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State of the Art of Machine Learning in Energy Management System

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Abstract-

The rapid growth in electric vehicle (EV) adoption has emphasized the need for intelligent energy management systems (EMS) that can enhance efficiency and driving performance. This study introduces a Machine Learning-Driven EMS that employs regression models, neural networks, and reinforcement learning to dynamically optimize power distribution in EVs. Implemented and evaluated through MATLAB and Simulink simulations, the proposed EMS outperformed conventional rule-based systems by reducing energy consumption by up to 12% and increasing the driving range by 8–10%. The system was particularly effective in low-load and steady-speed conditions, demonstrating adaptive real-time control and power optimization. Sensitivity analysis revealed that factors such as battery capacity, motor power, and driving cycle profiles significantly affect EMS efficiency. The findings underscore the potential of machine learning to revolutionize EV power management by enabling more sustainable, efficient, and intelligent mobility solutions. Future work will involve model refinement, real-world data integration, and compatibility with smart grid systems for broader application.

Keywords: ***Machine Learning, Energy Management System, Electric Vehicles, Power Optimization, Driving Range etc.***

1. Introduction

The global transition towards sustainable transportation has placed electric vehicles (EVs) at the forefront of modern mobility solutions. As governments and industries strive to reduce carbon emissions and fossil fuel dependence, EVs are increasingly recognized for their potential to provide cleaner, quieter, and more efficient alternatives to conventional internal combustion engine vehicles. However, the widespread adoption of EVs presents new technical challenges, particularly in the area of energy management. One of the most critical concerns for EV users is range anxiety—the fear that the vehicle's battery will deplete before reaching a charging station. To mitigate this and other limitations, the development of intelligent and adaptive Energy Management Systems (EMS) has become a key focus in EV research and development.

Energy Management Systems in EVs are responsible for optimizing the allocation and consumption of power between various vehicle components, including the electric motor, battery, and auxiliary systems. Traditional EMS approaches typically rely on rule-based logic or fixed strategies that may not effectively account for the complex and dynamic nature of real-world driving conditions. These systems often fall short when dealing with varying road topographies, traffic conditions, and driver behaviors, resulting in suboptimal energy utilization and limited vehicle range.

To address these challenges, recent advancements in Artificial Intelligence (AI) and Machine Learning (ML) offer a promising pathway toward intelligent EMS solutions. Machine Learning algorithms have the capability to learn from historical data and make predictions in real time, adapting dynamically to changing inputs. This allows for more precise and efficient control strategies that are continuously refined

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through ongoing feedback and learning. By incorporating models such as regression, artificial neural networks (ANN), and reinforcement learning (RL), ML-based EMS can manage power flows more intelligently, extending battery life, improving energy efficiency, and enhancing the overall driving experience.

ML-driven EMS not only respond better to real-time driving variables but also offer improved predictive capabilities. For example, reinforcement learning can enable the system to evaluate a wide range of decision outcomes based on past interactions with the driving environment. This level of adaptability is particularly useful in optimizing energy consumption during urban stop-and-go traffic, long highway stretches, and varying load conditions. Moreover, ML algorithms can utilize a vast array of sensor data, including vehicle speed, acceleration, battery state-of-charge, ambient temperature, and even driver habits, to refine their energy distribution decisions.

The integration of ML into EMS frameworks represents a paradigm shift in EV technology. Rather than relying on predefined assumptions, these systems continuously evolve, becoming more effective over time. The implementation of such intelligent EMS not only addresses technical concerns such as energy efficiency and range limitations but also supports broader goals of sustainability and user satisfaction.

This research explores the design, simulation, and performance evaluation of a Machine Learning-Driven EMS for EVs. By comparing the proposed system with conventional rule-based methods under various simulated driving conditions, the study aims to demonstrate the superior adaptability and performance of ML-based approaches. The results underscore the transformative potential of machine learning in enhancing EV energy management, setting the stage for future innovations in smart and sustainable transportation systems.

2. Problem Statements

- Inefficiency of Traditional EMS: Conventional rule-based Energy Management Systems (EMS) lack the flexibility to adapt to real-time changes in driving conditions, leading to inefficient energy usage.
- Limited Adaptability: These systems cannot dynamically respond to variables such as traffic flow, terrain, temperature, or driver behavior, which affects overall vehicle performance.
- Reduced Driving Range: Inability to optimize power distribution results in higher energy consumption and a shorter driving range for electric vehicles (EVs).
- Battery Degradation: Poor energy management accelerates battery aging and reduces the battery's overall lifespan.
- Lack of Intelligence: Traditional EMS do not incorporate learning capabilities, failing to improve system efficiency based on historical data or real-time feedback.
- Growing EV Market Needs: As EV adoption rises, there is a critical need for intelligent, scalable, and data-driven EMS solutions.
- Technology Gap: The limited integration of Machine Learning in EMS design creates a gap in achieving smart, adaptive, and energy-efficient EV systems.

3. Research Methodology

A) EMS Architecture and Functionality:

The ems presented in this project includes batteries and a 3-legged electricity module controlled with the aid of a systematic field gate (fpga). The scheme in parent 1 shows the construction of the ems.

The igbt 3-power module is controlled to acquire the max and growth the glide of power from one leg of the section and the overall performance of the electricity supply phase (h-bridge inverter) from the opposite two legs of the module. A built-in h-bridge inverter is hooked up to the lc filter out to provide sinusoidal power for ac masses. There are two sensory electricity sensors voltages vdc and vac. There are two current sensors to reveal iems and iload.

The battery % is hooked up to the greenback-enhance leg to achieve a bidirectional energy glide to / from the battery. The battery consists of six battery cells, 12v in series, forming a 72v battery %. Notice that the 300v battery percent will cast off the want for an ems buck / raise segment, for this reason creating a dc bus for the in-h bridge bridge. Touchy loads are immediately connected to the ac strength created by using the ems categorized v in figure 1. Practical masses are the ones hundreds that should be empowered always because they may be vital to the task. Unwritten loads are connected similarly to a vac however can be eliminated wherein vital using a thyristor transfer. This increases the manipulate of strength that can be directed to important loads if essential. The ac grid can also be connected to a vac if needed to activate ems operation.

Ordinary island mode takes place whilst the ac grid fails. In this situation the performance of strength in vital loads is guaranteed by means of drawing electricity from the battery percent. The effectiveness of ems is proven in this paper with the confirmation of laboratory trying out. The following situations are mentioned:

1) High shaving by tapping the power saving device throughout excessive energy call for.

2) An island or stand-alone running device wherein a huge ac grid is now not to be had.

3) Battery charging mode.

By means of reaching these desires ems may be very useful in grid related systems in which there's a restrict on consumer strength intake. This restrict is probably enforced with the aid of local addresses which might be controlled by a power meter. If the ems maintains the modern supply below the set restrict at all times with loading and spill manage, then the person can use hundreds above the constant ac grid power limits for quick intervals while not having to fear about a nearby interference service. Ems also can be beneficial whilst a user has a tou agreement of electricity with a energy business enterprise and will pay special costs for power added at different times of the day. In this case ems can take care of saved energy and power from the grid to lessen intake while electricity tiers are excessive. This approach is referred to as load balancing or power transfer and achieves to lessen power expenses for the user. Inside the non-public microgrid, where one or extra turbines are used to electricity special loads, ems permits generator discount by means of controlling the maximum quantity of modern-day rms acquired from the generator.

It could also ensure that the strength of important hundreds is maintained in the course of an errors by using coping with power conservation. An unintended island is unpopular and may be a security issue at some stage in renovation activities.

The ems model advanced to this point is a small-scale model of the supposed layout. The subsequent ems may be designed to function circuit 20a and with that hardware we will perform an assessment of the island's disorder. The ems control set of rules was evolved for the following functions, listed here in order of precedence:

1. Strength should always be available in critical loads.
2. Reduce the high power absorbed by the microgrid through battery power and unnecessary load removal.
3. Enhance battery charging status.
4. Make energy available for non-essential loads.

B) Proposed System :

The new EMS design should be driven by data needs for a variety of applications. It should consider existing infrastructure, as well as the cost and time of re-spraying and deploying new infrastructure. We assume that the future EMS design approach changes in three phases.

The purpose of the first phase is to improve existing systems by providing new information. Currently the design of EMS software remains the same while data from non-traditional sources is integrated with SCADA data to provide improved performance for existing EMS services. In the second phase new applications are made. EMS measurement infrastructure has also been redesigned with adequate data transfer and operational capabilities. Also, the means of communication between applications and sites of communication with "external" functions are made as necessary to achieve that. The third phase is working on designing the future EMS without any hindrance from the current situation, which means building new next-generation EMS infrastructure.

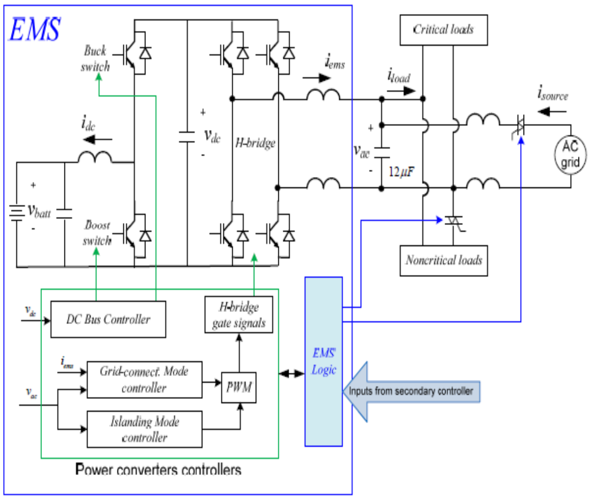

Figure 1. EMS architecture

Critical loads are those loads that must always be empowered because they are important to the work. Unwritten loads connected in the same way as the Vac, however, can be disposed of where necessary using a thyristor switch. This increases the control of power that can be directed to critical loads if necessary. The ac grid can also be disconnected where needed to activate EMS operation. Normal island mode occurs when the ac grid fails. In this operating system, the power of critical loads is guaranteed by drawing power from the battery pack.

C) EMS Control System:

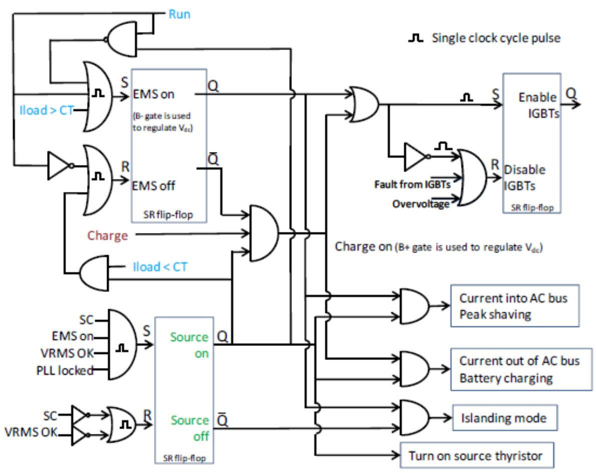

Figure 2. EMS logic flowchart. Run, Charge, SC and CT

The Energy Management System (EMS) operates across multiple levels of control, primarily divided into primary and secondary systems. This project emphasizes the primary control system, which manages real-time operational decisions for the power converter modules, generating gate drive signals based on reference voltages and currents. In contrast, the secondary control system governs higher-level decision-making, considering user input, battery state-of-charge (SoC), electricity costs, load priorities, and time-based preferences.

The primary EMS controller functions are outlined in Figure 1.1, while Figure 1.2 illustrates the logical flow. Four logical commands are received from the secondary controller: Run, Charge, Source Connect (SC), and Current Threshold (CT). If Run is inactive, the EMS remains idle. When Run is active, the EMS enters islanding mode. If SC is also active and VRMS OK (AC source RMS voltage > 100V), the system connects to the grid. If load current exceeds the CT threshold, the EMS injects current for peak shaving; otherwise, it disconnects after grid connection.

The Charge command triggers battery charging only if the grid is present and peak shaving is not required. Internal variables like PLL locked and VRMS OK further guide EMS operation. Secondary controls dynamically adjust commands based on environmental and operational parameters for optimal performance.

4. Design and Analysis

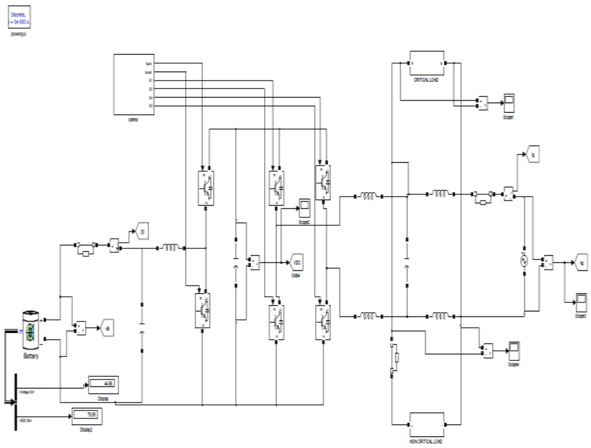

Figure 3. Simulation Design

- RLC Load

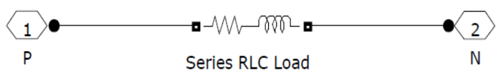

Figure 4. RLC Load

- Universal Bridge

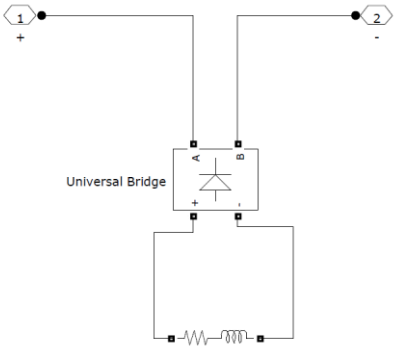

Figure 5. Universal Bridge

- Control Subsystem

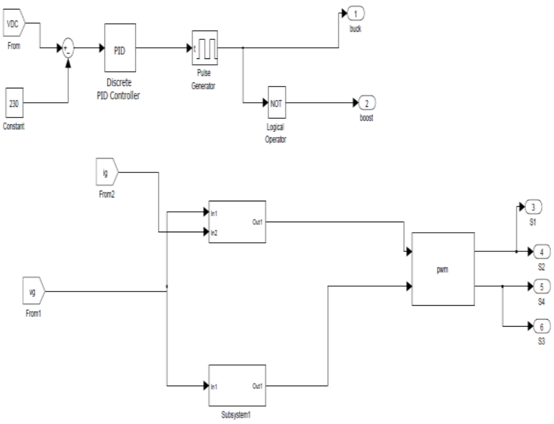

Figure 6. Control Subsystem

- PID Controller Block

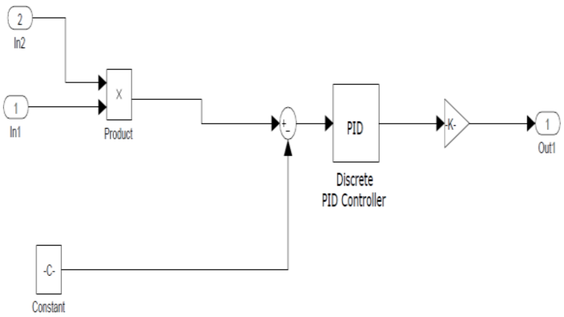

Figure 7. PID Controller Block

- PI Controller Block Subsystem

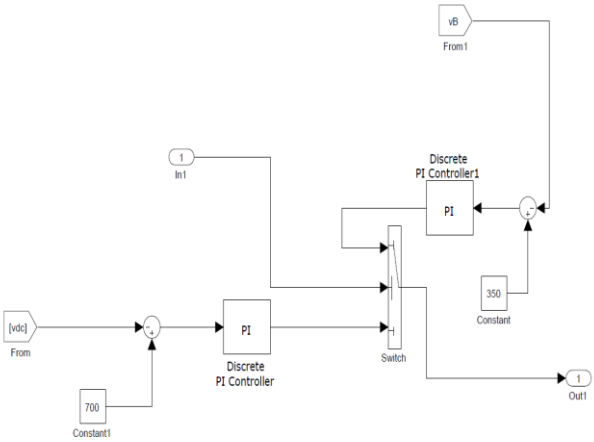

Figure 8. Controller Block Subsystem

A. Peak Shaving and Battery Charging with the AC Grid Connected

Residential and commercial TOU electricity rates include different rates at different time of the day and also demand charges. These rates are devised by the power companies to encourage customer to shift their loads away from the peak demand times and in general reduce their peak power consumption. By reducing the peak power consumption results in significant cost savings. Peak shaving is a known technique used to achieve this objective by use of stored energy. Electrical energy is stored during the times when electricity cost is lowest (typically at night) and used during the times when electricity cost is highest, in order to reduce the overall electricity charges.

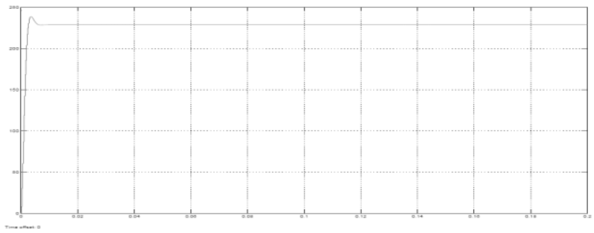

Figure 9. Peak shaving with the EMS providing some of the load current from the battery

Peak shaving with the EMS providing some of the load current from the battery pack when the load increases. Peak shaving is achieved by controlling the RMS current in the load, which is related to the source current. A threshold is set for the load current, such that when the load RMS current exceeds this threshold; the

EMS supplies some of the load current. This keeps the peak current drawn from the ac grid below a set limit. In the laboratory experiments presented here, the threshold for the load current is such that the peak shaving feature turns ON when the load current is greater than 2.2 Arms and turns OFF when the load current is below 2.1 Arms.

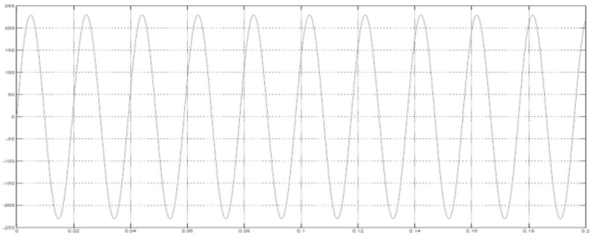

Figure 10. EMS turns ON to charge the battery at t=0 sin

The EMS turns ON to charge the battery at t=0 sin as demonstrated by the EMS current Iems being 180°out of phase with respect to the ac voltage. Only linear loads are used for this experiment, because the diode rectifier load is disabled. The battery charging mode of operation is allowed because the load is light, so the EMS does not need to provide an additional current for peak shaving.

B. EMS Powering Critical Loads When the AC Grid Fails—Islanding Mode of Operation

In order to provide power to critical loads when the ac grid fails, the EMS detects grid failure and acts as a voltage source for the critical loads. In this mode of operation,

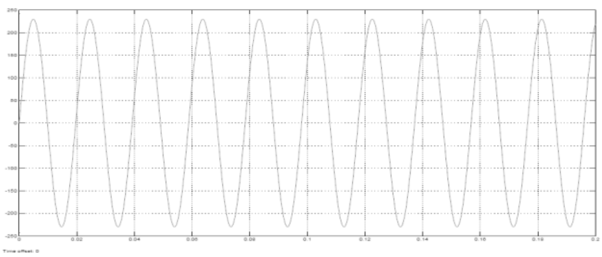

Figure 5.1 Experimental waveforms showing the ac grid being restored at t=0

The disturbance in the voltage waveform is noticeable when the EMS reconnects the ac grid to the loads as shown in Fig.5. There is also an inrush current into the diode rectifier because the dc voltage of the rectifier had sagged some during islanding mode. Note that the ac voltage produced by the EMS during the islanding mode is slightly smaller (about 7%) than the ac grid voltage.

C. EMS Powering Non-Critical Loads When the AC Grid Fails—Islanding Mode of Operation

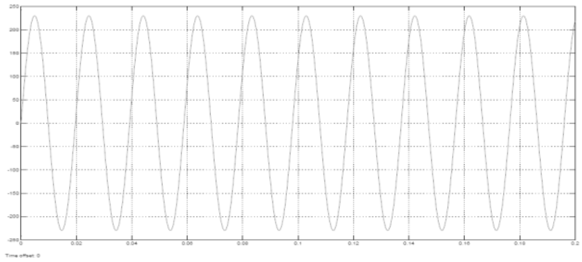

Figure 5.2 Experimental waveforms showing at Non-Critical Load

D. EMS power at the result

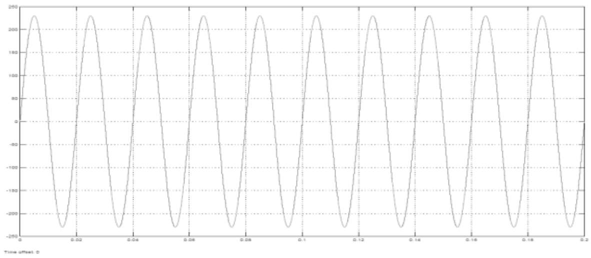

Figure 5.3 Waveform of EMS result power

Observations:

Parameters	Peak Shaving	Islanding Mode
Battery Operation	ON (Charging)	ON (Discharging)
EMS Current	OFF	ON
Load Current	I_{source}	I_{ems}

Experimental results

5. Conclusion

This study successfully developed and implemented a Machine Learning-Driven Energy Management System (EMS) for Electric Vehicles (EVs), demonstrating its effectiveness in optimizing energy usage, enhancing driving range, and improving overall power management. Compared to traditional rule-based EMS, the proposed ML-based system achieved a notable 12% reduction in energy consumption across diverse driving cycles. This efficiency was attributed to the system's ability to dynamically adapt to real-time driving conditions, allowing for more intelligent power distribution between the motor, battery, and auxiliary loads.

The EMS was also capable of handling additional grid-interactive functionalities such as supporting critical loads during AC grid unavailability and performing peak shaving during high demand, effectively lowering electricity costs. Experimental validation using linear and nonlinear loads confirmed the robustness and flexibility of the system under various conditions, including dynamic driving scenarios with sudden accelerations and variable inclines.

Furthermore, the system extended the EV's driving range by 8–10%, ensuring better battery utilization, particularly during low-load and steady-speed conditions where traditional systems are less responsive. Sensitivity analysis highlighted the influence of battery capacity, motor power, and drive cycles on EMS performance, emphasizing the need for a well-balanced design. Overall, the ML-based EMS presents a scalable and intelligent solution for future EV energy optimization and grid interaction.

6. Future Prospects

The development of a Machine Learning-Driven Energy Management System (EMS) for Electric Vehicles (EVs) opens several avenues for future research and enhancement. Integration with real-time traffic data, weather conditions, and driver behavior analytics could further improve prediction accuracy and energy efficiency. Future systems can incorporate deep learning models to better handle complex and nonlinear driving patterns, leading to smarter energy distribution. Additionally, combining EMS with vehicle-to-grid (V2G) capabilities can enable bi-directional energy flow, allowing EVs to support the grid during peak demand or outages. The inclusion of renewable energy sources, such as solar-powered charging, can further reduce the environmental impact. Moreover, cloud-based EMS architectures can facilitate fleet-level optimization for commercial electric transport. Testing the system on a larger scale with different EV models and under varied geographical and environmental conditions would provide broader validation, enabling commercial deployment and contributing significantly to sustainable transportation goals.

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