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Simultaneous Design and Control Optimization of a Series Hybrid Military Truck

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Abstract

This paper investigates the fuel saving potential of a series hybrid military truck using a simultaneous battery pack design and powertrain supervisory control optimization algorithm. The design optimization refers to the sizing of the Lithium-ion battery pack in the hybridized configuration. On the other hand, the powertrain supervisory control optimization finds the most efficient way to split power demands between the battery pack and the engine. Most of the previous literatures implement them separately. In contrast, combining the sizing and energy management problem into a single optimization problem produces the global optimal solution. This study proposes a novel unified framework to couple Genetic Algorithm (GA) with Pontryagin's Minimum Principle (PMP) to determine the battery pack sizing and the power split control sequence simultaneously. As GA and PMP are global optimization methodologies under suitable conditions, the results can be regarded as benchmark results for the application under study. Military drive cycles were further applied under the simultaneous optimization framework to evaluate the impact of different driving conditions.

Introduction

The challenges for military vehicles include the increasing power and energy needs for superior dynamic performance, reliable power exportability and durable silent watch capability. The fuel efficiency of military vehicles has always been the focus since the fuel cost can be as high as $100/L in the battlefield [1]. Powertrain hybridization is a common technology for passenger and commercial vehicles to achieve significant fuel efficiency improvement. The hybrid electric vehicle (HEV) combines multiple power sources onboard and enables several fuel-saving functions, such as regenerative braking, engine idling elimination and engine operating region shift. However, the deployment of military HEVs is still under active research due to challenges such as reliability in complex operating and environmental conditions [2]. A systematic research on the optimal design and control of military HEV considering various military driving conditions and unique military operating requirements must be carried out for a path forward.

The HEVs, comprised of series, parallel and power-split topologies, introduce alternative energy storage devices and power electronics. A high-level supervisory energy management strategy (EMS) manages the power flows among different power sources at any instance for certain objectives (maximized fuel efficiency or minimum tailpipe emission) under appropriate constraints (satisfactory drivability and component specifications) [3]. Two main research questions for HEVs are the optimal sizing of the added components and the optimal control of power flows, which have been often discussed but in a separate manner.

There are a variety of optimization algorithms available for the design of HEV with fixed EMS. As the design space of an HEV involves many local minima, gradient-based algorithms such as sequential quadratic programming (SQP) is disadvantageous in finding the global minima. In contrast, gradient-free algorithms have drawn much attention for the HEV design optimization because they tend to search the entire design space for the global solutions. Popular candidates consist of DIRECT, Simulated Annealing (SA), Genetic Algorithm (GA) and Particle Swarm Optimization (PSO). They were evaluated in [4] to find the optimal HEV design variables, including the battery pack sizing, engine power rating, motor power rating and battery cell operating State-of-Charge (SOC) limits. A similar performance in fuel consumption minimization was attained indicating the usefulness of all four optimization algorithms.

The EMSs for HEVs can be classified as optimal and sub-optimal strategies. The optimal EMSs can be obtained for off-line benchmarking given the a-priori information of drive cycles. In a real-time setting, only sub-optimal EMSs can be implemented since future driving conditions are unknown. In the category of optimal off-line strategies, the Dynamic Programming (DP) based on Bellman's principle of optimality can guarantee the global optimal solution by searching through all possible power trajectories; the Pontryagin's Minimum Principle (PMP) is a general case of the Euler-Lagrange equation in the calculus of variation and considers the optimality of a single trajectory with only necessary conditions for the global optimal solution [5]. In the context of HEV, its basic idea is to find the optimal trajectory of the so-called co-state to associate the electrical energy usage to future fuel consumption in the form of Hamiltonian function, which must be minimized at each time instant. With a-priori information of the drive cycle, PMP is freed from the curse-of-dimensionality and thus subject to much less computational burden compared to DP. The other category contains the sub-optimal strategies, for example, the rule-based strategy and the equivalent consumption minimization strategy (ECMS). The rule-based ones feature heuristic conditions for the coordination of power sources, similar to direct translation of natural languages [6, 7]. The ECMS, which is a real-time realization of the PMP, requires the calibration of the equivalence factor (an approximation of the co-state in PMP) in the form of piecewise constant function [8, 9].

However, the design and control optimization problem must be solved in a unified framework to explore the maximum potential of fuel efficiency improvement in the hybrid configuration. In previous literature [10, 11], the strategies to combine both design and control optimization for HEVs have been grouped into sequential, iterative and simultaneous ones. Both the sequential [12] and iterative [13] strategies decouple the HEV design and control optimization problem. The iterative ones optimize the plant with the fixed controller, then optimize the controller with the fixed plant, and so on until convergence. While the sequential and iterative optimization strategies generally fail to achieve the global optimal results, the simultaneous strategies which vary the design and control parameters at the same time have been merged and discussed widely. In [14, 15, 16], GA and rule-based EMS were integrated for simultaneous optimization. The authors of [17] instead studied the cooperation of PSO and rule-based EMS. The drawbacks are obvious because rule-based EMS is inherently sub-optimal and usually introduce many control parameters for tuning. Otherwise, GA and PSO have been combined with DP for optimal sizing and control strategies for HEV [18, 19]. Yet the computational intensity of DP adds up sharply as the number of design and control parameters increases. Recently, the efficient convex programming (CP) has been adopted in [11, 20] for simultaneous design and control optimization, yet the model requires a large amount of simplification into convex forms. A similar approach to the one in this study combines GA and ECMS in [21], yet detailed problem formulation was not defined and the inherent sub-optimality of the ECMS is an issue.

This study proposes the novel integration of GA and PMP for simultaneous design and control optimization of a military hybrid electric truck. The design variables of the battery pack (the number of cells in series and the number of cells in parallel) and control variable of the PMP (the co-state) are optimized in the GA routine for global minimum fuel consumption. An electro-thermal model is identified with data from the experimental study to represent the battery cell. Several military drive cycles are used in the study for the evaluation of the impacts of real-world driving conditions.

In following sections, the vehicle and the components will be reviewed first. The PMP, the GA, and the scheme of their integration will then be introduced. The results of simultaneous optimization of the battery pack design variables and the PMP control variable are reported before conclusions are finally made.

Vehicle Model Description

This study uses a series hybrid Mine-resistant Ambush-protected all-Terrain Vehicle (M-ATV) from [22], of which specifications are compiled in Table 1. The series hybrid electric vehicle (SHEV) configuration comprises a genset (Navistar 6.4 L 260 kW diesel engine +265 kW generator), four 95 kW brushless permanent magnet direct current (BLPMDC) motors, a battery pack with nickel manganese cobalt (NMC) lithium-ion cells, as shown in Figure 1 (top). A forward-looking simulator was set up in Simulink to model the power flow in Figure 1 (bottom), of which a virtual "driver" in the form of PID controller takes in the speed trace following error to calculate the propulsion power. The genset and the motor are represented by their quasi-static efficiency maps.

The NMC lithium-ion cell is described by an electro-thermal model. A second-order electric equivalent circuit model (ECM) models the voltage response in Figure 2, of which equations are listed from Eq. (1) to Eq. (3). The nominal capacity Q_{nom} can be referred to the manufacturer specification in Table 1. The terminal voltage response V_{cell} based on a hybrid pulse power characterization (HPPC) test current profile I_{cell} was obtained in the Battery Aging and Characterization (BACh) Laboratory at the Automotive Engineering Department, Clemson University. The open circuit voltage E_0 was measured by a C/20 low current rate discharge capacity test. Then the electrical parameters C_1, R_0, R_1 were fit as functions of SOC for discharge and charge scenarios under different temperatures (23 °C and 45 °C). The comparison between the predicted and the measured voltage is displayed in Figure 3. It shows that ECM captures the cell dynamics well under both temperatures, confirmed by the small values of root mean squared (RMS) error.

$$\dot{V}_c = -\frac{V_c}{R_1 C_1} + \frac{I_{cell}}{C_1} \tag{1}$$

TABLE 1 Vehicle Specifications

Parameter	Unit	Value
Vehicle		
Total Weight	kg	14,023
Frontal Area	m^2	5.72
Aerodynamic Drag Coefficient		0.7
Rolling Resistance Coefficient		0.01
Tire Radius	m	0.59
Genset + Motor		
Engine Power	kW	260
Generator Power	kW	265
Motor Power	kW	4x95 = 380
Motor Rated Voltage	V	430
Battery		
Battery Pack Configuration		116S11P
Cell Mass	kg	0.045
Cell Nominal Capacity	Ah	2
Cell Nominal Voltage	V	3.7 V
Cell Discharge Current/Voltage Limit	A/V	30/2.5
Cell Charge Current/Voltage Limit	A/V	12/4.2

FIGURE 1 The SHEV configuration (top) and the power flow (bottom)

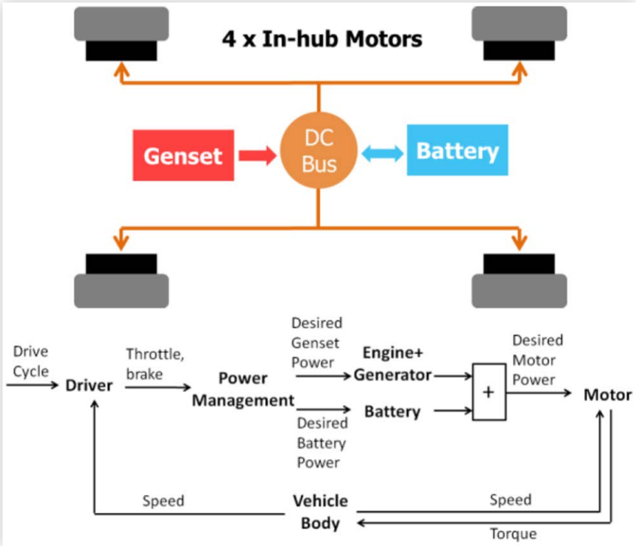
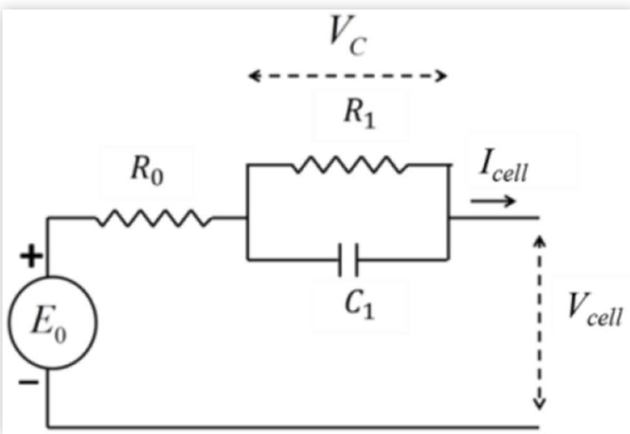


FIGURE 2 The 1st order electric ECM of battery cell



$$S\dot{O}C = -\frac{I_{cell}}{Q_{nom}} \tag{2}$$

$$V_{cell} = E_0 - R_0 I_{cell} - V_c \tag{3}$$

A two-state model is constructed as in [23] to describe cell thermal dynamics and summarized from Eq. (4) to (6). The surface temperature T_s and the core temperature T_c of the cell were measured according to a customized current profile. The heat conduction resistance R_c, the heat convection resistance R_u, the heat capacity of the cell core C_c, the heat capacity of the cell casing C_c are identified. The variable Q refers to the heat generation. The comparison between the thermal model response and experiment in Figure 4 shows that the thermal model captures the cell thermal dynamics well.

$$C_c \frac{dT_c}{dt} = Q + \frac{T_s - T_c}{R_c} \tag{4}$$

$$Q = \left(E_0 - V_{cell}\right) \cdot I_{cell} \tag{5}$$

FIGURE 3 For the input current in the top plot, the comparison of the cell voltage responses between the ECM and the experimental data under the HPPC test are shown for 23 °C (second plot) and 45 °C (third plot). Calculated RMS errors show that ECM can capture the measured cell dynamics well over the HPPC test length.

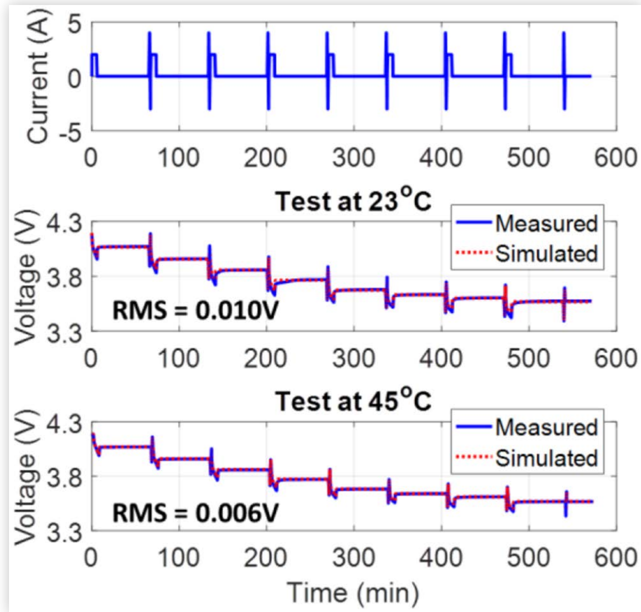
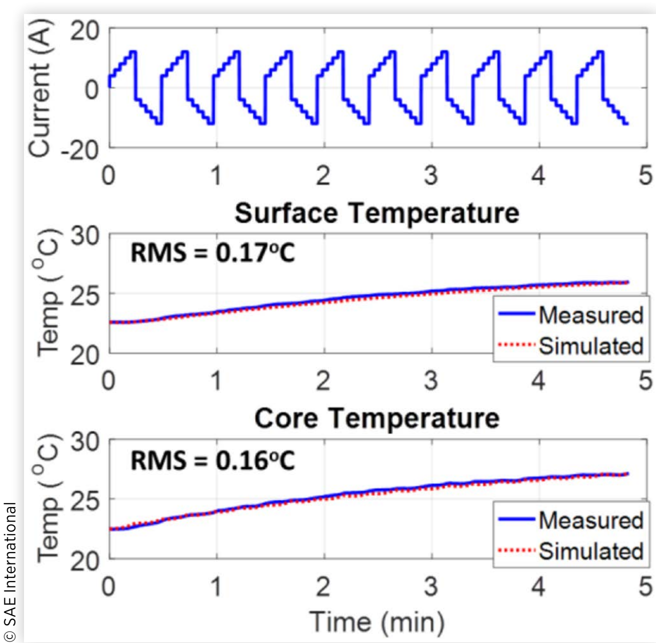


FIGURE 4 For the input current in the top plot, the cell surface temperature (second plot) and cell core temperature (third plot) is measured and also simulated using the fitted thermal model. Calculated RMS errors show that fitted thermal model can capture the measured core and surface temperature dynamics well over the test length. The experiment is started at the room temperature of 23 °C.



$$C_s \frac{dT_s}{dt} = \frac{T_f - T_s}{R_u} - \frac{T_s - T_c}{R_c} \tag{6}$$

Combined Optimal Design and Energy Management Problem

In this paper, the goal is to develop a unified framework to tackle, simultaneously, the design optimization problem and optimal energy management problem with application to military HEVs.

Traditionally, the optimal component sizing problem and the online energy management problem have been solved under a two-layer framework. On the outer layer, usually an exhaustive search or heuristic global search algorithm, such as GA, PSO, etc. is employed to randomly select a battery pack size. In the inner layer, an optimal energy management algorithm, such as DP, PMP, etc. is used to find the optimal energy split among different energy devices at every time step [18, 19, 21]. In [21], such a layered optimization algorithm is proposed where vehicle architecture, such as the number of the motor per axle, number of axles, size, and type of energy storage is considered as the design variables. It has six objective functions and fuel consumption minimization found through ECMS is one of them. ECMS is a heuristic approach and its performance is highly sensitive to the tuning parameters. A similar approach is proposed in [19], where GA is used in the outer loop for battery and supercapacitor sizing and DP is used in the inner loop to find the optimal power split between them. In these two-layer approaches, the interaction between the design parameters and control strategy is from top to bottom which results in a bi-level iterative process. Such a bi-level iterative process increases the computational time and complexity. The reason is, for such layered approach, multiple design strategies are visited and evaluated for which the control strategies might not be feasible in the first place. In this paper, a combined optimization framework and solution approach are proposed where control variables of the bottom level are optimized simultaneously with the design variables in the top level to minimize an objective function. In this combined approach, the Differential evolution algorithm (DE), a GA-based heuristic algorithm and the PMP are used together. PMP is suitable for such combined approach because of its structure. Unlike DP algorithm which suffers from the "curse of dimensionality", PMP can minimize a cost function by minimizing the Hamiltonian with less computation even for a large number of state variables. The next section describes a mathematical formulation of the design and optimal control problem.

Problem Formulation

In this work, the overall objective is to minimize the total fuel consumption over a given drive cycle over the time horizon $[0, t_f]$:

$$J = \int_0^{t_f} \dot{m}_{fuel}\left(P_{batt}(t)\right)dt \tag{7}$$

where $\dot{m}_{fuel}$ is the fuel mass flow rate (kg/s). In the SHEV configuration, $\dot{m}_{fuel}$ is a function of the instantaneous power demand from the battery pack, $P_{batt}(t)$. Assuming homogeneity in the battery pack, the power delivered from the pack can be expressed as a product of the number of Li-ion cells in a series string (N_s), number of parallel strings (N_p), and power delivered by a single cell ($P_{cell}(t)$) i.e., $P_{batt}(t) = N_s \cdot N_P \cdot P_{cell}(t)$.

$$J = \int_0^{tf} \dot{m}_{fuel}\left(N_s \cdot N_P \cdot P_{cell}(t)\right)dt \tag{8}$$

The PMP has been successfully used in the literature to solve the optimal power split problem in HEVs [5, 24]. Assuming that state of charge ($SOC(t)$) is the state variable and input power ($P_{batt}(t)$) is the control input, from PMP, a Hamiltonian function can be defined as follows [23],

$$H(t) = \dot{m}_{fuel}\left(P_{batt}(t)\right) + \lambda(t) \cdot \dot{SOC}\left(SOC(t), P_{batt}(t)\right) \tag{9}$$

where λ is the co-state. A zero-order equivalent circuit model of a Lithium-ion cell is used in the PMP to derive the state equation as following:

State dynamics:

$$\dot{SOC} = \frac{\partial H}{\partial \lambda} = -\frac{I_{cell}}{Q_{nom}} = \frac{E_0 - \sqrt{E_0^2 - 4R_0P_{cell}}}{2R_0Q_{nom}} \tag{10}$$

Co-state dynamics:

$$\dot{\lambda} = -\frac{\partial H}{\partial SOC} = -\frac{\partial \dot{SOC}}{\partial SOC} = -\frac{\partial}{\partial SOC}\left(\frac{E_0 - \sqrt{E_0^2 - 4R_0P_{cell}}}{2R_0Q_{nom}}\right) \tag{11}$$

In HEV charge sustaining operation, the SOC is usually constrained within a narrow window. Within that narrow range, the open circuit voltage (E_0) and the resistance (R_0) can be assumed as constant and SOC depends only on battery cell power (P_{cell}). Therefore, the co-state dynamics ($\dot{\lambda}(t)$) given in Eq. (11) becomes zero and the co-state $\lambda(t)$ is a constant which is unknown [5].

Charge sustainability:

$$SOC(t_0) = SOC(t_f) \tag{12}$$

Eq. (12) represents that ideally for a charge sustaining HEV, the final SOC is equal to the initial SOC.

For optimal power management in a charge sustaining HEV, the optimal battery power ($P_{batt}(t)$) needs to be found by minimizing the Hamiltonian function (Eq. 9) at each time step. In this paper, we combined battery pack design with the energy management problem (Eq. (13)) where the objective is to minimize the Hamiltonian at each time step for a given set of design (N_s, N_P) and control ($P_{cell}(t)$) variables. This proposed mathematical problem formulation combines the design and control variables to find a global solution.

$$\pi^* = \underset{\pi \in N_s^*, N_P^*, P_{cell}^*(t)}{argmin} H\left(N_s, N_P, P_{cell}(t), SOC(t), \lambda\right) \tag{13}$$

Subject to:

$$\text{State dynamics constraint}: \dot{SOC} = \frac{\partial H}{\partial \lambda} \tag{14}$$

$$\text{Co}-\text{state dynamics constraint}: \dot{\lambda} = 0 \tag{15}$$

Charge sustainability constraint:

$$SOC(t=0) = SOC(t=t_f) \tag{16}$$

Input power constraint:

$$N_s N_p\, P_{cell}(t) = P_{batt}(t) \tag{17}$$

SOC range constraint:

$$SOC_{\min}(t) \le SOC(t) \le SOC_{\max}(t) \tag{18}$$

Constraint on DC bus voltage for stable generation and motor operation:

$$V_{DC,BUS} \cdot 90\% \le N_s V_{Li,nominal} \le V_{DC,BUS} \cdot 110\% \tag{19}$$

Constraint on battery pack energy density:

$$E_{batt} \cdot 50\% \le N_s N_p\, E_{Li,nominal} \le E_{batt} \cdot 110\% \tag{20}$$

In the above constraints, $P_{cell}(t)$ and $P_{batt}(t)$ denotes the instantaneous power delivered by each cell and the whole pack, respectively. The nominal cell voltage and energy capacity is represented by $V_{Li,\,nominal}$ and $E_{Li,\,nominal}$, respectively. DC bus voltage, and energy capacity of the battery of the baseline vehicle is denoted as $V_{DC,\,BUS}$ and E_{batt}. Last two constraints allow small design variation of the baseline vehicle to search for optimal battery sizing and control solution.

Solution Method

For a given military drive cycle, the problem formulation described in Eq. (13)-(20) is used to find a global solution for minimum fuel consumption. A heuristic optimization algorithm named Differential Evolution (DE) is used to solve the fuel consumption minimization problem. Differential Evolution (DE) is a variation of GA where the real encoding of floating point numbers and the non-uniform crossover is used. DE is easier to tune compared to other evolutionary algorithms [25] and it is first proposed in [26]. In this work, a modified version of the DE algorithm similar to the one in [27] is used and applied to optimal battery pack design and control in military HEV. In the optimization framework, the decision variables are the number of cells in series (N_s), the number of cells in parallel (N_p), and the co-state (λ). Since λ is a measure of the cost of using electric energy from the battery, the optimal value of λ determines the optimal battery power ($P^*_{batt}(t)$) at each time step. At the beginning, an initial population is generated where each population member has a different combination of these three decision variables. Through crossover and mutation a larger population set is generated. If any population member violates the constraints in Eq. (16)-(20), that member is discarded and a new member is generated. The ideal charge sustaining constrain in Eq. (16) is relaxed and a population member is considered feasible if the final SOC is within 2% of the initial SOC. For each population member, the Hamiltonian function is minimized at every time step given the constraints of state and co-state dynamics in Eq. 15 and 15. From the optimal battery power ($P^*_{batt}(t)$) corresponding to the minimum value of the Hamiltonian, the total fuel consumption over the drive cycle for each population member is found using Eq. (8). Based on the fuel consumption of each member, a small set of population members are selected. The process is then repeated in the next generation until the stopping criteria is achieved. Then the best combination of decision variables with the minimum fuel consumption is selected. This global solution approach eliminates the need of solving a two-point boundary value problem iteratively [24] to find the optimal co-state. In Figure 5, the basic structure of differential evolution algorithm used in this paper is presented. The next subsection explains how the reasonable bounds on the number of cells in series (N_s), the number of cells in parallel (N_p), and the co-state λ are found from the constraints.

Bounds of Decision Variables

In the above problem formulation, the heuristic Differential Evolution algorithm has three decision variables, the number of cells in a series string (N_s), number of parallel strings (N_p) and the co-state (λ). Reasonable bounds for these three decision variables are necessary to effectively search for the optimal solution. The bounds should be determined based on the electrical system limitations and the vehicle dynamic performance requirements.

1. Battery pack voltage, which is equivalent to DC bus voltage, stays within [90%, 110%] of the rated voltage of the DC motor for reliable and safe operation. Thus the series cell number N_s must satisfy the inequality

FIGURE 5 The pseudo-code for differential evolution algorithm to solve combined design and energy management problem.

```
Initialize   Generate random population of N members.
Evaluate     Evaluate the objective function that needs to be
             minimized
             while constraint is violated
                  Discard that member and generate a new
                  feasible member.
             end
for generation = 1
    Crossover    Take N feasible parent members, generate N
                 feasible offspring.
    Mutation     Take 2N feasible members, generate 2N
                 feasible mutants by small perturbation.
    Evaluate     Calculate objective functions for each member.
    Selection    Sort the non-dominated members in fronts
                 based on objective functions and select N or
                 fewer members from the fronts.
    Increment generation = generation +1
    Initialize next generation with selected members.
end
Return N or fewer sets of optimal controller parameters.
```

constraint in Eq. (21). For a DC bus voltage of 429 V, the constraint on the number of cells in series can be expressed as follows:

$$104 \le N_s \le 128 \tag{21}$$

2. The energy capacity of the battery pack is assumed to vary within [50%, 110%] of the capacity of the original pack on baseline vehicle. This asymmetric inequality constraint, with more emphasis on smaller pack for economic concerns, is illustrated in Eq. (22). With nominal cell voltage, $V_{cell} = 3.7\ V$, nominal charge capacity, $Q_{nom} = 2\ Ah$, and energy capacity of the baseline battery pack, $E_{batt,\,pack} = 9867\ Wh$, the resulting constraint on the number of cells in series and number of parallel strings are given in Eq. (23).

$$E_{batt,pack} \cdot 50\% \le N_s \cdot N_p \cdot V_{cell} \cdot Q_{nom} \le E_{batt,pack} \cdot 110\% \tag{22}$$

$$667 \le N_s \cdot N_p \le 1466 \tag{23}$$

3. The values of the optimal co-state λ for military drive cycles are typically around 2.5 for the military HEV with the 116S11P battery pack in this study. So the feasible bound of λ is fixed between [0.1 10] for a wide-range search given in Eq. (24).

$$0.1 \le \lambda \le 10 \tag{24}$$

Results

The simultaneous design and control optimization routine was applied to the available military drive cycles, including DCE4 Convoy Escort, DCE5 Urban Assault, Churchville, Munson, Harford. As they inherently represent various driving conditions for military trucks, shown in Figure 6, the optimal design and control solutions can be evaluated across real-world scenarios. To investigate the efficacy of the simultaneous optimization routine, their results are compared against the ones found by solving PMP with the original battery pack. As shown in Figure 6, with either the original or the optimal battery pack, the vehicle can follow these military drive cycles well while respecting the PMP control optimization routine. Some cycle following errors sporadically happens where sharp acceleration power demands are requested, especially in artificial drive cycles composed of constant velocity or constant acceleration segments, such as Churchville, Munson, and Harford cycles. The results on simultaneous optimization of PMP control variable (λ) and battery pack sizing (N_s, N_p) are compiled in the "Optimal Pack" rows of the Table 2 for five military drive cycles. In comparison, the "Original Pack" rows collect the baseline cases in which only the λ is tuned with the fixed original battery pack sizing ($N_s = 116$, $N_p = 11$). It is clearly shown that decreased fuel consumption in the ranges of [2%, 5%] can be attained by simultaneously optimizing the design and control variables. Besides, several other findings can be derived and discussed as follows:

- The Munson cycle achieves the least fuel consumption decrease at 2%. Its long highway cruising period, which steadily allows the engine operation points around the most efficient zone ("sweet-spot"), may diminish the fuel saving potential of hybridization.
- The fuel efficiencies are all improved due to the simultaneous optimization routine, therefore, engine operating points must have moved into more efficient and thus higher power region. Referring to Figure 7, for the city-style DCE5 Urban Assault cycle, most engine operating points around low power region (between 1000 and 1300 rpm) are eliminated and should have been substituted into higher power region. In contrast, for the highway-style DCE4 Convoy Escort cycle and Harford cycle, the shift of engine operation takes place around the high power region (between 1400 and 1800 rpm).
- For all cycles, larger battery pack compared to the original pack in the baseline is found by the optimizer. Small variation in the baseline vehicle design allows the optimizer to pick a pack size and control strategy that produces minimum fuel consumption. And PMP co-state λ increases correspondingly, indicating that battery usage is actually discouraged. The suppressed battery usage may help push the engine operating points to higher power region, closer to the most efficient "sweet-spot". As pack size increases, the additional monetary

FIGURE 6 Five military drive cycles (blue) are simulated with the original battery pack using PMP for energy management (red dotted line) and also with the optimal battery pack using proposed combined design and control optimization approach (red dashed line). For all the drive cycles, the simulated vehicle velocity follows the drive cycles well which confirms the validity of the vehicle simulator.

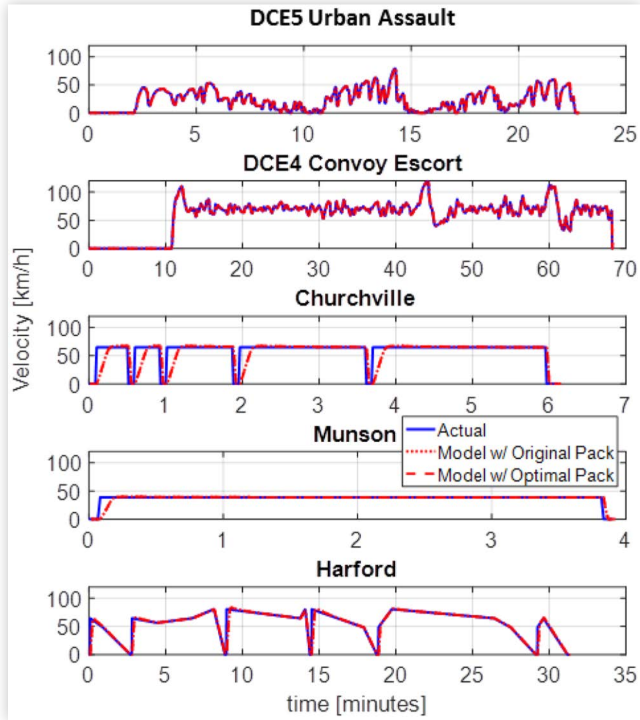


TABLE 2 Comparison between the original and optimized battery pack configurations in terms of the number of cells, co-states, and fuel consumptions for five military drive cycles. The proposed combined optimization framework finds the best battery pack configuration and the co-state to minimize fuel consumption within the vehicle design constraints.

	N_s	N_p	$N_s \cdot N_p$	λ	Fuel Consumption (L/100 km)
DCE5 Urban Assault					
Original Pack	116	11	1276	2.2710	**33.59**
Optimized Pack	112	13	1456	2.5960	**32.08 (−4.5%)***
DCE4 Convoy Escort					
Original Pack	116	11	1276	2.2918	**21.95**
Optimized Pack	109	12	1308	2.3299	**21.02 (−4.2%)**
Churchville					
Original Pack	116	11	1276	2.2380	**30.92**
Optimized Pack	110	13	1430	2.4052	**29.79 (−3.7%)**
Munson					
Original Pack	116	11	1276	2.0780	**9.49**
Optimized Pack	117	12	1404	2.2961	**9.30 (−2.0%)**
Harford					
Original Pack	116	11	1276	2.0270	**19.73**
Optimized Pack	113	12	1356	2.2881	**18.74 (−5.0%)**

cost needs to be evaluated over the efficiency gain for a discussion on feasibility.

- Since the objective function only considers the minimization of fuel consumption, a post-analysis of the battery usage is necessary and related statistics are compiled in Table 3. For each cycle, the mean values of cell current in discharge and charge periods are separately compared between "Original Pack" and "Optimized Pack" configurations. With larger optimized pack ($N_s \cdot N_p$) and co-state (λ), the battery usage on cell level becomes milder as discharge and charge currents both decrease in average. This may imply long-term benefits in terms of battery health by using the optimized pack.
- Beside average cell current statistics, the cell SOC profiles are also reviewed in Figure 8. Most SOC profiles are similar in terms of minimum SOC (SOC_{min}), maximum SOC (SOC_{max}), ΔSOC (SOC_{max} - SOC_{min}). However, the Harford cycle exhibits a much flatter SOC profile with the optimized pack. The decreased ΔSOC adds another potential benefit to long-term battery health.

The results in this study show that using a single energy storage technology as the baseline vehicle (NMC in this case) and allowing small variation in total energy storage capacity (10% more than the baseline), fuel efficiency can be improved

FIGURE 7 The engine operating points with the original and optimal battery pack on the engine BSFC map for DCE5 Urban Assault, DCE4 Convoy Escort and Harford drive cycles. The reduction in fuel consumption from the original battery pack to the optimized battery pack can be attributed to the shift of engine operating points toward the more efficient region.

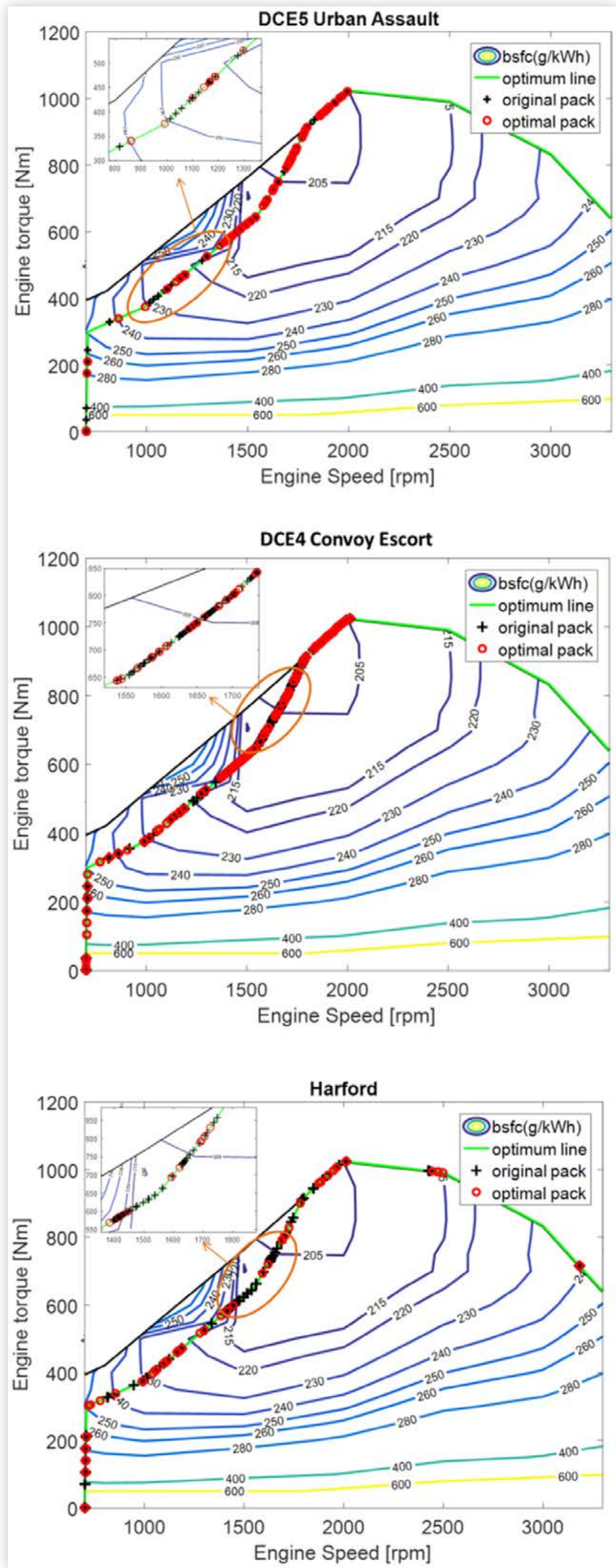
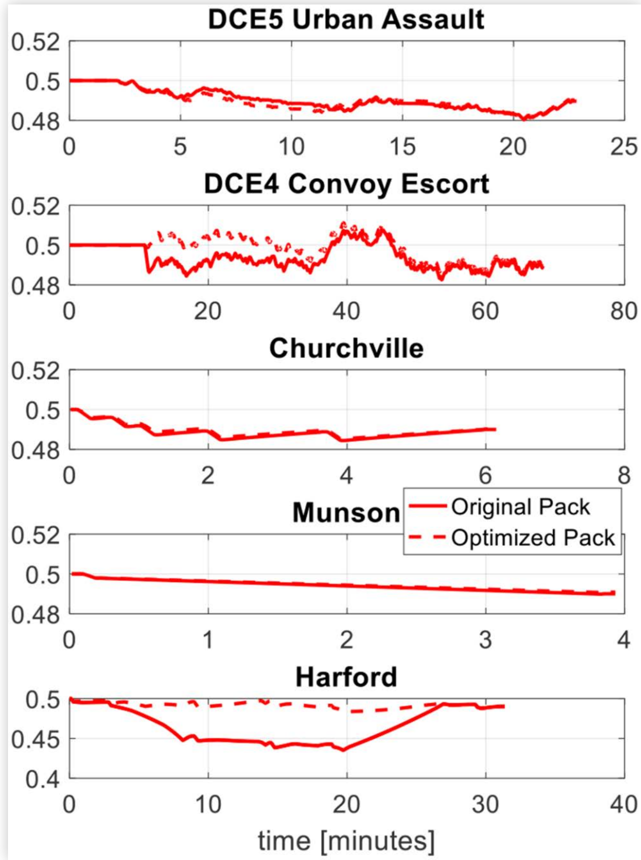


TABLE 3 Comparison between the original and optimized battery pack configurations in terms of average cell discharge and charge current for five military drive cycles. Reduction in average cell current from the original pack to the optimized pack can benefit the battery health in the long run.

	Total Cell Number $N_s \cdot N_p$	Average Cell Discharge Current (A)	Average Cell Charge Current (A)
DCE5 Urban Assault			
Original Pack	1276	**6.64**	**7.17**
Optimized Pack	1456	**6.08 (−8.4%)***	**7.11 (−0.8%)**
DCE4 Convoy Escort			
Original Pack	1276	**8.68**	**7.09**
Optimized Pack	1308	**8.05 (−7.3%)**	**6.63 (−5.8%)**
Churchville			
Original Pack	1276	**23.10**	**3.40**
Optimized Pack	1430	**20.88 (−9.6%)**	**2.95 (−13.2%)**
Munson			
Original Pack	1276	**3.29**	**7.97**
Optimized Pack	1404	**3.05 (−7.3%)**	**7.72 (−3.2%)**
Harford			
Original Pack	1276	**6.81**	**6.15**
Optimized Pack	1356	**5.83 (−14.4%)**	**2.34 (−62.0%)**

FIGURE 8 The battery SOC profiles in the original and optimized battery pack configurations for five military drive cycles. The optimal battery pack design and control policy produces less SOC variations compared to the original battery pack for all drive cycles, especially Hartford cycle.



from 2-5% depending on the drive cycle. These results confirm that the optimization algorithm presented in this paper is capable of finding the optimal size of the energy storage system and power management policy within the allowable design space for minimum fuel consumption. The results also show that lower fuel consumption is attained by adding more cells within the allowable design space. This confirms the general understanding that lower fuel consumption comes at a cost of higher initial investment of the battery pack when a single energy storage technology is used. These results inspire the provision of additional degrees of freedom, such as hybrid energy storage system in the optimization process. The optimization approach developed in this paper is general enough to include additional degrees of freedom for better fuel economy or additional objective functions.

To validate the dynamic capabilities of the hybrid electric military truck, both acceleration and grade tests were performed. However, there is an absence of standard performance requirements for military trucks according to [1]. The authors of [1] reviewed the previous literature and summarized that, for the medium-duty truck (gross vehicle weight between 4 and 9 tons), being capable to accelerate from 0 to 60 km/h in less than 22 seconds and traverse at least 20% grade is critical for military applications. These requirements are used to calibrate the dynamic performance of the hybrid electric M-ATV military truck in this study. The Figure 9 and 10 show the accelerating and grading performance of the truck with different battery packs in this study. The dynamic capability tests were performed under "sport mode", in which both genset and battery are used with their maximum power. In Figure 9, with the original battery pack from the baseline vehicle (N_s = 116, N_p = 11), the truck can accelerate from 0 to 60 km/h in about 11 seconds and overcome the 20% grade. In contrast, with the largest optimized battery pack (N_s = 112, N_p = 13) which is derived for the DCE5 Urban Assault drive cycle, the truck still meet the dynamic capability requirements as in Figure 10. The extra weight due to the larger battery pack degrades the acceleration performance of the truck, but only to a minor extent.

Summary

This paper proposes a simultaneous design and control optimization routine and applies it to a series hybrid military truck. The powertrain design and power management strategy both are optimized to utilize the maximum benefit from hybridization. Previous literature decoupled the design and control optimization problem by using either sequential or iterative optimization approaches. In this study, the co-state λ in the PMP optimal power management strategy is integrated into

FIGURE 9 The acceleration performance test, without grade (top plot) and with 20% grade (bottom plot) for the hybrid electric military M-ATV truck using the original battery pack (N_s = 116, N_p = 11). The truck achieves the 0~60 km/h acceleration time of 10.92 seconds and manages to overcome the 20% grade.

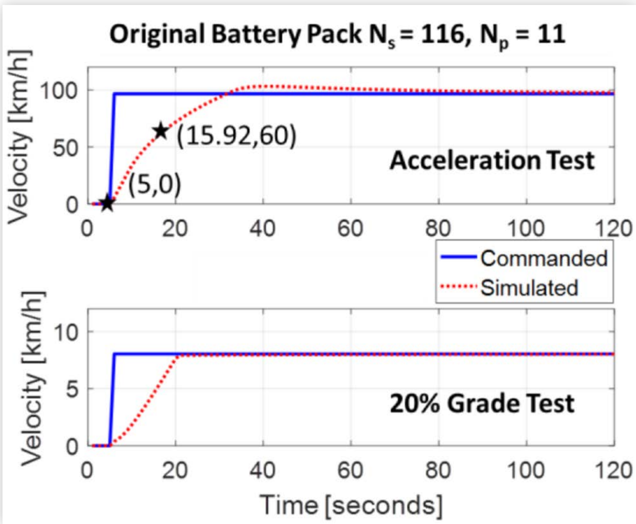
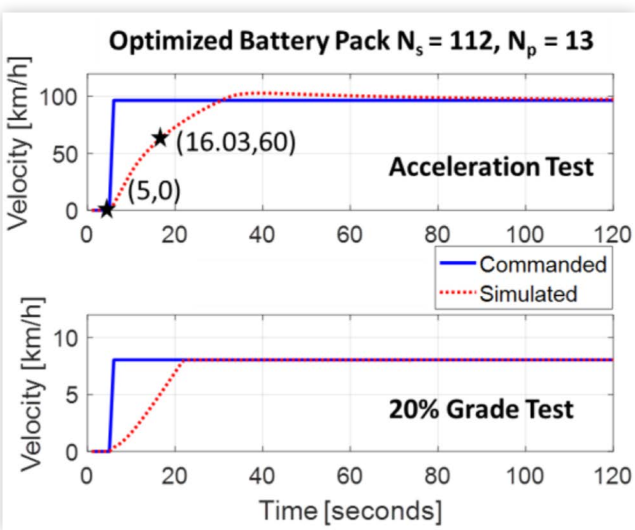


FIGURE 10 The acceleration performance test, without grade (top plot) and with 20% grade (bottom plot) for the hybrid electric military M-ATV truck using the largest optimized battery pack from Table 2 (N_s = 112, N_p = 13). The truck achieves the 0~60 km/h acceleration time of 11.03 seconds and manages to overcome the 20% grade.



the battery pack design optimization framework based on GA. Three variables, including co-state λ, number of battery cells in series and number of battery cells in parallel, are being optimized. The hybrid M-ATV military truck with the optimized battery packs can achieve 2-5% reduction in fuel consumption across different military drive cycles. The simultaneous optimization routine proposed in this paper produces larger battery packs compared to the original pack in the baseline powertrain. Moreover, the optimal battery pack size turns out to be dependent on the drive cycles. Consequently, the average current going in and out of the battery is lower than the one experienced by the battery in the baseline powertrain configuration. Such a reduction is beneficial for battery health in the long run. The optimal fuel efficiency obtained in this study cannot be fully achieved in real-time control applications due to the lack of a-priori drive cycle information. However, the optimization algorithm proposed here provides a benchmark against which online EMSs can be evaluated. For real-time implementation, it is possible to suitably adapt the co-state of the PMP as driving conditions change, and the general supervisory controller is referred to as adaptive optimal supervisory controller [28]. The simultaneous optimization framework in this study can be generalized to powertrain optimization problem with hybrid energy storage system.

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