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Article Title: Optimal Design of Electric Vehicles using Deep Convolutional Neural Network

Optimal Design of Electric Vehicles using Deep Convolutional Neural Network

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ABSTRACT

This paper proposes the importance of energy storage systems (ESS) in electric vehicles (EVs) and the challenges associated with them, such as size, cost, and weight, which limit the vehicle's capabilities. It highlights how fuel cells (FCs) can work in conjunction with ESS to handle rapid power changes, contributing to performance and dependability. It proposes a solution using a Honey-Badger Algorithm (HBA) integrated with Deep CNN technology to enhance EV power efficiency. The goal is to optimize several factors in the EV charging process, including Orderly charging efficiency, Load fluctuation management, User cost satisfaction, User convenience. The HBA method reportedly outperforms other algorithms in terms of accuracy and power optimization. To manage the power flow between different energy sources, including supercapacitors, multiple control mechanisms are suggested. This approach likely aims to address the real-time dynamic nature of power demand in EVs.

Keywords: Energy management, HESS, Supercapacitors, HBA, Deep Convolutional Neural Network

1 Introduction

Hybrid Energy Storage Systems (HESS) in electric vehicles (EVs) using modern artificial intelligence (AI) techniques such as machine learning (ML) and deep learning (DL). Specifically, incorporating a DC-DC converter to enhance efficiency by minimizing power losses and stabilizing battery current fluctuations. The optimization problem involves complex models of the DC-DC converter that consider both conduction and switching losses.

By using AI techniques along with the Honey-badger algorithm (a nature-inspired optimization algorithm), the study aims to optimize and predict the control parameters for HESS, leading to better overall energy management for EVs. This combination of deep learning and machine learning models helps forecast these control parameters, which will likely result in increased efficiency, prolonged battery life, and more optimized power flow in EVs across different driving cycles.

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2 HESS for EVS's Energy Management System (EMS)

The Energy Management Scheme (EMS) of a Hybrid Energy Storage System (HESS) in Electric Vehicles (EVs) is crucial for optimizing energy distribution and improving vehicle performance. The HESS integrates two power sources: a primary energy storage system (ESS), typically a battery, and a secondary ESS, such as a supercapacitor (SCAP). The battery is responsible for handling steady loads, while the SCAP manages frequent transient loads. Both components contribute to regenerative braking, recovering mechanical energy to recharge the ESS.

The SCAP's role in the system is particularly valuable during high power demand scenarios, as it reduces the strain on the battery by absorbing and delivering energy during rapid acceleration or deceleration. This reduces battery peak current, extending its lifespan and enhancing overall efficiency. The DC/DC converter plays a key role in regulating energy flow between the SCAP and the EV's components. It converts electricity from the traction battery to power accessories and, during regenerative braking, sends electricity back to recharge the battery.

In terms of energy management, the driving cycle (representing different speed and load conditions an EV experiences) is an essential factor in evaluating the performance of the HESS. The effectiveness of the SCAP and battery system is directly influenced by the driving conditions, and the system's optimization relies on tailoring the energy flow to meet these conditions. As a result, proper EMS design allows for smoother transitions, cost savings, and improved overall performance.

Through the hybrid use of SCAPs and batteries, the energy extraction from the system becomes more efficient, reducing wear on the battery and ensuring higher performance levels in EVs. This combination leads to increased longevity of the ESS and more reliable energy management, ultimately supporting the successful implementation of EVs.

2.1 Hybrid Technique for EMS in EVS

A Hybrid Energy Storage System (HESS) approach, where the goal is to efficiently manage energy flow between different storage devices (such as a battery and a Supercapacitor (SCAP)) to meet load demands. This system seems to integrate real-time optimization using Deep CNN (Convolutional Neural Networks) for improved power distribution and reduced energy losses. The key components and strategy's are

System Division:

- One part calculates the **SCAP reference voltage**, ensuring that the supercapacitor operates within an optimal voltage range for energy storage and delivery.
- The second part optimizes **power flow** across the HESS, balancing between the battery and the SCAP to meet dynamic load demands.

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Initial Estimation:

- Estimation of motor characteristics (such as **driving conditions**, **vehicle dynamics**, and **regenerative braking**) based on real-time load dynamics and SCAP reference voltage.
- The **battery and SCAP work together**, with real-time adjustments to provide the appropriate power while taking into account the system's requirements.

Optimization Goals:

- **Minimize power losses**: The algorithm focuses on reducing energy loss during power transfers and operation.
- **Reduce battery power change**: Large fluctuations in battery power can reduce its lifespan, so the system smooths out the power output.

Deep CNN Model:

- The **Deep CNN model** is employed to predict the best operational parameters for HESS. It likely uses historical and real-time data on power demands, battery and SCAP characteristics, and load conditions to provide accurate predictions and adjustments.

Performance Enhancements:

- The method ensures **optimal battery power** usage while also managing fluctuations in current to improve overall system efficiency.
- The **SCAP voltage** and **battery current** are fine-tuned to maintain stability and prolong battery life by minimizing energy spikes and sudden drops.

This system seems designed for applications like electric vehicles, where efficient energy management between batteries and supercapacitors can enhance performance, extend battery life, and make better use of regenerative braking. The use of Deep CNN adds intelligence to the system by learning patterns in energy demand and adjusting accordingly.

2.2 Battery voltage control loop:

The **Constant Current–Constant Voltage (CCCV)** charging method is a widely used technique for charging batteries, especially lithium-ion types. Its include.

Constant Current (CC) Phase: The charging process begins with a constant current. During this phase, the charger supplies a fixed current to the battery, and the battery voltage gradually increases as it charges. The charging current remains constant until the battery voltage approaches the reference voltage (**vbat;ref**), which is the desired voltage for a fully charged battery.

Constant Voltage (CV) Phase: Once the battery voltage approaches **vbat;ref**, the charging switches to the constant voltage phase. In this phase, the charger maintains the voltage at the reference value (**vbat;ref**).As the battery continues to charge, the current gradually decreases

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to prevent overcharging, protecting the battery and increasing its lifespan. When the current reduces to a predefined threshold, the charging process is usually considered complete. Here, **qbat** represents the battery capacity (often measured in ampere-hours, Ah), indicating the total charge the battery can store. The process ensures efficient charging while minimizing risks like overvoltage, overheating, or damage to the battery.

3 Description of proposed system:

Deep Convolutional Neural Network (CNN) technology is used to optimize a hybrid energy storage system (HESS), focusing on tuning the parameters of a Fractional Order Proportional Integral Derivative (FOPID) controller. **HESS**: The hybrid energy storage system combines different energy storage technologies (e.g., batteries and supercapacitors) to balance power demand efficiently and improve system performance. **Deep CNN**: A Deep Convolutional Neural Network is being used to approximate and optimize complex systems in this case, such as a HESS. CNNs are chosen for their quick convergence, robustness, and ability to model non-linear relationships. **FOPID Controller**: A Fractional Order PID controller offers more flexibility than a traditional PID controller by introducing fractional orders for the integral and derivative terms, improving control system precision. **Deep CNN for Parameter Tuning**: The Deep CNN model is used to optimize the parameters of the FOPID controller (likely the proportional, integral, derivative gains, and possibly fractional orders). This ensures efficient energy management in the HESS. **Performance Validation**: The relationship between the expected and actual output is used to assess the performance of the Deep CNN, ensuring the control signals generated lead to efficient HESS performance. **MI-HBA Algorithm**: The Modified Improved Harris Hawks Optimization (MI-HBA) algorithm is proposed to fine-tune the Deep CNN model's weights. MI-HBA helps optimize CNN performance for better power management by fine-tuning the weights to minimize errors in control signals. The model is shown in Figure 1

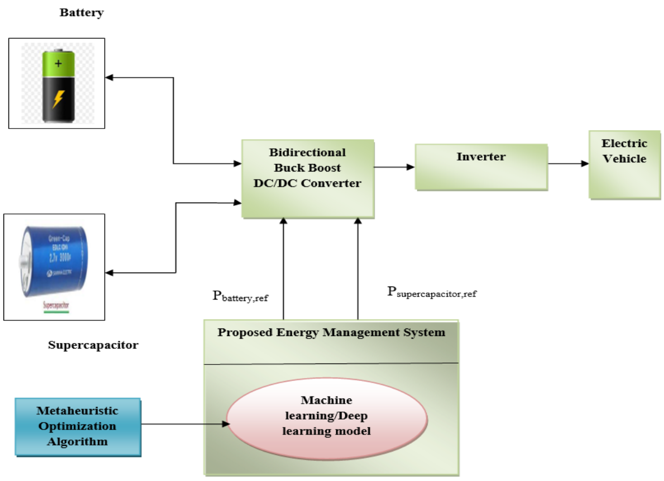

Figure 1: *Overall Structure of proposed model*

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3.1 Deep Convolutional Neural Network Model

The development of a Deep Convolutional Neural Network (D-CNN) based approach for estimating power/energy in Electric Vehicles (EVs) and optimizing parameters for a Fractional Order Proportional-Integral-Derivative (FOPID) controller. Here's a refined and structured version of the explanation:

In this study, a novel D-CNN (Deep Convolutional Neural Network) based method is proposed for estimating power and energy in Electric Vehicles (EVs). The D-CNN model will be used to optimize the parameters of a Hybrid Energy Storage System (HESS). Deep CNNs are known for their rapid convergence, robustness, and ability to approximate complex systems effectively, making them ideal for this application.

The Deep CNN will be employed to optimize the tuning parameters of the FOPID controller, specifically: Kp (proportional gain),Ki (integral gain), Kd (derivative gain),λ (fractional order of the integral),μ(fractional order of the derivative)

The model will be trained using a dataset designed to capture the dynamics of the system. To validate the Deep CNN's performance, the correlation between the predicted and actual outputs will be evaluated, ensuring the accuracy and efficiency of the parameter tuning process.

By incorporating the Deep CNN model, the study aims to enhance the tuning of FOPID controller parameters for better system performance, ensuring that the relationship between expected and real-world results is carefully accounted for during optimization. Estimating energy consumption for electric vehicles (EVs), particularly using a D-CNN (Deep Convolutional Neural Network) model gives the following advantages.

Nonlinearity and Complexity: Due to the complexity and nonlinear relationships among the parameters affecting energy consumption, a deep learning approach, such as a D-CNN, is deemed more suitable than traditional regression techniques.**-CNN Model**: The proposed D-CNN approach estimates energy consumption based on three key parameters: road grade, tractive effort, and vehicle speed. These are external factors influencing energy use. **Training Flexibility**: The model can be easily trained using either simulated data (as used in this instance) or real-world driving data, depending on availability. This highlights the adaptability of the model to different data sources. **Feature Descriptors**: The model's performance is evaluated using three distinct feature descriptors: **Gramian Angular Field (GAF)**: A technique for encoding time-series data into images. **Covariance**: Measuring how changes in one parameter affect others. **Eigen Vectors**: Used in mathematical computations, possibly for dimensionality reduction or to identify key components influencing the system. **Impact of Hidden Layers**: The impact of different numbers of hidden layers on model performance has been investigated, suggesting that the model's architecture can be optimized based on this parameter. The Structure of Deep CNN model is shown in **Figure 2**

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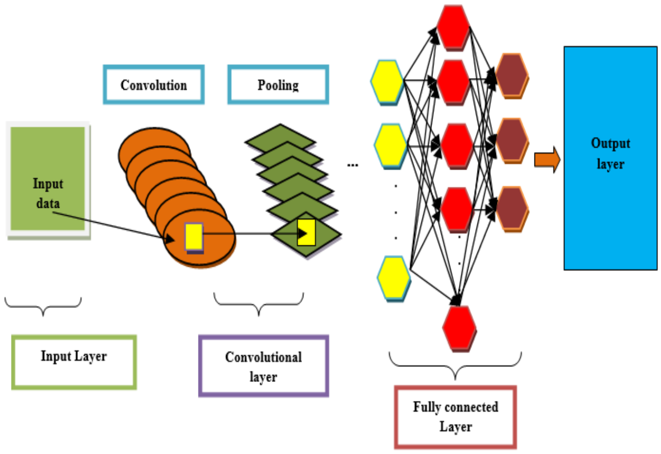

Figure 2: *Structure of Deep CNN model*

3.2 Deep CNN Algorithm

The **Memory Integrated Honey Badger Algorithm (HBA)** is an innovative meta-heuristic optimization technique aimed at improving the performance of deep convolutional neural networks (Deep CNNs) through optimal parameter selection. By fusing traits from two conventional optimization algorithms, one of which is the Honey Badger Algorithm (HBA), a novel mathematical model is developed to refine the weight optimization of Deep CNNs.

This novel approach enhances the capability of the Deep CNN model to minimize errors and maximize prediction accuracy for critical parameters. Specifically, it optimizes the proportional (Kp), integral (Ki), derivative (Kd), fractional derivative order (ƛ), and fractional integral order (μ) parameters of the **Fractional Order Proportional Integral Derivative (FOPID) controller**. This meta-heuristic framework supports the dynamic adjustment of these parameters, making it a promising solution for complex optimization tasks in control systems, where high accuracy and reduced error margins are vital.

The **Memory Integrated HBA** effectively leverages the global search capabilities of HBA while adding memory-driven mechanisms for efficient exploration and exploitation in the optimization landscape. This improves the robustness and adaptability of the technique when applied to Deep CNN models, leading to superior performance in terms of both error reduction and prediction accuracy.

3.2.1 Honey Badger Optimization Algorithm

In order to determine the gains of PID controllers, this work presents a load frequency control utilizing a meta-heuristic method. This work proposes the Honey Badger Algorithm, a unique meta-heuristic technique, to determine the ideal K p, K i, and K d parameters for a PID controller. A two-area power system is used to test the suggested algorithm. Nonetheless, the two-area power system now includes an electric vehicle battery, one of the electrical energy storage devices. As a result of the load disturbance, the frequency's settling time has been studied. Lastly, a comparison was done between the Honey Badger Algorithm, Ziegler-Nichols technique, and Genetic Algorithm, which are the traditional methodologies. Comparing the outcomes reveals that the suggested method exhibits steady-state aberrations that are quickly dampened.

4 Conclusion

Thus the Deep Convolutional Neural Network (Deep CNN), which is utilized to train and forecast the controller parameters related to the HESS, hence optimizing the performances of EVs. Suggests the Honey Badger technique (HBA), a cutting-edge meta-heuristic technique that enhances the Deep CNN model's performance in choosing the ideal parameters, like those of the FOPID controller. Consequently, the greatest accuracy parameters are found. This approach combines machine learning and optimization techniques to enhance EV performance, making the vehicles more efficient and effective.

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