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Strategies of Different Hybrid Energy Storage Systems for Electric Vehicles Applications

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ABSTRACT

Integrating energy storage systems with complementing features increases the efficiency and longevity of electric cars. A high-energy-density battery, when combined with a high-power-density supercapacitor, efficiently manages peak energy demands during acceleration and regenerative braking while reducing battery deterioration. This system, known as a Hybrid Energy Storage System (HESS), provides considerable financial and operational savings due to battery deterioration over time. This work presents a control approach for optimizing power flow between two storage components. The energy management problem is treated as an infinite-horizon inventory control scenario and reconstructed as a linear program to improve computing efficiency. To manage the complexity typically associated with dynamic programming, we employ a value function approximation using basis functions, allowing the policy to be computed offline and minimizing the need for intensive real-time calculations. In contrast to existing heuristic and model predictive control techniques, which either lack future demand forecasting or rely on suboptimal solutions, our approach offers a scalable and flexible approximation of the optimal strategy. Moreover, unlike previous dynamic programming methods that often suffer from the curse of dimensionality, our optimization programming-based method remains computationally viable even in high-dimensional state spaces. Simulation results on an electric vehicle equipped with both a battery and supercapacitor validate the proposed method. The findings show that the derived suboptimal control policy effectively approximates the optimal one, especially when a sufficient number of basis functions are utilized.

1. Introduction:

In recent years, a variety of environmental pollution control strategies have emerged, particularly targeting emissions from transportation systems, which are a major contributor to global pollution. These initiatives aim to improve energy efficiency and reduce harmful emissions. Notably, transportation powered by fossil fuels contributes approximately 26% of the global carbon dioxide (CO_2) emissions, a figure expected to rise sharply due to ongoing industrial expansion and increased vehicle usage. To combat these environmental concerns, electric vehicles (EVs) and plug-in hybrid electric vehicles (PHEVs) have gained traction as sustainable alternatives. These technologies significantly lower greenhouse gas emissions and also help reduce noise pollution in urban environments.

2. Methodology

Battery life is a factor that is crucial to the operation of electric cars. It determines the greatest distance that may be driven on a single charge, among other influences on vehicle performance. It seems sense to want to extend battery life.

Using a hybrid power source, which combines a battery and secondary energy storage, is a typical tactic used by car designers in this regard. The rationale is that each of these storage devices is most appropriate for a particular profile of energy demand (load) for the vehicle's operations, which may change as the journey progresses. By using a combination of storages, one may improve the efficiency of the energy delivery, and hence the battery life. Note that the secondary storage is usually a supercapacitor and so will be referred to as such in this paper, even though the results would apply for other devices too.

In order to improve its lifetime, experiments show that the battery should be operated with constant, low output power. Nevertheless, its overall energy capacity is higher. Conversely, the supercapacitor has the opposite properties: low energy capacity but the potential for great power output. Therefore, it is evident that maximizing battery lifespan while always meeting demand—which fluctuates over time based on vehicle operation—requires optimally discharging energy from the battery and supercapacitor.

The energy fluxes in a two-storage system are described by this model. As a dynamic programming problem, it is stated.

2.1 Model Definitions

Indices

t: discrete time step index

j: storage device number (1: battery, 2: supercapacitor)

• Parameters

αC: charging efficiency

αD: discharging efficiency β: storage efficiency factor (constant) *N*: number of steps (DP horizon)

K: cost weighting factor for rate (relative to cost of energy loss)

• Variables

L: load energy demand (random variable) *E*: energy state of storage device

D: energy released by discharging (AFTER loss) *C*: energy consumed by charging (BEFORE loss) *J*: cost function

NOTE: *C*1 does not exist because not possible to charge the battery while driving. (Assuming no regenerative braking at the moment.)

2.2Constraints

• Supply-demand balance:

$$[D_1(t)] + [D_2(t) - C_2(t)] = L(t)$$

Bounds on stored energy:

$$E_j^{min} \leq E_j(t) \leq E_j^{max}$$

Bounds on charging:

$$0 \leq C_2(t) \leq C_2^{max}$$

Bounds on discharging:

$$0 \leq D_j(t) \leq D_j^{max} \tag{4}$$

2.3Recursive State Equations

The state of the system is the energy in a storage device ($Ej(t)$). This evolves according to the charging and discharging of the storage device, which is the control.

The following recursive equations describe the changes in the state, including due to constant leakage loss:

$$E_1(t+1) = \beta_1 E_1(t) + \left[-\frac{1}{\alpha_1^D} D_1(t)\right] \tag{5}$$

$$E_2(t+1) = \beta_2 E_2(t) + \left[\alpha_2^C C_2(t) - \frac{1}{\alpha_2^D} D_2(t)\right] \tag{6}$$

Substituting (1) into (6), one obtains:

$$E_2(t+1) = \beta_2 E_2(t) + \left[\alpha_2^C [D_1(t) + D_2(t) - L(t)] - \frac{1}{\alpha_2^D} D_2(t)\right] \tag{7}$$

2.4Cost Function

• Minimize discharge rate for the first storage device (battery):

$$J_{rate} = min\left[\sum_{t=0}^{N-1} K\,[D_1(t)]^2\right] \tag{8}$$

This is convex.

• Minimize power loss due to energy transfers

$$J_{loss} = min\left[\sum_{t=0}^{N-1} (1-\alpha_1^D) D_1(t) + (1-\alpha_2^C) C_2(t) + (1-\alpha_2^D) D_2(t)\right] \tag{9}$$

Substituting (1), one obtains:

$$J_{loss} = \mathop{\mathbb{E}}_{L(t)}\left\{min\left[\sum_{t=0}^{N-1} (1-\alpha_1^D) D_1(t) + (1-\alpha_2^C)[D_1(t) + D_2(t) - L(t)] + (1-\alpha_2^D) D_2(t)\right]\right\} \tag{10}$$

This is constrained to be non-negative.

Hence the combined cost function is convex:

$$J = \mathop{\mathbb{E}}_{\substack{L(t)\\ \forall t\in 1\ldots N}}\left\{min\left[\sum_{t=0}^{N-1} K\,[D_1(t)]^2 + (1-\alpha_1^D) D_1(t) + (1-\alpha_2^C)[D_1(t) + D_2(t) - L(t)] + (1-\alpha_2^D) D_2(t)\right]\right\} \tag{11}$$

It is chosen to take the expectation after the minimization. This is done so that the net energy discharged (control, *D*) exactly matches the demand, *L*, at all times, and not its expected value.

In the general case, for state $x(t)$, control $u(t)$ and random perturbation $w(t)$, the cost function may be expressed as:

$$J = \mathop{\mathbb{E}}_{w(t)}\left\{\min_u\left[\sum_{t=0}^{N-1} g(x(t), u(t), w(t))\right]\right\} \tag{12}$$

where $g(\cdot)$ is the stage cost.

This can be re-written in the form of Bellman's equation, which allows the problem to be solved by recursion:

$$J_t[x(t), w(t)] = \min_u g(x(t), u(t), w(t)) + \mathop{\mathbb{E}}_{w(t+1)} \{J_{t+1}[f(x(t), u(t), w(t)), w(t+1)]\} \quad (1$$

Note that by choosing the perturbation $w(t)$ to be a component of the state as well, can determine the optimal control for any arbitrary load at time t, in addition to arbitrary state.

Based on this formulation, the optimization problems for the battery and supercapacitor are individually as follow:

• Battery storage:

$$J_t[E_1(t), L(t)] = \min_{D_1, D_2} (1-\alpha_1^D)D_1(t) + K[D_1(t)]^2 + (1-\alpha_2^D)[D_2(t)] + (1-\alpha_2^C)[D_1(t)+D_2(t)-L(t)] + \mathop{\mathbb{E}}_{L(t+1)} \{J_{t+1}[f_1(E_1(t), D_1(t)), L(t+1)]\} \quad (14)$$

where $f1(\cdot)$ is (5), the state equation for the battery.

• Supercapacitor storage:

$$J_t[E_2(t), L(t)] = \min_{D_1, D_2} (1-\alpha_1^D)D_1(t) + K[D_1(t)]^2 + (1-\alpha_2^D)[D_2(t)] + (1-\alpha_2^C)[D_1(t)+D_2(t)-L(t)] + \mathop{\mathbb{E}}_{L(t+1)} \{J_{t+1}[f_2(E_2(t), D_1(t), D_2(t), L(t)), L(t+1)]\} \quad (15)$$

where $f2(\cdot)$ is (7), the state equation for the supercapacitor.

Combining the above gives the final form of the optimization problem of interest:

$$J_t[E_1(t), E_2(t), L(t)] = \min_{D_1, D_2} (1-\alpha_1^D)D_1(t) + K[D_1(t)]^2 + (1-\alpha_2^D)[D_2(t)] + (1-\alpha_2^C)[D_1(t)+D_2(t)-L(t)] + \mathop{\mathbb{E}}_{L(t+1)} \{J_{t+1}[f_1(E_1(t), D_1(t)), f_2(E_2(t), D_1(t), D_2(t), L(t)), L(t+1)]\} \quad (16)$$

3. Result:

We tested our approach in simulation on a typical electric vehicle with a battery and a supercapacitor described in [5]. We used R = 6mΩ for the battery and $P2$max = 274.2kW for the supercapacitor to calculate the charging and discharging efficiencies for each device, based on the datasheets of the devices in [5]. We also used a as leakage factor of βloss = 1 for both, based approximately on the same. In this paper, the approximate linear program was modelled in CVX [19] and resolved for different demand sequences using Gurobi [20]. The discount factor α = 0.99, the weighting factors $K1$ = $K2$ = 1000, and the weights $\nu1$ = 100 and $\nu2$ = 1 for the SoE penalties on the battery and supercapacitor, respectively, were also held constant. Lastly, we employed R = 496 basis functions, which are made up of 210 state aggregations and monomials up to order 10, to carry out the approximation.

The energy storage system was sized in accordance with [5]. The battery's and the supercapacitor's respective energy capacities are roughly $E1$max = 33.7kWh and $E2$max = 160Wh. The maximum energy discharge ratings for the Li-Ion batteries and supercapacitors in [5] were roughly $D1$max = 4.5Wh for the battery and $D2$max = 7.5Wh for the supercapacitor, given their respective power densities of 0.43 kW/kg and 6.7 kW/kg. We found that Δt = 0.1s is a realistic time step for energy transfers, and this rating is based on that assumption. Given that the input and output power ratings of the supercapacitor are symmetric [14], we chose to set $C2$max = $D2$max. However, the input power rating of a battery is generally lower than its output rating [21, pg. 14]. We selected $C1$max = 0.50Wh because the battery's rated charging power is 48 W/kg, according to the datasheet for the battery utilized in [5]. An artificial Beta distribution parameterized by β is used to distribute the probability pi,(up) of discrete demands in set W. To find the optimal policy, we first solved the approximation linear program offline. In order to ascertain the best way to operate the battery and supercapacitor under various circumstances, The continuous random demands were then sampled from the same distributions using demand sequences. The storage units in [5] were sized to have a maximum power demand of 9600s. As a result, we started with the initial energy states of $E1$ = $E1$max and $E2$ = $E2$max and simulated for the same length of time. When the demands are produced by two distinct beta distributions, one parameterized by β = 1 and the other by β = 10, we conducted an online test of the best policy. In order to compare, we also tested both with and without regenerative braking (i.e., Lmin = 0 and Lmin = -min($E1$max + $E2$max, $C1$max + $C2$max)).

The simulation for the first situation (when β = 1 and regenerative braking is not present) is displayed in Figure 4.1.

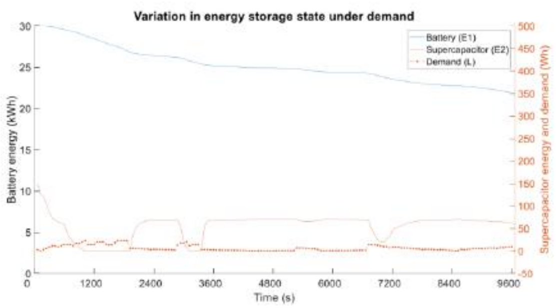

Fig 1: Using a distribution-generated sequence with β=1 and no regenerative braking to test the best course of action online.

We see that when the supercapacitor is exhausted and for extremely low demands, the battery will typically provide the majority of the energy. Additionally, we note that the supercapacitor frequently meets longer-duration needs, as seen in Figure 1 between 130 and 140 s. Large battery discharges come at a comparatively high cost, therefore this outcome is to be expected. The supercapacitor is occasionally recharged by the battery when there is no demand. Since a trade-off is made between immediate transfer loss and addressing variable demands later by charging the supercapacitor in advance, this further demonstrates that the ideal strategy is not myopic. Such energy transfers wouldn't be necessary if it weren't for the latter's advantages. However, due to the relatively limited energy capacity of the supercapacitor, the demand must decrease until it is ideal for this to happen.

Additionally, we observed that by reducing $K1$ and $K2$ to 1, there is less cost for charging and discharging the battery. One can see this in Figure 2, This displays the reaction in the absence of regenerative braking when the demand sequence is produced by a distribution with β = 10.

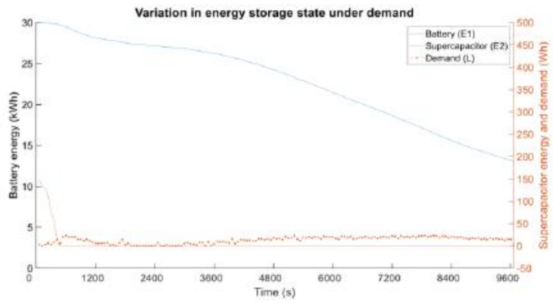

Figure 2: Using a sequence produced by a distribution with β=10, test the best course of action online. Reduced costs for charging and discharging batteries and the absence of regenerative braking (K1=K2=1).

By reducing the cost of discharging from the battery, we discover that the optimal strategy is to avoid recharging the supercapacitor even when there is no demand. This is because, in contrast to the last test, the cost of energy transfer losses is comparable to the cost of battery discharge. Our expectations are confirmed by the outcome. Finally, we tested the case with regenerative braking to compare to the above policies. Figure 3 shows the optimal response to a demand that is generated by a distribution with β = 1.

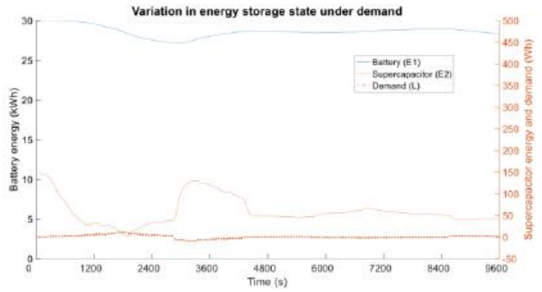

Figure 3: Online testing of the best course of action using a sequence produced by a distribution with β=1 and regenerative braking.

It is clear that charging and draining the supercapacitor before the battery is the best way to meet the demand in this scenario. This is comparable to what occurs in Figure 1 in the absence of regenerative braking. One difference is that when demand is low, the battery charges the supercapacitor less than in Figure 1. enables the supercapacitor to collect future energy via regenerative braking.

We examined the value function approximation as well as the best policy. We measured the approximation error for small-scale problems. For instance, Figure 4 shows the trade-off between the number of iterations and the approximation error in solving the approximate LP, where the latter is dependent on the number of basis functions.

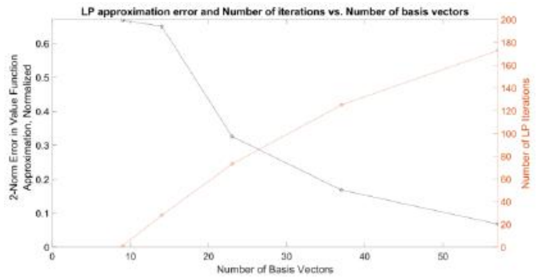

Figure 4: variation in solution time and approximation error as the number of basis functions is increased. Size of test: M=16, N1=6, N2=5.

This demonstrates that adding more basis functions flexibly can truly make the approximation error arbitrarily tiny.

In addition to testing the optimal policy, we also tested the value function approximation. We quantified the approximation error for problems of small size. Figure 4, for example, illustrates the trade-off made between the approximation error and the number of iterations in solving the optimization problem, where the latter depends on the number of basis functions.

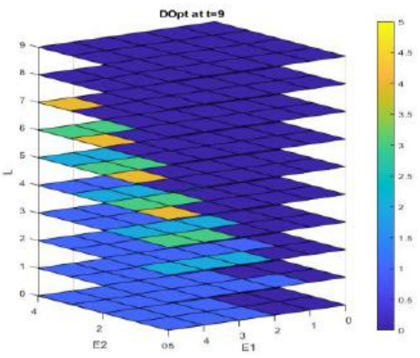

Figure 5:Percent Error between Costs in ACO and at Supercapacitor Energy (E2) , Battery Energy (E1) Demand (L)

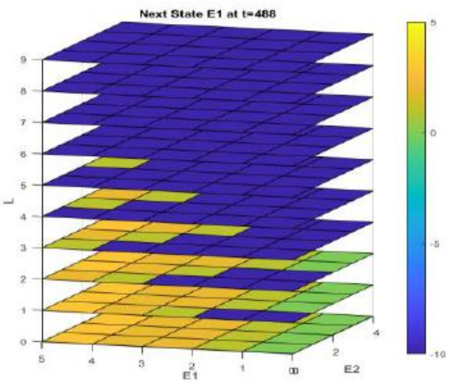

Figure 6: Percent Error between Costs in PSO and at Supercapacitor Energy (E2) , Battery Energy (E1) Demand (L)

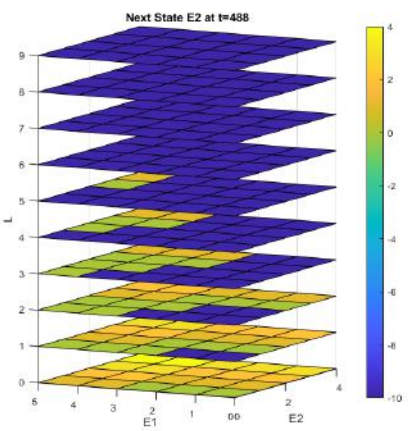

Figure 7: Percent Error between Costs in DP and at Supercapacitor Energy (E2) , Battery Energy (E1) Demand (L)

Table 4.1: Performance Analysis

Optimization	Convergence speed	Best Fitness Value Percentage	Efficiency Improvement
DP	1106 iteration	63%	6%
PSO	1045 iteration	74%	7.2%
ACO	936 iteration	76%	8.5%

CONCLUSION

The integration of energy storage devices with complementary characteristics has become increasingly important in advancing the performance and durability of electric vehicles (EVs). Relying solely on a single energy storage device—such as a lithium-ion battery—poses challenges in coping with sudden power demands and can significantly accelerate aging due to high charge-discharge cycles. To address this issue, a hybrid energy storage system (HESS) that combines a high-energy-density battery with a high-power-density supercapacitor has emerged as a promising solution. While the battery serves as the primary energy reservoir due to its high energy storage capacity, the supercapacitor excels in delivering and absorbing power during rapid transients such as acceleration and regenerative braking. This complementary arrangement not only ensures smoother energy distribution and improved vehicle performance but also helps to mitigate the degradation of the battery, thereby extending its operational life and reducing long-term maintenance and replacement costs.

5.1 Conclusions

Despite these advantages, the control and management of power flow between the two energy storage units remain a non-trivial problem. Determining how to dynamically allocate power between the battery and supercapacitor to meet time-varying vehicle demands while optimizing overall system performance introduces a high-dimensional and computationally complex control problem. Conventional approaches, including rule-based heuristics and model predictive control (MPC), provide viable solutions but often struggle with scalability and real-time computational demands. Moreover, they may not always guarantee performance close to the theoretical optimum, especially when system uncertainties or high state-space dimensionality are present.

In this work, we propose a novel control strategy for optimal power management within a dual-source HESS architecture, employing optimization. The power allocation problem is modeled as an infinite-horizon inventory control task, where the objective is to minimize a long-term cost associated with battery degradation and power inefficiency. This formulation allows for the incorporation of both immediate and future implications of control actions. To tackle the computational intractability of classical dynamic programming—particularly the curse of dimensionality—we reformulate the problem as a optimization algorithm and employ a basis function approximation to estimate the value function. By choosing an appropriate set of basis functions, we are able to derive a near-optimal policy offline, drastically reducing the computation required during real-time execution.

Our approach stands out from existing heuristic and MPC methods in two significant ways. First, it provides a more systematic and scalable method for policy approximation, ensuring better generalization across a wide range of operating conditions. Second, unlike many earlier DP-based techniques that often ignore the dimensional limitations of the value function approximation, our optimization-based programming formulation enables efficient computation even in high-dimensional state spaces, making it suitable for more complex and realistic EV models.

We validate the proposed framework through detailed numerical simulations involving an electric vehicle equipped with a representative battery and supercapacitor setup. The experimental results demonstrate that the derived control policy achieves performance levels very close to that of the true optimal policy, as long as a sufficiently rich set of basis functions is used. This indicates that the method can effectively balance computational efficiency and control performance, offering a practical and high-performing solution for real-world HESS power management.

In summary, this work contributes a robust and efficient optimizaion-based control framework for HESS-equipped electric vehicles, addressing key limitations of previous methods and offering promising results in terms of both policy accuracy and computational feasibility.

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