

Design Optimization of a Hybrid Electric Vehicle Powertrain

Firdause Mangun, Moumen Idres and Kassim Abdullah

Department of Mechanical Engineering, Kulliyyah of Engineering, International Islamic University Malaysia, P.O. Box 10, 50728 Kuala Lumpur, Malaysia

midres@iium.edu.my

Abstract. This paper presents an optimization work on hybrid electric vehicle (HEV) powertrain using Genetic Algorithm (GA) method. It focused on optimization of the parameters of powertrain components including supercapacitors to obtain maximum fuel economy. Vehicle modelling is based on Quasi-Static-Simulation (QSS) backward-facing approach. A combined city (FTP-75)-highway (HWFET) drive cycle is utilized for the design process. Seeking global optimum solution, GA was executed with different initial settings to obtain sets of optimal parameters. Starting from a benchmark HEV, optimization results in a smaller engine (2 l instead of 3 l) and a larger battery (15.66 kWh instead of 2.01 kWh). This leads to a reduction of 38.3% in fuel consumption and 30.5% in equivalent fuel consumption. Optimized parameters are also compared with actual values for HEV in the market.

1. Introduction

Over recent years, many researchers are working to improve HEV technology especially regarding fuel economy. Among these improvements are downsizing of internal combustion engine, implementation of energy recovery system, addition of supercapacitors, implementation of optimal energy management strategy, and various parameter optimizations.

Design optimization of powertrain has significant impact on fuel economy. The main components of HEV powertrain are internal combustion engine, electric motor-generator, battery pack, and supercapacitors. A proper sizing of these components will result in better fuel economy and ensures maximum benefit of supercapacitor addition. This will lead to higher fuel economy, improvement of vehicle performance, and increases of battery life.

In order to achieve such proper sizing, optimization offers a reliable solution. It is capable of determining a set of best values to meet design objective. In this study, Genetic Algorithms (GA) method was utilized. To achieve global optimization, different settings such as; different objectives and different GA options are being considered.

Ceforolini [1] conducted dynamic programming (DP) optimization for determining the best topology for HEV. Many topologies were considered in order to compute its best fuel economy achievable. Then, overall fuel consumption of different topologies were compared to find best topology. Ceforolini [1] concluded that parallel HEV shows the lowest fuel consumption. Thus, this work is based on parallel HEV due to its fuel economy benefits. This probably resulted from smaller component sizes, and it also requires only one electric motor-generator (EMG).

Multidisciplinary optimization of a series HEV was considered by Fan [2]. Optimization includes both components sizing and power management logic. The objective is to find minimal amount paid by consumers for fuel, electricity and battery. The design variables are number of battery banks, state of charge (SOC) threshold and engine torque and its speed. Optimizations were carried out using Genetic Algorithm (GA), Simulated Annealing (SA), Pattern Search and Nelder-Mead method. GA



method was able to find optimal solution for this vehicle design. It shows improvement in fuel economy by about 4.3%, and demonstrated lower computational time than SA method.

Zhang and Mi [3] performed optimization for parallel HEV using DIRECT, SA, GA, and PSO method. Based on his results, PSO ranked at the bottom (least improvement in fuel economy), and SA ranked at the top (most improvement in fuel economy; 15.01%). GA optimization shows improvement about 7.12%. Although GA method is not as good as SA, it was mentioned earlier that SA requires significantly more time, about as twice as GA. This lower improvement shows by GA could had resulted from the fact that this optimization method uses random candidates to form initial population, this population that will yield final optimal results. Thus, to overcome this issue, different settings were considered to ensure best optimal can be achieved.

2. Methodology

In this section, optimization setup of powertrain design problem will be presented. Vehicle modeling and energy management strategy (EMS) are based on Mangun *et al.* [4]. A parallel HEV topology is utilized as shown in figure 1. Quasi-Static-Simulation (QSS) (Guzella and Amstutz [5]) using backward-facing approach is utilized instead of dynamic approach (forward-facing). The former computes fuel consumption from a known drive cycle. The latter computes fuel consumption from a known driver input. EMS is built using Fuzzy Logic to manage power flow between ICE and EMG, and to manage power flow between battery and supercapacitor.

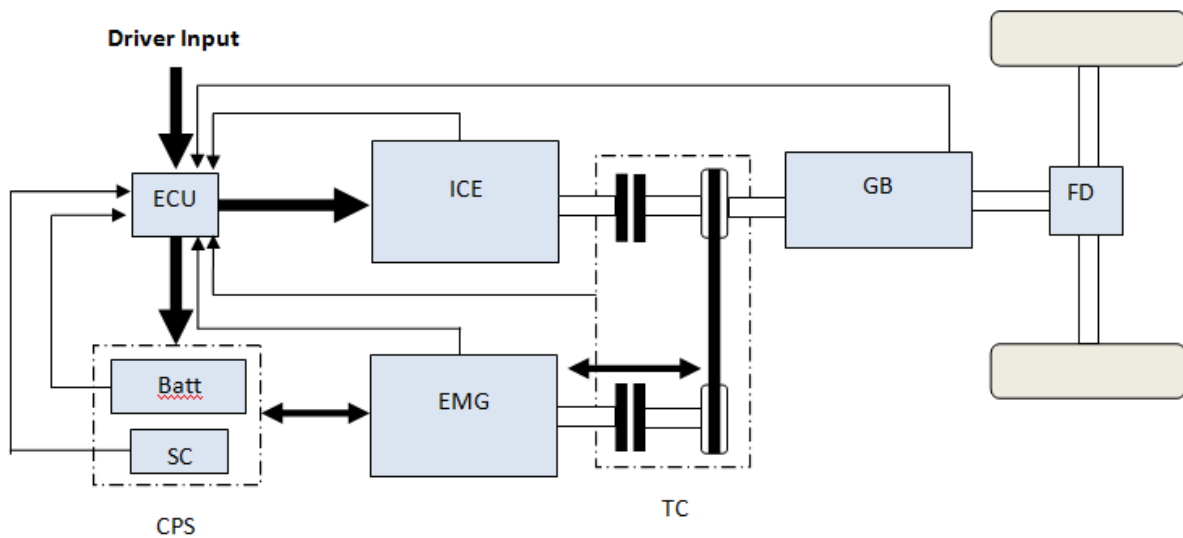


Figure 1. A parallel HEV with supercapacitor (ECU: electronic control unit, Batt: battery, SC: supercapacitor, ICE: internal combustion engine, EMG: electric motor-generator, TC: torque coupler, GB: gearbox, FD: final drive).

Table 1. Specifications of supercapacitor (per module).

Parameter	Symbol	Value	Unit
Rated capacitance	C_{SC}	165	F
Voltage	V_{SC}	48	V
Maximum current	I_{SC}	1900	A
Energy to weight ratio	SC_{ψ}	3.9	Wh/kg

Brief information on Fuzzy Logic-based EMS regarding supercapacitors is mentioned here. Despite presence of battery, supercapacitor usage is prioritized during regenerative braking and acceleration. This means, supercapacitor main energy source is regenerative braking, and it will only be used during

acceleration. The specifications of supercapacitor are shown in table 1. The supercapacitor has a low self-discharge rate (as low as 20% per month [6]). Within the timeframe of operation of the vehicle (hours), the supercapacitor can be used for energy storage. Additionally, supercapacitor has adequate specific energy (energy per weight) to supply power during acceleration period which lasts for small time.

2.1. Mass Estimations

In order to ensure changes in vehicle mass are considered during optimization process, several sets of equations were utilized [7, 8, 9 & 10]. Equations for estimating the mass of ICE (M_{ICE}), EMG (M_{EMG}), battery (M_B), and supercapacitor ($M_{SC,total}$) are listed below (mass in kg):

$$M_{ICE} = 1.62 P_{ICE} + 41.8 \quad (1)$$

$$M_{EMG} = 0.833 P_{EMG} + 21.6 \quad (2)$$

$$M_B = \frac{B_{capa}}{B_\psi} \quad (3)$$

$$M_{SC,total} = N_{sc} M_{SC} \quad (4)$$

Vehicle curb mass (M_{vc}) is estimated using the ratio method:

$$M_{vc} = \left(\frac{M_n}{\gamma_n} \right) + (M_{SC,total}); \quad \gamma_n = \frac{M_{n,ref}}{M_{vc,ref}} \quad (5)$$

where P_{ICE} is rated power of ICE (kW), P_{EMG} is rated power of EMG, B_{capa} is battery capacity (kWh), B_ψ is battery specific energy (99 Wh/kg for Lithium-ion battery), N_{sc} is number of supercapacitors (in parallel), M_{SC} is mass of one unit of supercapacitor, γ_n is the ratio between reference vehicle nominal mass ($M_{n,ref}$) and vehicle curb mass ($M_{vc,ref}$), and M_n is vehicle nominal mass (mass of ICE, EMG and battery).

2.2. Genetic Algorithms method.

GA is based on natural evolutionary process that is occurring in nature, where it represents reproduction and evolutions of generations after generations, which selects the fittest or the best that survived. A built-in function in Matlab [11] used for GA optimizations. Objective function is

$$F_f(x) = m_f \text{ or } m_{f,e} \quad (6)$$

Fuel consumption (m_f) can be directly obtained from simulation results. Equivalent fuel consumption ($m_{f,e}$) can be calculated as:

$$m_{f,e} = m_f + \frac{EE}{33.7 \times 1000 \times 3600 \times 0.264172 \rho_f} \quad (7)$$

where EE (joule) is electrical energy consumed ($EE = Eb + Esc$, Eb is battery net discharge energy, Esc is supercapacitor net discharge energy), and ρ_f is gasoline density.

For design variables, lower and upper bounds were determined based on data for 5 HEV SUV (Mitsubishi Outlander, Toyota Highlander, Nissan Pathfinder, Volkswagen Tuoreg & Ford Escape), as presented in table 2. For example, ICE capacity range from 2.0 litres (Mitsubishi Outlander) to 3.6 litres (Toyota Highlander). EMG rated power and battery capacity range were determined by the same

method. Since there are no data for the number of supercapacitors, its range is selected based on initial simulation runs.

Table 2. Design variables bounds.

Design Variables	Symbol	Lower Bound	Upper Bound	Units
ICE capacity (X_1)	l_{ICE}	2.0 (gasoline)	3.6 (gasoline)	Litres
EMG rated power (X_2)	P_{EMG}	20	130	kW
Battery capacity (X_3)	B_{capa}	2	20	kWh
No. of Supercapacitors (X_4)	N_{sc}	2	10	-

The curb mass of the vehicle is limited to 2000 kg (an average mass between lightest and heaviest HEV from dataset). This condition is implemented as a constraint for the optimization problem. This is represented by:

$$M_{v,c} < 2000 \quad (8)$$

Table 3. Summary of different optimization settings (sets).

Objective function	Set 1	Set 2	Set 3	Set 4	Set 5	Set 6
Minimize (m_f or $m_{f,e}$)	P=20	P=60	P=100	P=100 S=Tournament	P=100 C=Heuristic	P=100 MD= forward and backward

For best optimal search, different GA settings including population (P), selection (S), crossover (C), and migration direction (MD) were considered as in table 3. Number of optimization runs is 12, this means 6 cases for each objective function.

3. Results and Discussion

A combined drive cycle (CDC) that is closely representing real-world driving cycle is used for design optimization (figure 2). It consists of FTP-75 and HWFET from EPA city and highway drive cycle respectively.

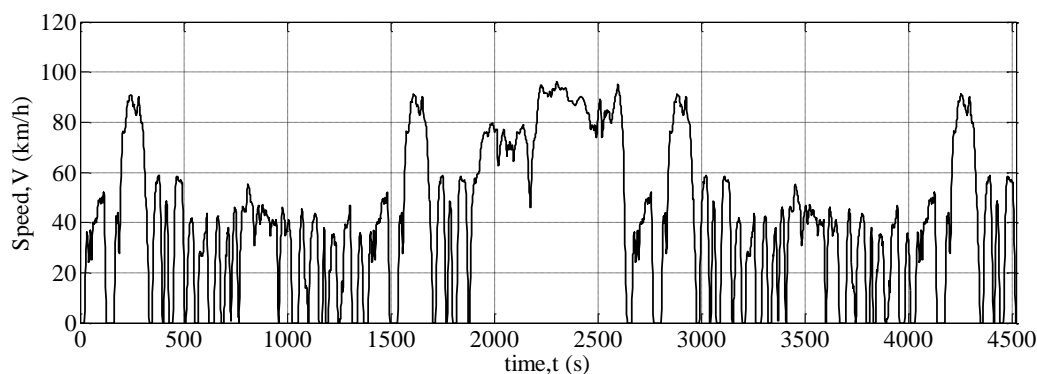


Figure 2. Combined FTP-75-HWFET drive cycle (CDC).

It is observed from table 4, that best fuel economy at set 3 and best equivalent fuel economy at set 5. The difference is 2%.

Table 4. Fuel consumption for different optimization settings.

Objective function		Set 1	Set 2	Set 3	Set 4	Set 5	Set 6
Minimize m_f	m_f (kg)	1.7362	1.6487	1.4799	1.6326	1.6728	1.5848
	$m_{f,e}$ (kg)	1.7489	1.7932	1.6671	1.7825	1.8157	1.7600
Minimize $m_{f,e}$	m_f (kg)	1.8053	1.6563	1.8734	1.7646	1.4502	1.9036
	$m_{f,e}$ (kg)	1.8581	1.7628	2.0027	1.8779	1.6447	1.91311

Table 5. Component sizes for both optimization objectives at optimal point

Objective function	l_{ICE} (l)	P_{EMG} (kW)	B_{capa} (kWh)	N_{SC} (unit)	$M_{v,c}$ (kg)	m_f (kg)	$m_{f,e}$ (kg)
Minimize m_f	2.0	24.7077	15.2434	5	1811	1.48	1.66
Minimize $m_{f,e}$	2.0	21.6430	15.6608	2	1778	1.45	1.65

As shown in table 5, the major difference between objective 1 and 2 (m_f and $m_{f,e}$ respectively) is that objective 2 (minimize $m_{f,e}$) shows lower number of supercapacitor. For both objectives, EMG rated power and battery capacity shows little difference. It was decided that setting optimization objective to minimize $m_{f,e}$ at option 5 (crossover by heuristic) yielded best optimal component size. This is because it has minimal fuel consumption and lower number of units of supercapacitors. The best optimal parameters are summarized in table 6.

Table 6. Optimal HEV powertrain parameters.

Parameter	Reference	Optimized	Market HEV	Market HEV
Name	Generic HEV	Generic HEV	Mitsubishi Outlander	Volkswagen Tuoareg
Configuration	Parallel	Parallel	Series-Parallel	ISAD system
Transmission	5-speed GB	5-speed GB	Single-speed GB	8-speed GB
ICE capacity, l_{ICE} (l)	3.0	2.0	2.0	3.0 Supercharged
EMG power, P_{EMG} (kW)	40	21.64	60 (front) 60 (rear)	35
Batt capacity, B_{capa} (kWh)	2.0093	15.66	12.4 (Li-Ion)	1.7 (Ni-MH)
No. of SC, N_{SC} (units)	2	2	-	-
Curb Mass, $M_{v,c}$ (kg)	1800	1778	1845	2329
Fuel consumption, m_f (kg)	2.3496	1.4502 (-38.3%)	-	-
Equivalent fuel consumption, $m_{f,e}$ (kg)	2.3674	1.6447 (-30.5%)	-	-

Table 6 lists the optimized HEV as compared to HEV available in the market. Compared to Mitsubishi Outlander, the optimized HEV has the exact same capacity of ICE (2 l) and slightly higher battery capacity (15.66 kWh compared to 12.4kWh). EMG size is significantly lower (21.64 kW compared to 60 kW). This is due to absence of multi-speed gearbox in Mitsubishi Outlander (for high torque output, gearbox is replaced by higher EMG rated power). Volkswagen Tuoareg has a multi-speed gearbox (for higher torque output), which leads to a relatively low EMG rated power (35 kW). This is compatible with the optimized HEV (21.64 kW), which has a multi-speed gearbox.

The improvement in equivalent fuel economy is a result of several design changes. Firstly, ICE was downsized from 3 litres to 2 litres (smaller ICE capacity consumes less fuel). Secondly, increment of battery capacity from 2.0093 kWh to 15.66 kWh, this increased electrical energy usage which has high efficiency. Moreover, larger battery capacity reduces ‘on-board charging’ by ICE. This leads to a less usage of engine only mode, and more electric and hybrid mode. Thirdly, vehicle curb mass was maintained around initial value (1800 kg). Despite the increment of battery size, the final vehicle curb mass is reduced to 1778 kg, mainly due to ICE downsizing. This leads to lower inertial and frictional forces acting on the vehicle, which improves fuel economy.

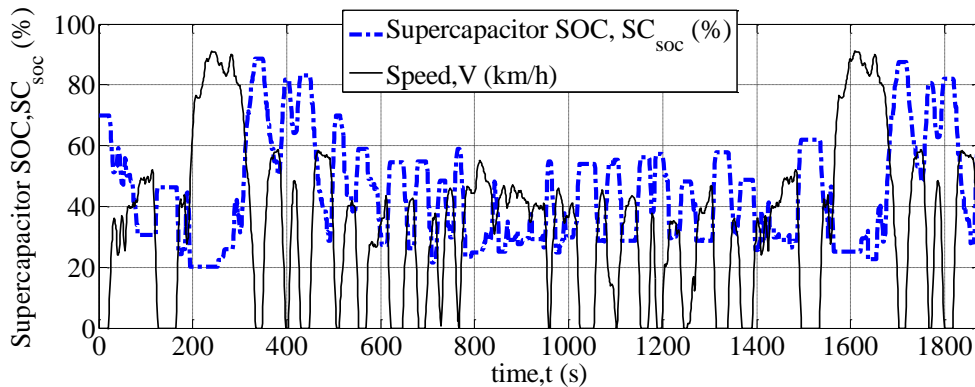


Figure 3. Supercapacitor state of charge (SOC) during initial period of combined cycle.

Figure 3 shows pattern of supercapacitor SOC for best optimal HEV, during combined drive cycle. During regenerative braking and acceleration periods, SOC has fast increase and decrease. This is compatible with supercapacitor characteristics since it has fast charging and discharging rates. For battery, its minimum SOC is limited to 55% to ensure longer life cycle. On the contrary, supercapacitor life cycle is significantly longer than battery life cycle. Hence, its minimum SOC is limited to a lower value (20% in this study). It was observed that supercapacitor voltage was fluctuating because it changes linearly with SOC during discharge operation (supplying power to EMG). However, this voltage fluctuation can be regulated by adding a DC-DC converter downstream of supercapacitor.

4. Summary

Parallel HEV powertrain optimization process was carried out using GA. It yielded improvement in fuel economy and equivalent fuel economy. Optimized HEV has smaller components sizes and higher fuel economy. It can be concluded that optimized HEV suits a plug-in type hybrid vehicle. This is because it has higher battery capacity than most non plug-in HEV. This work on plug-in parallel HEV is in progress. The moderate size of EMG had raised an important question about vehicle performance and gradeability. This will probably increase both ICE and EMG sizes and result in a reduction of electric energy storage size. Therefore, this issue will be investigated in future work by adding performance and gradeability constraints.

Acknowledgments

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References

- [1] Cerofolini A 2014 *Optimal Supervisory Control of Hybrid Vehicles* (Bologna: University of Bologna) pp 153-155

- [2] Fan B SM 2011 *Multidisciplinary Optimization of Hybrid Electric Vehicles: Component Sizing and Power Management Logic* PhD Thesis (Waterloo, Ontario, Canada: Univesity of Waterloo) pp 76-85
- [3] Zhang X and Mi C 2011 *Vehicle Power Management: Modeling, Control and Optimization* (Berlin: Springer Verlag) pp 295-301
- [4] Mangun M F, Idres M, Abdullah K 2015 Power management controller for hybrid electric vehicle using fuzzy logic *ARPN Journal of Engineering and Applied Sciences* **10** (Asian Research Publishing Network (ARPN)) pp 9682-9687
- [5] Guzella L and Amstutz A 2005 *The QSS Toolbox Manual* (Zurich: Swiss Federal Institute of Technology (ETH))
- [6] Diab Y, Venet P, Gualos H and Rojat G 2009 Self-discharge characterization and modeling of electrochemical capacitor used for power electronics applications *IEEE Transactions in Power Electronics* (IEEE) **24**(2) p 511
- [7] Delucchi M, Burke A, Lipman T and Millar M 2000 *Electric and Gasoline Vehicle Lifecycle Cost and Energy-Use Model* Report for the California Air Resources Board, Institute of Transportation Studies, Davis, CA (University of California) pp 31-37
- [8] Lui X, Diallo D and Marchand C 2011 Design methodology of hybrid electric vehicle energy sources: application to fuel cell vehicles *International Journal of Automotive Technology* (Berlin: Springer Verlag) p 435
- [9] Malen D E, and Kundan R 2007 *Preliminary Vehicle Mass Estimation Using Empirical Subsystem Influence Coefficients* Mass Compounding Project Team report, Ann Arbor, Michigan, United States (InterProfessional Programs, University of Michigan) p 8
- [10] Simpson A 2006 *Cost benefit analysis of plug-in hybrid electric vehicle technology* NREL/CP-540-40485 (Oak Ridge, TN,USA: National Renewable Energy Laboratory)
- [11] MATLAB R2013a 2013 (Natick, Massachusetts, United States: The MathWorks, Inc)