Hybrid Energy Storage System Integration For Vehicles

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ABSTRACT

Energy consumption and the associated environmental impact are a pressing challenge faced by the transportation sector. Emerging electric-drive vehicles have shown promises for substantial reductions in petroleum use and vehicle emissions. Their success, however, has been hindered by the limitations of energy storage technologies. Existing in-vehicle Lithium-ion battery systems are bulky, expensive, and unreliable. Energy storage system (ESS) design and optimization is essential for emerging transportation electrification.

This paper presents an integrated ESS modeling, design and optimization framework targeting emerging electric-drive vehicles. Based on an ESS modeling solution that considers major run-time and long-term battery effects, the proposed framework unifies design-time optimization and run-time control. It conducts statistical optimization for ESS cost and lifetime, which jointly considers the variances of ESS due to manufacture tolerance and heterogeneous driver-specific run-time use. It optimizes ESS design by incorporating complementary energy storage technologies, e.g., Lithium-ion batteries and ultracapacitors. Using physical measurements of battery manufacture variation and real-world user driving profiles, our experimental study has demonstrated that the proposed framework can effectively explore the statistical design space, and produce cost-efficient ESS solutions with statistical system lifetime guarantee.

Categories and Subject Descriptors

C.4 [**Performance of Systems**]: Design studies; J.6 [**Computer-Aided Engineering**]: Computer-Aided Design

General Terms

Algorithms, Design, Experimentation

Keywords

Energy Storage System, Battery, Electric-Drive Vehicle, Design, Optimization

1. Introduction

Transportation electrification has drawn significant attention over the past decade, mainly driven by the pressing energy and environmental challenges. Indeed, the transportation sector currently accounts for 70% of petroleum consumption and over one third of greenhouse gas emissions. Electric-drive technologies show great promises to address these challenges [3]. Hybrid electric vehicles (HEVs) have been fast adopted and widely deployed over the past decade. Currently, plug-in hybrid electric vehicles (PHEVs), which allow the vehicle to be directly charged by the electric power grid, are under active development and will become market ready in the coming few years. These electric-drive vehicles are usually featured with an internal combustion engine powered by fuel and an electric motor powered by battery. With the assistance of the electric-drive system, (P)HEV fuel use can be significantly reduced by operating the vehicle in an electric mode without using the combustion engine, or allowing the combustion engine to operate more efficiently.

The success of electric-drive technologies, however, has been seriously hindered by shortcomings of electric energy storage systems (ESS). Indeed, for decades, energy storage technology has been the key bottleneck in electric-drive vehicle design [7, 13]. This is mainly due to the fact that the advances of battery technology, the primary energy storage solution, have not kept pace with the fast-growing energy demands. Among (P)HEV technical challenges, ESS has been singled out as a potential show stopper due to its high cost, limited energy capacity, safety issues, and limited long-term cycle life.

More specifically, Lithium-ion (Li-ion) rechargeable battery is the mainstream energy storage technology for (P)HEVs, thanks to its superb energy storage density. Cost and long-term cycle life are the major concerns of Li-ion based ESS solutions. Considering recently developed Toyota Prius PHEVs, a 10-mile electric mode driving requires a Li-ion battery system with a total cost of over $10,000 USD. ESS long-term cycle life is another major challenge caused by various electrochemical and mechanical aging effects. Due to the high energy storage capacity demand, a PHEV ESS consists of a large number of battery units, typically over 1000, and the ESS overall capacity and lifetime are determined by the weakest unit. Manufacturing tolerance, along with heterogeneous run-time use and ambient environment, lead to significant degradations and variations among individual battery units, resulting in serious ESS lifetime reliability concerns. Energy storage technology and system innovation is timely and important.

Related Work

(P)HEV energy storage technology and system development have drawn significant attention over the past decade. Markel et al. investigated PHEV technologies and pointed out that power and energy capacity are the two critical factors in PHEV battery system design [12]. Rousseau et al. presented an ESS development process considering the impact of vehicle design, control strategies and drive cycle [17]. Recent studies have started to consider hybrid energy storage technology integration. Dumitrescu et al. proposed hybrid integration of NiMH battery and double-layer capacitor technologies [16]. Smith discussed how to integrate fuel cells with ultracapacitors (ultracaps) for ESS power and energy optimization [19]. Andrew analyzed the feasibility of incorporating ultracaps into electric vehicle battery system [4]. Cooper et al. developed a hybrid lead-acid battery–ultracap energy storage system called UltraBattery, which demon-

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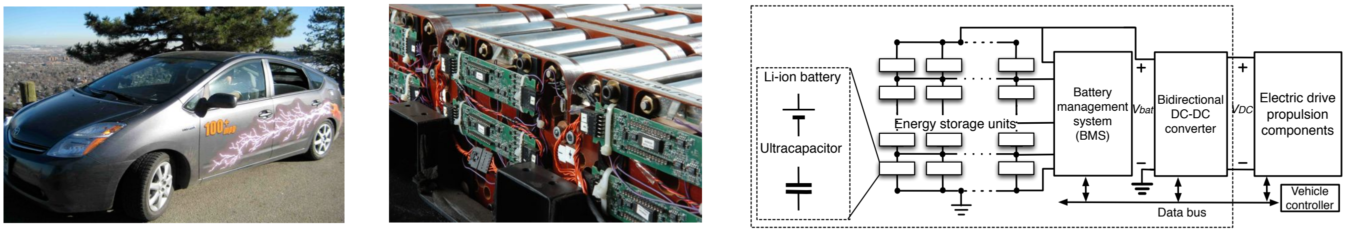

Figure 1: Energy storage systems (ESS) for electric-drive vehicles.

strated that both run-time power demand and lifetime can be enhanced [6]. Cegnar et al. developed an ultracap-only ESS [5].

These past studies largely focus on energy storage technology and system development. These engineering efforts lack in-depth understanding and comprehensive consideration of the limitations and challenges of battery technologies. For instance, battery aging effects and their impact on ESS system long-term cycle life and overall system cost are typically ignored. In addition, the past work failed to consider the significant variances of manufacture tolerance and heterogeneous run-time use and environment during ESS design and optimization. Their design efforts essentially target worst-case system design, leading to significant increase of ESS system cost. In summary, the past work shows promises but more in-depth and rigorous research study is required.

Our Contributions

In contrast to existing engineering and development efforts, the goal of this work is to, for the first time, provide an integrated modeling, design and optimization framework to enable rigorous (P)HEV ESS analysis, design and optimization. Building upon our recent work on ESS modeling [11] that considers major run-time and long-term effects, this framework optimizes the ESS design by incorporating complementary energy storage technologies and conducts statistical optimization for ESS cost and lifetime. Specifically, we present an ESS design and optimization solution that considers the variances due to battery system manufacture tolerance and user-specific driving behavior, as well as statistical optimization techniques to optimize ESS cost, yet providing statistical lifetime guarantee. The proposed optimization framework allows hybrid system integration by considering two complementary energy storage technologies, i.e., Li-ion battery and ultracap, for ESS cost optimization under run-time performance and long-term cycle life constraints. The proposed solution is evaluated using physical measurements of battery manufacture variation and real-world user driving profiles. The results demonstrate that the proposed design and optimization framework can effectively explore the statistical ESS design space, minimize ESS cost, and provide statistical system lifetime guarantee.

2. Motivation and Rationale

This section overviews the energy storage technologies for emerging electric-drive vehicles and summarizes the design challenges.

2.A ESS Overview and Design Metrics

Figure 1 shows a block diagram of an ESS connected to electric-drive propulsion components. Regardless of the chemistry specifics, a single battery unit's voltage, current and energy storage capacity are relatively low. Therefore, an ESS usually consists of a large number of energy storage units connected in parallel and series, controlled by a battery management system (BMS). The BMS monitors the battery run-time current, temperature, as well as unit voltage to assess battery state of charge (SOC) and state of health (SOH), which are then communicated to a vehicle system controller. The following design metrics are commonly considered during ESS design for electric-drive vehicles [2].

- **Energy capacity:** It determines the maximal available energy within an ESS charge cycle. Compared with other electrochemical energy storage technologies, e.g., NiMH and ultracap, Li-ion battery offers superb energy storage density, hence higher total energy capacity under the same weight and form factor.
- **Peak power:** This determines the maximal instantaneous power that can be delivered by the ESS to the vehicle. Note that energy capacity and peak power are two distinct design metrics. Compared with Li-ion battery, ultracap provides significantly higher power density, hence higher peak power support [13].
- **Cost:** As the primary hurdle for transportation electrification, ESS cost is mainly contributed by energy storage units. Minimizing ESS cost is a primary objective of this work.
- **Lifetime:** ESS lifetime is characterized as long-term cycle life, i.e., the total number of charge–discharge cycles before the system capacity permanently degrades below certain threshold. (P)HEVs impose stringent lifetime constraints on ESS. For instance, automotive vendors typically target a 10∼20-year ESS lifetime guarantee with 20∼30% maximal capacity degradation [1]. Aging effects are the primary lifetime concern of Li-ion battery technology, which is strongly affected by temperature. In contrast, ultracap demonstrates excellent life span [13].

2.B ESS Design Challenges

ESS design and optimization need to jointly consider system cost, run-time performance, and long-term cycle life. More specifically,

- Since Li-ion battery is the primary energy storage technology, ESS system lifetime is mainly affected by Li-ion run-time aging effects. The dominant aging effects are strong functions (typically exponential) of temperature, which is mainly due to the battery run-time charge–discharge induced battery heating. Therefore, to improve ESS lifetime, constraining the battery run-time current becomes essential. One possible approach is to increase the number of battery units connected in parallel to reduce the per unit run-time current. Even though the battery system cost also increases, battery system lifetime improvement is more significant due to the exponential temperature–aging dependencies. A more effective approach is to consider hybrid ESS integration. For instance, ultracap has limited aging effects, leveraging ultracap to offload run-time current demand can effectively improve the ESS lifetime. However, ultracap has substantially lower energy capacity density, hence higher per energy capacity cost (approximately 30× over Li-ion). Hybrid ESS integration is challenging.
- The ESS performance, e.g., energy capacity, and cycle life are constrained by the weakest battery unit. Due to the limited capabilities of monitoring unit and system SOC and SOH over high-voltage boundaries, existing BMS offers limited control over individual units. As a result, mismatches among units (due to manufacturing tolerance, temperature gradients across the pack, and mismatched degradation over cycle and calendar life) can lead to overcharge and excessive discharge of individual units, resulting in overall system performance degradation and severe cycle life limits. This problem becomes increasingly worse with the increase of the number of battery units. We conducted capacity degradation measurement on 30 Li-ion battery modules in a PHEV. Over 40% capacity variation is observed among these modules due to manufacture variation dependent aging. There-

fore, manufacture variation must be carefully considered during ESS design and optimization.

- Furthermore, (P)HEV operation, hence ESS use and aging, are heavily affected by users' run-time driving behaviors. User-specific driving patterns are dynamic and differ substantially among drivers, so do ESS run-time performance and long-term cycle life. Aggressive driving patterns, e.g., frequent speeding up and slowing down, result in high run-time charge–discharge current. Such intensive use causes significant battery self-heating, accelerating temperature-dependent aging effects, hence battery long-term capacity degradation. Using the battery system model we recently developed [11] and the daily commute driving profiles of ten users, our study shows that user driving behavior has significant impact on ESS lifetime. Targeting the worst-case driving scenario would dramatically increase the ESS cost.

3. System Design and Statistical Optimization

In this section, we formulate the ESS Design Optimization as a statistical optimization problem for minimizing the total cost under the energy/power capacity and lifespan constraint, considering both the ESS manufacture process variation and run-time heterogeneous user-specific use profiles. Contrary to a worst case optimization problem which may incur unrealistic cost for the majority users, a statistical optimization can substantially reduce the system cost with only a very low increase on the yield loss. The problem is formulated and solved within a risk-aversion two-stage stochastic optimization framework.

3.A Problem Formulation

Targeting the proposed ESS architecture, the design-time optimization is to quantitatively determine the ESS configuration, including the number of storage units, as well as the type and size of each unit, to minimize the system cost while ensuring the target lifetime for most (P)HEV vehicle drivers.

As shown in Figure 1, the ESS system is composed of $N = m \times n$ energy storage units organized in an $m \times n$ regular array, meaning that there are m modules connected in series and n units connected in parallel for each module. Each of the units can be any type of battery cell or ultracap. The design-time optimization needs to decide the numbers m, n, the unit type $q_{i,j} \in Q$, the unit size $s_{i,j}$ for each i, j, such that the ESS cost is minimized while satisfying the usage demand for a target lifetime.

Under a reasonable run-time control, it can be assumed that two units of the same type and of the sizes $s1$ and $s2$ connected in parallel is equivalent to one unit of the size $s1+s2$ in the same type. Therefore, we only need to consider an ESS with $n = |Q|$, that is, there is only one unit of each type in the parallel connection in each row. Such a setup does not prevent a solution without using any unit type, since a solution with $s_{i,j} = 0$ excludes type j unit in the ith row. Therefore, the unit type selection has been formulated into the unit sizing. Assume the cost function for type j unit with size s is $c_j(s)$, then the total cost of the ESS is given by

$$cost(\mathbf{s}) \triangleq \sum_{i=1}^{m} \sum_{j=1}^{n} c_j(s_{i,j}), \tag{1}$$

where $\mathbf{s}$ is the vector of all unit sizes. Normally, $c_j(s)$ is a linear function of s with constant offset, representing the setup cost of a unit no matter how small it is.

Let $\mathcal{S}$ be the set of all feasible assignments of the unit sizes, which normally contains lower- and upper-bounds for each size. Two probabilistic spaces $\mathcal{W}$ and $\mathcal{P}$ are introduced to model user-specific run-time driving patterns and manufacture tolerance induced process variation respectively. Assume some run-time control policy is enforced. At the end of the desired ESS lifespan, the aging of each unit, measured as the percentage difference of the remaining capacity and the initial capacity, is modeled by a function $A_{i,j} : \mathcal{S} \times \mathcal{P} \times \mathcal{W} \to [0,1]$. Let the initial power and energy capacity per unit size for type j be P_j and E_j respectively. Since the capacity of ESS is determined by the weakest module, the power and energy capacities of the ESS at the end of the lifespan are,

$$P^{ESS}(\mathbf{s}, w, p) \triangleq m \min_{1 \le i \le m} \sum_{j=1}^{n} s_{i,j}(1 - A_{i,j}(\mathbf{s}, w, p))P_j, \tag{2}$$

$$E^{ESS}(\mathbf{s}, w, p) \triangleq m \min_{1 \le i \le m} \sum_{j=1}^{n} s_{i,j}(1 - A_{i,j}(\mathbf{s}, w, p))E_j, \tag{3}$$

respectively.

For a particular user w, there are a set of conditions that need to be satisfied in order for the ESS to work correctly for the user-specific power usage demand $k_w(t)$ for the during $t \in [0, T]$.

- The ESS power capacity $P^{ESS}(\mathbf{s}, w, p)$ must be at least the maximal power demand $P^d(w) \triangleq \max_t k_w(t)$.
- The ESS energy capacity $E^{ESS}(\mathbf{s}, w, p)$ must be at least the maximal energy demand $E^d(w) \triangleq \int_0^T k_w(t)dt$.
- For each unit to be efficiently used, an upper-bound $\eta \in (0, 1)$ should be enforced on the percentage-wise aging of every units.

Based on the above discussion, the following *Hybrid ESS Design Optimization* (HEDO) problem can be formulated intuitively to determine the sizes of the ESS units in order to meet a specific statistical yield guarantee at a minimum cost.

PROBLEM 1 (HYBRID ESS DESIGN OPTIMIZATION). *Given the battery unit types, prices, and aging models, as well as the user driving profiles and the process variations of the units. Let δ be the statistical yield guarantee. The Hybrid ESS Design Optimization (HEDO) problem is formulated as follows:*

$$\begin{aligned} \textit{Minimize} \quad & \textit{cost}(\mathbf{s}) \\ \textit{s.t.} \quad & \Pr[P^{ESS}(\mathbf{s}, w, p) \ge P^d(w) \\ & \wedge E^{ESS}(\mathbf{s}, w, p) \ge E^d(w) \\ & \wedge A^{ESS}(\mathbf{s}, w, p) \le \eta] \ge \delta, \qquad \mathbf{s} \in \mathcal{S}, \end{aligned} \tag{4}$$

where $A^{ESS}(\mathbf{s}, w, p) \triangleq \max_{1 \le i \le m, 1 \le j \le n} A_{i,j}(\mathbf{s}, w, p)$ is the worst aging among all ESS units, and the probability is taken over all $w \in \mathcal{W}$ and $p \in \mathcal{P}$.

3.B Risk-Aversion Hybrid ESS Design Optimization

To solve the HEDO problem as formulated in the previous section is challenging. First, because the problem is not necessarily convex even when there are guarantees of the convexity of the individual terms, a local optimal solution is not necessarily a global optimal solution. Second, there is no guarantee that HEDO does have a feasible solution. Moreover, since any ESS failed during the designated ESS lifespan should be serviced at the cost of the manufacturers, it is preferable to optimize also for the failures. The above issues can be addressed by introducing a risk-aversion coherent measure [15]. Based on this measure, the HEDO problem can be reformulated as a two-stage stochastic programming problem with fixed recourse [8, 21]. Details follow.

Instead of explicitly computing the system yield at the end of the ESS lifespan, we introduce a random variable on the joint probabilistic space of driving patterns and process variations to represent the violations of the ESS constraints, such that the tail beyond 0 is the risk of failures within the ESS lifespan. Formally, this random variable takes the following quantity $V^{ESS}(\mathbf{s}, w, p)$ for a specific corner (w, p) within the joint probabilistic space,

$$\begin{aligned} V^{ESS}(\mathbf{s}, w, p) \triangleq \max \Big(& \beta_P \big(P^d(w) - P^{ESS}(\mathbf{s}, w, p)\big), \\ & \beta_E \big(E^d(w) - E^{ESS}(\mathbf{s}, w, p)\big), \beta_A \big(A^{ESS}(\mathbf{s}, w, p) - \eta\big) \Big). \end{aligned} \tag{5}$$

Here β_P, β_E, and β_A are positive weights to set preferences over individual constraints. To simplify the presentation, we assume $\beta_P = \beta_E = \beta_A = 1$ hereafter.

Eq. (5) is actually the so-called *fixed recourse* within the second stage of the two-stage stochastic programming optimization framework. The optimal $\mathbf{s}$ sizing depends not only on the decision made at design time but also on the uncertainty of process variations at manufacture-time and of driving patterns at run-time. To determine the best $\mathbf{s}$ is therefore separated into two stages as suggested by the name of the optimization framework. In the first stage, a decision of $\mathbf{s}$ is made and will incur an initial cost (not necessarily the ESS cost, and will be 0 in our problem formulation). In the second stage, the uncertainty (w, p) is realized and a second stage cost relevant to the risk is determined from both $\mathbf{s}$ and (w, p) through the known deterministic relation Eq. (5). Note that since the output of the second stage is random, a measure that maps the distribution of the second stage output to a real value must be chosen so that a decision in the first stage can be made to minimize the total cost of the two stages.

Rockafellar [15] proposed to use coherent measures in order to obtain preferred properties for optimization, i.e. convexity, for the whole problem, from that of the second stage deterministic relation, and showed that a risk-aversion measure called *conditional value-at-risk* is actually coherent, which is defined as follows. Let X be a random variable. For a risk aversion level α, the value-at-risk $\mathrm{VaR}_\alpha[X]$ is first defined as the value satisfying that $P(X \le \mathrm{VaR}_\alpha[X]) = \alpha$, or in other words the value to achieve the yield α. The conditional value-at-risk $\mathrm{CVaR}_\alpha[X]$ is defined as the average of the $1-\alpha$ tail, i.e. $\mathrm{CVaR}_\alpha[X] \triangleq \mathrm{E}\big[X | X > \mathrm{VaR}_\alpha[X]\big]$.

We reformulate the HEDO problem into the *Risk-Aversion Hybrid ESS Design Optimization*(RA-HEDO) problem leveraging the two-stage stochastic programming optimization framework with fixed-recourse and the conditional value-at-risk measure as follows.

Problem 2 (Risk-Aversion HEDO). *Given the battery unit types, prices, and aging models, as well as the user driving profiles and the process variations of the units. Let α be the risk-aversion level and C be the ESS cost upperbound. The Risk-Aversion Hybrid ESS Design Optimization (RA-HEDO) problem is formulated as follows:*

$$\begin{aligned} \textit{Minimize} \quad & \mathrm{CVaR}_\alpha[V^{ESS}(\mathbf{s}, w, p)] \\ \textit{s.t.} \quad & \textit{cost}(\mathbf{s}) \le C, \mathbf{s} \in \mathcal{S}. \end{aligned} \tag{6}$$

Roughly speaking, the constraint for yield and the ESS cost are exchanged in the HEDO problem to formulate the RA-HEDO problem. The risk-aversion level α plays a similar role as the yield guarantee δ. To minimize $\mathrm{CVaR}_\alpha[V^{ESS}]$ would be of high fidelity to improve the yield. In addition, while the HEDO problem could be infeasible, the RA-HEDO problem is always feasible and one can sweep the cost upperbound C to obtain the curve to trade-off the statistical yield guarantee with the ESS cost.

3.C Solving the RA-HEDO Problem

We show in this section that under mild assumptions, the RA-HEDO problem is convex and can be solved efficiently using convex programming techniques.

Since normally $\textit{cost}(\mathbf{s})$ is an affine function of $\mathbf{s}$, and $\mathcal{S}$ contains lower- and upper-bounds for each size, we have the proposition concerning the convexity of the feasible region.

Proposition 1. *The feasible region of the RA-HEDO problem is convex.*

Moreover, the aging of the units in ESS satisfies that,

Proposition 2. *For any given driving pattern w, process variation p, and i, j, both $A_{i,j}(\mathbf{s}, w, p)$ and $s_{i,j}A_{i,j}(\mathbf{s}, w, p)$ are convex functions of* $\mathbf{s}$.

Intuitively, Proposition 2 holds due to the diminishing marginal returns of the increasing unit sizes to the reduction in aging. When the sizes of the ESS units increase, the ESS internal power consumption decreases because the effective ESS internal resistance decreases. Therefore, the temperature across the whole ESS decreases and so does the aging of each unit. However, the reduction in aging diminishes as the sizes increases further more, and both $A_{i,j}(\mathbf{s}, w, p)$ and $s_{i,j}A_{i,j}(\mathbf{s}, w, p)$ are convex functions of $\mathbf{s}$.

Based on Proposition 2, we first show that $V^{ESS}(\mathbf{s}, w, p)$ is a convex function of $\mathbf{s}$ for any given driving pattern w and process variation p. We may choose to omit the symbols w and p for the conciseness of the presentation whenever there is no confusion. According to Eq. (5) and the definitions for P^{ESS}, E^{ESS}, and A^{ESS}, the V^{ESS} can be obtained by computing the maximum of the violations in ESS constraints. Let $P_i^{sub}(\mathbf{s})$, $E_i^{sub}(\mathbf{s})$, and $A_{i,j}^{sub}(\mathbf{s})$ be the subgradients of $P_i^M(\mathbf{s})$, $E_i^M(\mathbf{s})$, and $A_{i,j}(\mathbf{s})$ with respect to $\mathbf{s}$ respectively. Define

$$V^{sub}(\mathbf{s}) \triangleq \sum_{i=1}^{m} \Big(\sum_{j=1}^{n} A_{i,j}^{sub}(\mathbf{s}) - P_i^{sub}(\mathbf{s}) - E_i^{sub}(\mathbf{s}) \Big). \tag{7}$$

Applying Proposition 2 and introducing the a Lagrange multiplier for each constraint, we have proved that,

Lemma 1. *$V^{ESS}(\mathbf{s}, w, p)$ is a convex function of $\mathbf{s}$ with the subgradients $V^{sub}(\mathbf{s}, w, p)$.*

We will then show that the objective function of the RA-HEDO problem $\mathrm{CVaR}_\alpha[V^{ESS}(\mathbf{s}, w, p)]$ is convex based on Lemma 1. Given a risk aversion level α, let $I(\mathbf{s}, w, p)$ be 1 if $V^{ESS}(\mathbf{s}, w, p) \ge \mathrm{VaR}_\alpha[V^{ESS}(\mathbf{s}, w, p)]$ and 0 otherwise. We have proved that,

Lemma 2. *$\mathrm{CVaR}_\alpha[V^{ESS}(\mathbf{s}, w, p)]$ is a convex function of $\mathbf{s}$ with the subgradients $\frac{1}{1-\alpha}\mathrm{E}\big[I(\mathbf{s}, w, p)V^{sub}(\mathbf{s}, w, p)\big]$.*

Therefore,

Theorem 1. *When Proposition 1 and 2 hold, the RA-HEDO problem is a convex programming problem.*

Since the subgradients of the objective function are known according to Lemma 2, we can solve the RA-HEDO problem using Kelley's cutting-plane method [9]. In practice, since $P_i^M(\mathbf{s}, w, p)$, $E_i^M(\mathbf{s}, w, p)$, and $A_{i,j}(\mathbf{s}, w, p)$ are obtained by simulations, we can compute the subgradients of the cost function $\mathrm{CVaR}_\alpha[V^{ESS}]$ by approximating them with the finite differences. We rely on the statistical aging analysis technique introduced in the next section to compute $\mathrm{CVaR}_\alpha[V^{ESS}]$efficiently for each $\mathbf{s}$ by obtaining the distribution of $V^{ESS}(\mathbf{s}, w, p)$.

3.D Statistical Aging Analysis with Generalized Stochastic Collection Method

With fabrication process variations and driving behavior variations, the ESS aging is a random variable dependent on the basic random variables. We use $\vec{\xi}$ to represent the basic independent random variables (i.e. (w, p)) with arbitrary distributions. Given a sample point composed of a specific value for each basic random variable, the aging effect of the system can be calculated through our model presented in [11]. To compute the aging distribution is more complicated. Monte Carlo simulation can be used but incurs a huge computation time. We employed the generalized stochastic collection method with sparse grid technique [23, 20] to improve the efficiency of the statistical aging analysis.

The statistical aging distribution is first approximated by generalized polynomial chaos (gPC) as follows,

$$V(\vec{\xi}) \approx \hat{V}(\vec{\xi}) \triangleq \sum_{i_1+\ldots+i_N=0}^{M} v_{i_1,\ldots i_N} H_N^{i_1,\ldots,i_N}(\vec{\xi}), \tag{8}$$

where V is the exact distribution (i.e. $V^{ESS}(\mathbf{s})$) while $\hat{V}$ is the approximated one, N is the number of basic random variables, M is the highest order of the polynomial, $H_N^{i_1,\ldots,i_N}(\vec{\xi})$ represents the N-dimensional polynomial chaos, and $(i_1 + \ldots + i_N)$ is its order. The coefficients $v_{i_1,\ldots i_N}$ will be estimated by equating distribution V and the polynomial chaos (8) at a set of collocation points in the measure space, which can be computed through multi-dimensional integrals. We use the sparse grid technique [23] to compute these integrals. Compared with the direct tensor product scheme [22], the sparse grid technique can significantly reduce the number of collocation points. Furthermore, it is established in [14] that sparse grid is exact for d-dimensional polynomials of order up to $(2k+1)$. The number of collocation points in the sparse grid method is about $\frac{2^k}{k!}d^k$. Compared with the direct tensor product scheme having $(k+1)^d$ sample points, sparse grid technique avoids the exponential computation cost in terms of the dimensionality [14].

3.E Run-Time Control Consideration in Design Optimization

The proposed design and optimization flow takes the run-time ESS control policies into consideration, which determines the actual ESS run-time use. More specifically, to minimize the overall ESS cost, ESS design only targets the majority manufacture and run-time usage profiles and ensures statistical lifetime guarantee. It is the run-time controller's responsibility to dynamically manage the ESS use based on individual user's driving profile, and provide ESS lifetime guarantee and optimize run-time ESS efficiency. Considering the run-time control in the design optimization provides another flexibility and increases the design space, improving the solution quality while introducing more challenge in optimization.

We consider the hybrid Li-ion–ultracap ESS integration, where each ESS row consists of both Li-ion units and ultracap units. The design rationale is to leverage ultracap's high power density feature to support run-time high peak power demand, and Li-ion's high energy density feature to satisfy the stringent energy capacity requirement. The run-time power demand is split into low-frequency and high-frequency components via run-time filtering conducted by battery manage system. Energy capacity (peak power) demand is mainly contributed by the low (high) frequency components, and is thus distributed to Li-ion (ultracap) units. This hybrid design is also essential to minimize Li-ion battery run-time aging, as the high-frequency components, if handled by Li-ion units, will cause serious battery heating and aging. At run-time, the cutoff frequency is further dynamically controlled based on user-specific driving patterns.

Besides the process variation and the user drive profiles, our statistical optimization engine also considers the cutoff frequency. It computes the best cutoff frequency for each user profile that will entail the minimal yield loss, and use it for statistical optimization.

4. Experimental evaluation

This section evaluates the proposed ESS design and optimization framework using physical measurement data of battery manufacture variations and real-world user driving profiles. The proposed solution conducts statistical optimization to effectively and quickly explore the statistical ESS design space and generate cost-efficient hybrid ESS solutions with statistical lifetime guarantee. For instance, targeting 15-year lifespan, compared against the worst-case based Li-ion only ESS design, the produced hybrid ESS solutions reduce the system cost on average by 57.0% with only 10% yield loss.

4.A Experimental setup

We first summarize the experimental evaluation settings.

Battery manufacture induced variation: We conducted measurement on 30 Li-ion battery modules used in a PHEV. The nominal energy capacity of each battery module is 8.32 Wh. These battery modules were operated under the same condition. Overall, manufacture variation combined with aging introduced over 40% capacity variation among these 30 battery modules. The manufacture variation is extracted using polynomial regression method and integrated with ESS analysis.

User driving profile: We have conducted a set of driving studies using converted Toyota PHEVs. Overall, ten studies have been conducted and the daily commute driving patterns along with the ESS run-time charge–discharge current profiles were recorded with second-scale time resolution. Our evaluations also leverage the large-scale kansas city user driving studies, which collected user daily commute driving behavior with second-scale resolution [18]. Using the Kansas city driving profile as input, we use PSAT PHEV vehicle model [10] to estimate second-scale ESS charge–discharge profile. Overall, the following studies include 100 user-specific ESS usage profiles, with 19.95 A current on average and 9.80 A variance, and 0.75 hour per day driving duration on average and 0.56 hour variance.

Types and costs of ESS units: Two types of ESS units are used: Li-ion battery and ultracap. The same type of ESS units have the same initial size. The cost of Li-ion battery is \$1 per Wh and the cost of ultracap is \$30 per Wh [1].

Running time analysis: The following studies were conducted on a workstation with a 1.4 GHz Intel processor and 2 GB of memory. Overall, the proposed design and optimization flow with builtin ESS modeling is highly efficient, with a running time of 3.4 seconds on average and 5.5 seconds maximum for each design specification.

4.B Hybrid ESS Statistical Design Optimization

First, we evaluate the performance of the proposed design and optimization flow. For each design specification, the proposed solution yields the following two types of ESS designs with minimum cost – (1) hybrid ESS design integrating Li-ion and ultracap, and (2) Li-ion only ESS design. The ESS design specifications target (i) 15-year ESS lifespan; (ii) three settings of the required ESS remaining capacity from 70% to 90% with a stepping of 10%, and (iii) three settings of the statistical system yield guarantee from 80% to 100% with a stepping of 10%. Therefore, a total number of $2 \times 3 \times 3 = 18$ ESS configurations are considered.

We present the aforementioned 18 configurations in Figure 2. The subfigure on the left shows the 18 configurations targeted at the same lifespan, which are then organized into 9 pairs of bars to facilitate the comparison between Li-ion only and hybrid ESS. The 9 pairs of bars are further clustered into 3 groups, one for each of the three remaining capacity (RC) settings. The 3 pairs of bars within each group are sorted according to the statistical system yield guarantee. While the height of each bar corresponds to the ESS cost for the subfigures on the left, the cost of a hybrid ESS configuration is decomposed into the cost of Li-ion battery and the cost of ultracap, as shown in the subfigures on the right.

These studies demonstrate that the ESS cost increases substantially when the targeted statistical system yield guarantee increases. At a yield guarantee of 100%, it is equivalent to the deterministic optimization that targets at the worst-case scenarios of both the ESS manufacture process variations and the driving patterns (i.e., ESS run-time use) to meet a particular remaining capacity requirement. Therefore, the proposed statistical ESS design optimization greatly reduces the ESS cost with carefully controlled yield loss in comparison to worst-case design optimizations. Quantitatively, for Li-ion only ESS, average ESS cost reductions of 43.1% and 17.1% are observed for every 10% yield loss from 100% to 80%; for hybrid ESS, the reductions are 51.2% and 16.6% for every 10% yield loss.

These studies also demonstrate the advantages of hybrid energy storage technology integration. Through the incorporation of Li-ion battery and ultracap, two complementary energy storage technologies, the overall ESS cost can be reduced substantially. Of all the 9 hybrid design specifications studied, hybrid ESS design achieves a maximum reduction of 38.5%, a minimum of reduction of 34.6%, and an average

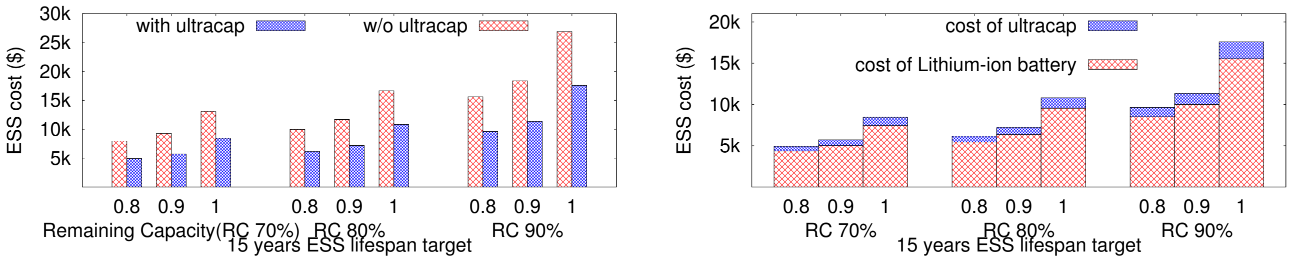

Figure 2: ESS system cost under different yield constraints. The cost is subject to a maximum $50,000 cost constraint.

reduction of 37.2% in terms of the ESS cost, compared with Li-ion only ESS design.

These studies demonstrate the performance of the proposed ESS design and optimization flow. Overall, compared against the worst-case based Li-ion only ESS, the produced hybrid ESS designs reduce the system cost on average by 57.0% with only 10% yield loss.

5. Conclusions

This article presents an integrated design and optimization framework for (P)HEV energy storage technology and system integration, a foremost design challenge of emerging transportation electrification. The proposed design and optimization flow is driven by an accurate and fast ESS modeling and analysis solution. It targets hybrid energy storage technology integration, allowing an optimal integration of complementary energy storage technologies, i.e., Li-ion battery and ultracap, during ESS design and optimization. It conducts statistical optimization to efficiently address the ESS manufacture and run-time usage variances. The proposed work is evaluated using physical measurements of battery manufacture variation and real-world user driving profiles. Our experimental study shows that, the proposed solution can effectively explore the system design space and produce low-cost and reliable (P)HEV energy storage solutions.

6. References

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