



AI-Based Control of Energy Storage Capacity in High-Power-Density Systems for Electric Vehicles

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ABSTRACT:

The goal of the paper is to lessen the strain that unexpected power demands place on electric vehicle (EV) batteries, which reduces their lifespan and raises their cost. It suggests combining batteries with ultracapacitors (UCs) or flywheels, two examples of high-power-density energy storage systems (HPESS). The storage capacity can change dynamically while the system is operating thanks to the introduction of a novel Variable-Step HPESS (VS-HPESS). The method consists of three steps: a sizing algorithm for single- and dual-capacitance systems; an energy management strategy utilising Constrained Pontryagin's Minimum Principle (C-PMP) for optimal power distribution; and a Nonlinear Autoregressive Neural Network with Exogenous Inputs (NARX-NN) for real-time control. This combined approach provides a dependable and wise solution for sustainable EV energy management by lowering battery stress, increasing adaptability, increasing energy efficiency, and prolonging battery life.

Key words: Hybrid energy storage system, flywheel energy storage system (FESS), electric vehicle (EV), energy management, and ultra capacitor (UC).

1) Introduction:

The role of electric vehicles (EVs) in lowering environmental pollution and reliance on fossil fuels is becoming more and more significant. Despite EVs' great efficiency and zero emissions, their widespread adoption is hampered by battery-related problems like short lifespan, high cost, and performance degradation under high-power transients. Under frequent charge-discharge cycles, lithium-ion batteries degrade more quickly, producing heat, losing capacity, and becoming less reliable.

Researchers have created Hybrid Energy Storage Systems (HESSs) to overcome these obstacles. These systems combine batteries with High-Power-Density Energy Storage Systems (HPESSs), like flywheel energy storage systems (FESSs) or ultracapacitors (UCs). In these systems, batteries provide constant power while cruising, while HPESSs manage high transient loads during braking or acceleration. The Constrained Pontryagin's Minimum Principle (C-PMP) is used to optimise power management, and a Nonlinear Autoregressive Neural Network with Exogenous Inputs (NARX-NN) is used to achieve intelligent control in real time. The VS-HPESS is a scalable, intelligent solution for next-generation sustainable electric vehicles that improves energy efficiency, prolongs battery life, and combines adaptive capacity with AI-based prediction.[2]

1.2) Problem Statement:

Although electric vehicles (EVs) cut emissions, their lifespan is shortened and their costs are increased due to battery degradation caused by high-power transients during braking or acceleration. Batteries and flywheels (FESSs) or ultracapacitors (UCs) are combined in hybrid energy storage systems (HESSs) to help balance intermittent and continuous loads. Fixed-capacity systems, however, are not flexible enough to adjust to changing circumstances. Adaptive-capacity HPESSs improve efficiency by dynamically adjusting storage capacity. In next-generation EVs, combining artificial intelligence (AI) with adaptive control and optimal sizing enhances overall reliability, energy efficiency, and battery life.[1-5]

2) Literature Review:

By lessening degradation from transient loads, integrating high-power-density energy storage systems (HPESS) with electric vehicle (EV) batteries enhances performance, efficiency, and lifespan. Batteries and flywheel energy storage systems (FESSs) or ultracapacitors (UCs) are combined in hybrid systems to balance power and energy demands. UCs handle brief, high-power bursts, while flywheels handle quick energy exchange. However, in dynamic driving conditions, fixed-capacity HPESSs are not flexible. Multi-bank UCs and variable-inertia FESSs are examples of adaptive-capacity

HPESSs that modify storage capacity in real time to improve efficiency. Power sharing is coordinated by Energy Management Strategies (EMS); optimization-based strategies like PMP require a lot of computing power, while traditional rule-based approaches are straightforward but inflexible. Real-time prediction, adaptive control, and effective energy management are made possible by integrating artificial intelligence (AI), especially NARX neural networks, which enhances the overall performance and dependability of EVs.[1-7]

2.1) Research Gaps:

1. Under dynamic conditions, traditional HPES systems are inefficient; self-learning, AI-based control can improve power management and allow adaptive capacity adjustment.[2]
2. The need for resilient, scalable, and adaptable HPES designs is highlighted by the computational limitations of techniques like C-PMP and mechanical wear from frequent switching.[2]

2.2) Research Objectives:

1. To propose a comprehensive method for sizing and control of variable-step high-power-density energy storage systems (VS-HPESs):

The primary objective of this objective is to determine the optimal storage capacities (e.g., dual-inertia flywheels or dual-capacitance ultracapacitors) and their involvement priority. [2]

2. To develop an artificial intelligence-based real-time control strategy for adaptive storage capacity management:

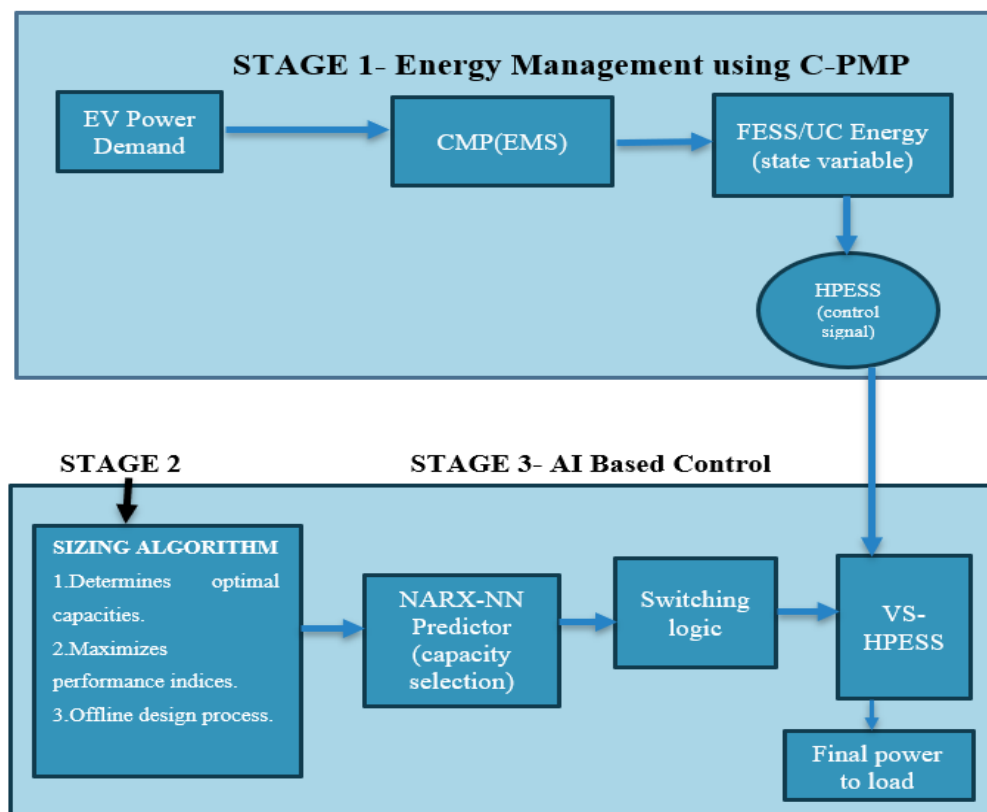
The study uses a nonlinear autoregressive neural network with exogenous inputs (NARX-NN) to enable dynamic switching of HPES capacities under different driving conditions. [2]

3) Methodology:

The suggested Variable-Step High-Power-Density Energy Storage System (VS-HPES) methodology combines three main phases to increase the lifespan, adaptability, and efficiency of electric vehicle (EV) energy systems: [2]

Stage 1: Energy Management using C-PMP

In this stage, the best power split between the battery and the Variable-Speed Hybrid Power Energy Storage System (VS-HPES) is determined by an Energy Management Strategy (EMS) based on Constrained Pontryagin's Minimum Principle (C-PMP), as illustrated in Figure 4.1.



The cost function to be minimized is:

$$C_e = \int_0^T [Z_1 (E_{fly}(t) - E_{fly0})^2 + Z_2 (P_{bat}(t))^2] dt \quad \text{----(1)}$$

where Z_1 and Z_2 are weighting factors that regulate the trade-off between smoothing the battery power and minimising energy deviations.

Additionally, the EMS needs to meet the operational limits $E_{min} \leq E_{fly} \leq E_{max}$. The necessary optimality conditions derived from the Hamiltonian yield:

$$P_{bat}(t) = -\lambda_1 / 2Z_2 \quad \text{----- (2)}$$

where the Lagrange multiplier is represented by λ_1 . The ideal battery and FESS power trajectories are obtained by solving this two-boundary value problem.

Stage 2: Sizing Algorithm

The ideal energy storage physical parameters—capacitance C for ultracapacitors or inertia J for flywheels—are established by the sizing algorithm. Two performance indices are used:

1. Energy Interaction Index (ME): Derived from the FESS state-of-energy waveform, it quantifies the usable amount of storage energy.
2. Battery Degradation Index (MB): Uses electro-thermal ageing equations to quantify the reduction of battery stress.

The overall objective function is:

$$C_\gamma = \omega_1 ME + \omega_2 MB \quad (\gamma = \text{SIFESS, DIFESS}) \quad \text{----- (3)}$$

where ω_1 and ω_2 are weighting factors. The determination of C_1 and C_2 for ultracapacitor systems follows a similar methodology, guaranteeing effective energy use in various EV operating modes. Figure 4.1 shows how the parameters interact and are sized.[2]

Stage 3: AI-Based Real-Time Control

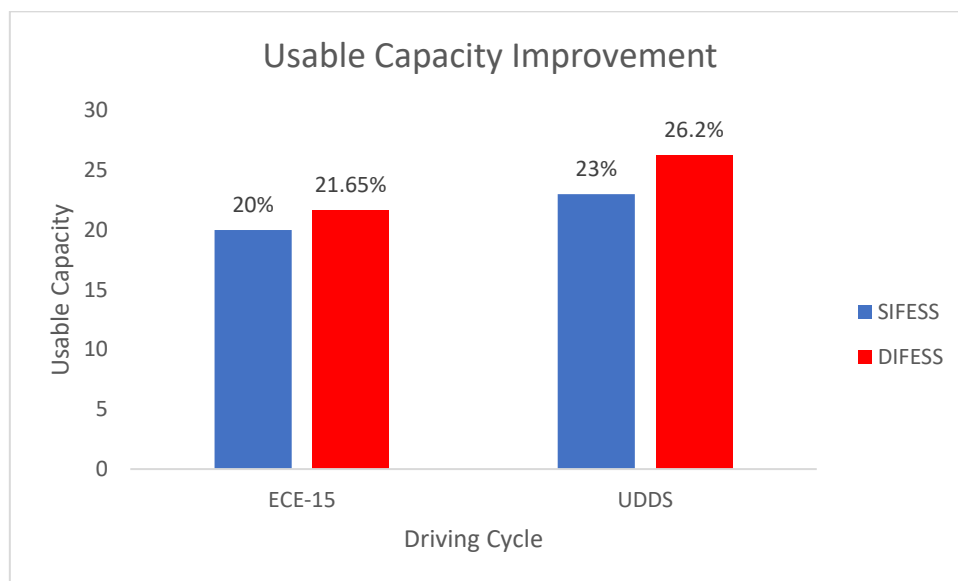
Adaptive control is necessary for real driving, whereas the earlier phases are offline optimisation processes. As shown in Figure 4.1, this is accomplished by using a Nonlinear Auto Regressive Neural Network with Exogenous Inputs (NARX-NN) for real-time switching of the secondary capacity (J_2 or C_2).

Using historical system outputs ($y(t-1) \dots y(t-m)$) and external input trends like power demand ($x(t-1) \dots x(t-n)$), the NARX-NN forecasts control actions:

$$y(t) = f(x(t-1), \dots, x(t-n), y(t-1), \dots, y(t-m)) \quad \text{----- (4)}$$

where f is a nonlinear mapping learned through training. Using two hidden layers with 20 neurones each and two-step input/output delays, the network employs Levenberg–Marquardt optimisation for fast convergence. [2]

5) Results and Discussion:



Comparing the suggested framework for sizing and intelligent control of Variable-Step High-Power-Density Energy Storage Systems (VS-HP ESSs) to fixed-capacity systems, notable improvements in energy efficiency, flexibility, and battery protection are shown. The Dual-Inertia FESS (DIFESS) achieved greater gains of 21.65% and 26.2%, respectively, while the Single-Inertia FESS (SIFESS) increased usable capacity by 20% and 23% under the

ECE-15 and UDDS driving cycles. Dynamic inertia switching in the DIFESS allows for effective energy absorption during transients, lowering fluctuations in battery current and enhancing State of Health (SoH). Optimal power distribution was guaranteed by C-PMP-based optimisation, and real-time, oscillation-free capacity control was offered by the AI-powered NARX-NN. VS-HP ESS is a highly effective and clever solution for next-generation electric vehicles because of its adaptive framework, which improves powertrain stability, reduces energy loss, and prolongs battery life.[2]

6) Conclusion:

According to the study, the Variable-Step High-Power-Density Energy Storage System (VS-HP ESS) successfully raises the dependability and efficiency of energy systems for electric vehicles. In comparison to fixed-capacity designs, the system achieves superior energy utilisation and adaptive power management by combining AI-driven real-time control using a NARX-NN model with C-PMP-based optimal sizing. The Dual-Inertia FESS (DIFESS) performs better than the Single-Inertia FESS (SIFESS) in terms of transient power handling and usable capacity, according to simulation results conducted under UDDS and ECE-15 cycles. Its dynamic capacity adjustment effectively controls regenerative braking and acceleration, lowering battery stress and increasing lifespan. By reducing losses and enhancing stability, intelligent control guarantees seamless power transitions. The VS-HP ESS framework advances sustainable and adaptive hybrid energy storage technology by offering a reliable, intelligent, and energy-efficient solution for next-generation electric vehicles.

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