory control algorithms; heuristics, fuzzy logic and reinforcement learning (RL). An advanced framework using MATLAB/

Simulink was established for analyzing the performance of battery utilization, switch operations, energy distribution and SoC balance of batteries in realistic load condition of agriculture. It is shown in this comparison that each controller performs differently from others. The heuristics controller had the least switching rate but performed poorly in battery balancing. The fuzzy logic controller optimized energy sharing among the two batteries and gave the best Balance Index (0.985) by adopting intelligent rule-based decision-making approach. The RL controller gave the most balanced performance by having adaptive selection of batteries with keeping the maximum minimum SoC (82.1%).

The key contributions of this paper include the development and analysis of the intelligent RL-based supervisory energy management scheme that allows for increasing the usage of batteries, ensuring the maintenance of their condition and reliable functioning of agricultural electric vehicles. Thus, the proposed solution provides an effective way towards intelligent batteries management in future agricultural electrification.

Limitations

- a) The current study uses only simulated data.
- b) The effects of battery degradation, thermal behavior and environment have not been considered yet.
- c) Also, the load profile of the agriculture was calculated on the basis of the typical load case.

Practical Implications

- a) The developed DBEMS may be used in electric tractors, autonomous agricultural equipment and precise farming systems to increase energy efficiency, decrease maintenance costs and improve reliability of the whole system.
- b) Due to the adaptive character of the decision making of the RL-based system, the proposed approach is applicable for highly dynamic agricultural environments.

Future work

- a) Coupling comprehensive battery aging and thermal models into the DBEMS.
- b) Expanding the framework of the reinforcement learning to Deep Reinforcement Learning such as DQN, DDPG and PPO.
- c) Verification of the proposed controller using HIL and real-time embedded systems.
- d) Demonstrating the performance of the controller under practical agricultural

operation conditions through electric tractors and autonomous agricultural machines.

Abbreviations

AEV: Agricultural Electric Vehicles, DBEMS: Dual-Battery Energy Management System, EV: Electric Vehicles, FLC: Fuzzy Logic Controller, HC: Heuristic Controller, RL: Reinforcement Learning, SoC: State of Charge.

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Author Contributions

All authors contribute equally to the research, design the study, analyzed data and approved the final manuscript.

Conflict of Interest

The authors declare that they have no conflict of interest.

Data Availability

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

Declaration of Artificial Intelligence (AI) Assistance

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Ethics Approval

This study does not involve human participants, animals, or any biological materials. Therefore, ethical approval was not required for conducting this research work.

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