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A Methodology for Component Sizing of Hybrid Electric Vehicles based on a Range of Driving Patterns

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Abstract

Driving patterns have a significant influence on the variation in fuel economy of hybrid electric vehicles. Previous studies on component size optimization of hybrid electric vehicles typically use a single driving pattern. The optimum components based on a particular driving pattern are not the optimum for other different driving patterns. Selections of the optimum component sizes in previous studies are designer dependent as different driving patterns lead to different optimum component sizes. This paper proposes a methodology of component size optimization for the optimum fuel economy by considering a range of different driving patterns simultaneously. This study is carried out on a series-parallel Toyota Prius hybrid vehicle and the electric assist control strategy is used for the energy management. A genetic algorithm is used as the optimization method. Both urban and highway driving patterns are classified into conservative, normal and aggressive and all the six driving patterns are used simultaneously for the proposed methodology. To compare the effectiveness of the proposed methodology and the existing single driving pattern based methodology, component sizes are also optimized for each of the three driving patterns - NEDC, LA92 and HWFET. All the optimum components are evaluated for fuel economy on four driving patterns - NEDC, LA92, HWFET and ARTEMIS. The proposed methodology reduces the variation in fuel economy over the range of driving patterns and provides designer independent component size selection.

Keywords: Component, Optimization, Hybrid Electric Vehicle, Simulation

1 Introduction

Technological advancement in the automotive industry is influenced by the availability of fossil fuel and the threat of global warming. Increased fuel prices and stringent emission norms due to global warming are the major challenges for the survival of the automotive industry. Hybrid Electric Vehicles (HEVs) have come out as one of the most promising technologies to counter the problem. HEV is benefited with low emission of electric vehicle and high efficiency of internal combustion (IC) engine. A HEV is a complex combination of various components involving a large number of design parameters which must be considered carefully to get better performance [1]. Development and testing of each design combination is expensive and time consuming. Design optimization is the only feasible technique for optimum selection of components [2]. In those several components, IC engine, electric machine and energy storage device are the most significant components on which vehicle performance is dependent. So, the optimum selection of these components can ensure the optimum performance. Analytical-based optimization of a HEV is impractical as deriving an equation involving hundreds of parameters is very difficult [3]. The simulation-based optimization where the optimization algorithm works with vehicle simulation model is proved well suited for finding optimum component sizes of HEV [3].

The real world driving patterns are varied due to route selection, traffic conditions and driver behaviour. Different drive cycles are developed to represent different driving patterns. Automotive manufactures use drive cycles to predict the performance of vehicle on road. Driving patterns have a significant influence on the automotive vehicle fuel consumption, emissions and performance [4-7]. So, a design based on a single driving pattern is not be able to predict the performance on other driving patterns and therefore, a range of driving patterns need to be considered at the design stage to get near optimal results on various driving patterns on road. Similarly, a range of different driving patterns need to consider for the design of components of HEV for optimum performance.

Several studies on component size optimization of HEV exist, but no study considers a range of driving patterns simultaneously. A study [8] on a power-split hybrid electric vehicle optimized component sizes based on UDDS driving pattern only. No study was done on other driving patterns. Another study [9] on a parallel HEV optimized component sizes for each of the three drive cycles – FTP, ECE-EUDC and Tehran city cycle TECH-CAR and results concluded that the optimum components on one driving pattern were not the optimum on other driving patterns. Three different component sizes were found for three drive cycles. There is no study of which design to choose and what would be the performance of any optimum components if evaluation would have done on other driving patterns. Another study [10] on a plug-in parallel HEV used the UDDS, the FTP, the LA92 and the US06 separately for component size optimization and found four different sets of optimum components one for each drive cycle. It also concluded that the optimum component sizes were different with different driving patterns and component sizes were increased with aggressiveness of driving patterns. Results from another study [11] on a parallel HEV showed that the optimum component sizes for the FTP and the ECE-EUDC drive cycles were different.

As component sizes for one driving pattern are not the optimum for other driving patterns, the performance of the optimum components based on a single drive cycle might vary widely when evaluated on other driving patterns. A research study [12] on a parallel HEV used the FTP drive cycle only for component size optimization. The results indicated that the optimum components based on a particular driving pattern could generate as high as 50% variation in fuel consumption when evaluated on other driving patterns.

It can be concluded from all the previous studies that no systematic methodology exists for component size optimization of hybrid electric vehicles for a range of driving patterns. The knowledge in existing literature is only applicable for component size optimization on a single driving pattern. There is no direction available for the justification for choosing any particular design from different sets of optimum designs. No knowledge also exists for reducing the variation in fuel economy (FE) due to the single driving pattern based component size optimization. As single driving pattern based optimization provides a separate set of optimum components for each of the driving pattern, it is designer's personal experience which leads to the choice of any particular design from all the available designs. Therefore the choice of components for an application becomes designer dependent. Little study was done to evaluate the performance of the optimum components based on any particular driving pattern when evaluated on other driving patterns.

This paper proposes a systematic methodology for component size optimization over a range of driving patterns by considering all the driving patterns simultaneously. The paper also studies the variation in FE of the optimum designs for four different driving patterns.

2 Proposed methodology

In the conventional methodology for the component size optimization, a single driving pattern is considered to find the optimum component sizes. The proposed methodology considers a range of different driving patterns simultaneously for the component size optimization. In the proposed methodology, at first, driving patterns are classified into different categories and then all the driving patterns under

different categories are considered simultaneously for the optimization. Each driving pattern is associated with a weight of preference. To give equal importance to all driving patterns under consideration all weights need to be same. Higher weight could be given to any particular driving pattern to give it higher importance over the others. During optimization, the objective function needs to be evaluated for all driving patterns under consideration. The optimization decision needs to be made based on the combined output of the objective function over all the driving patterns under consideration. The flow diagram of the conventional methodology and the proposed methodology are shown in Figures 1 and 2 respectively. Thus the approach outlined in Figure 2 is expected to lead to a solution that works better (lower variation in FE) than the approach outlined in Figure 1.
In the subsequent study in this paper, a single drive cycle based component size optimization and the proposed methodology based component size optimization will be called as the method 1 and the method 2 respectively.

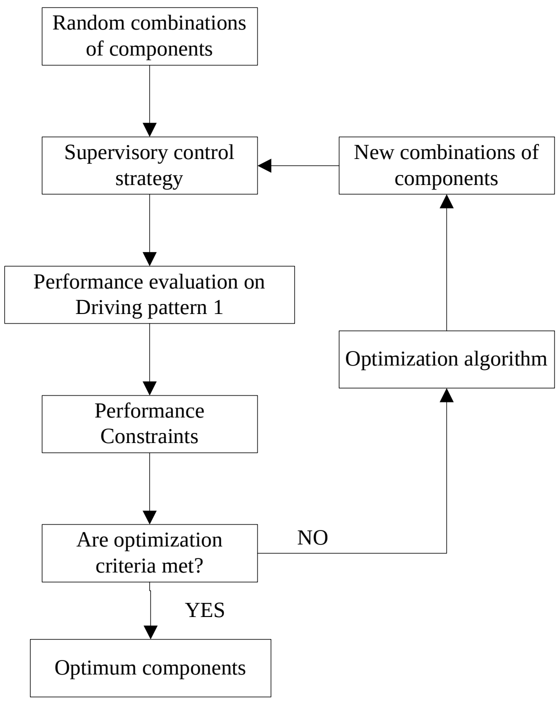

Figure 1: Conventional methodology

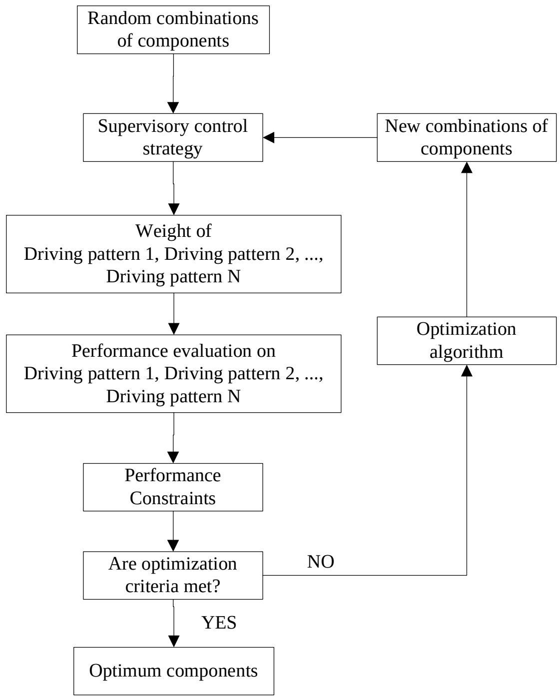

Figure 2: Proposed methodology

3 Simulation study

A series-parallel Toyota Prius hybrid vehicle is considered for this study, as the component size optimization is a major challenge for this type of architecture. The WARwick Powertrain Simulation Tool for ARchitectures (WARPSTAR) [13] an in-house software is used as vehicle simulation software. The simulation model of a Toyota Prius 1.5L hybrid vehicle available in the WARPSTAR is considered for this study. The vehicle simulation model consists of the following major parameters

- Vehicle mass: 1368 kg
- Rolling resistance coefficient: 0.009
- Body aerodynamic drag coefficient: 0.29
- Vehicle frontal area: 2.0 m^2
- Transmission: Power-split
- Initial battery state of charge (SOC): 0.7

3.1 Problem formulation

The problem can be defined as a constraint optimization problem where FE needs to minimize without sacrificing vehicle performance.
The vehicle performance requirements are defined as constraints. In this study, the Toyota Prius vehicle performance values have been considered as constraints to ensure that the vehicle

performance is not sacrificed during optimization. These constraints are listed below

- 0-60 mph: < 12.9 seconds
- Maximum speed: > 104 mph
- Gradeability: 5°

Another constraint is the battery SOC which needs to be considered to be able to compare different driving patterns. The final battery SOC of all the driving patterns needs to be same. For this study, the constraint is

- Difference between the final battery SOC and the initial battery SOC: < 1%

The IC engine, the electric motor and the battery are the components to be optimized. The Toyota Prius 1.5L SI engine with maximum power of 43kW is used as the baseline IC engine. For the baseline electric motor, the Toyota Prius permanent magnet brushless DC motor with maximum power of 30kW is used. For battery sizing, the Toyota Prius NiMH battery pack with maximum capacity of 6Ah is considered as the baseline battery. Different power ratings of the components are achieved by linear scaling of the maps of the baseline components. The generator and the transmission are kept same as that of the Toyota Prius 1.5L hybrid vehicle. Three design parameters are considered as optimization variables. These variables are the IC engine power (P_{IC}), the electric motor power (P_{EM}) and the battery capacity (C_B). The ranges of the variations for each design parameter are determined based on the desired performance characteristics of components as listed in Table 1.

Table 1: Range of variation of each design parameter

Design parameters	Lower limit	Upper limit
P_{IC}, kW	12.9	73.1
P_{EM}, kW	9.0	30.0
C_B, Ah	1.8	10.2

The problem can be formulated as a constraint optimization problem as follows:

Minimize, $f(x), \quad x \in X$
Satisfy, $\quad h_i(x) \le 0, \qquad i=1,2,..,N$

Where x is the solution to the problem within the solution space X. X is the upper and lower limit of the design variables. $f(x)$ is the objective function and each inequality $h_i(x) \le 0$ represents one of the non-linear constraints shown above. N is the number of constraints.

3.2 Supervisory control strategy

The rule based electric assist supervisory control strategy [14] is considered for the energy management. The control strategy is described as follows

- The electric motor supplies all the driving torque if the battery SOC is higher than SOC_L and the vehicle speed is below a certain minimum speed V_C or the required torque is smaller than T_C.
- When the required torque is higher than T_C and the engine runs in its efficient region with the required driving torque, the engine produces the torque to drive the vehicle alone.
- When the required torque is higher than the maximum torque of the engine at the engine's operating speed, the motor provides the additional torque.
- When the battery SOC is lower than SOC_L, the engine provides additional torque which is used by the motor to recharge the battery.
- When the battery SOC is lower than SOC_H, the motor charges the battery by regenerative braking.

SOC_L: Lowest desired battery SOC
SOC_H: Highest desired battery SOC
V_C: Vehicle speed below which vehicle operates electric only mode
T_C: Required vehicle torque below which vehicle operates electric only mode

3.3 Optimization method

The component size optimization of hybrid electric vehicles is a multi-modal problem [2]. The optimization algorithm for solving such a problem can be classified into two categories: gradient-based and derivative-free algorithms [15]. Gradient-based algorithms [2, 16] use derivative information and they are weak in global optimization. They require strong assumptions for the objective function, such as continuity, differentiability, satisfaction of Lipschitz condition etc., which cannot be trivially assumed. On the other hand, derivative-free algorithms such as genetic algorithms (GA) are robust, global and may be generally applied without recourse to domain specific knowledge [12]. Genetic algorithms are well proved for component size optimization of hybrid electric vehicles [9, 12, 15, 17]. In this study, a genetic algorithm is selected as the optimization method.

3.3.1 Genetic algorithm

Genetic algorithm is a stochastic global search and optimization method that mimics the process of natural biological evolution [9, 15]. GA is population based method and every individual of the population is a potential solution. Each individual of the population is an encoded string known as chromosome that contains the decision variables known as genes.

The structure of the GA consists of the following main steps

- Creation of an initial population
- Evaluation of each individual of the population by means of a fitness function
- Selection of individuals
- Crossover and mutation of selected individuals of the population

At the start of the algorithm, an initial population of individual is selected randomly. Each individual of the population is evaluated using a fitness function that needs to be minimized. Selection is the process to select the individuals with higher fitness over the others to produce new individuals for the next generation of population. Crossover is the method of merging the genetic information of two individuals called parents to produce the new individuals called children. Mutation is a probabilistic random deformation of the genetic information for an individual. Following the evaluation of the fitness of all chromosomes in the population, the genetic operators are applied to produce a new population.

The selection method used in this study is the roulette wheel method in which the probability for choosing a certain individual is proportional to its fitness. The simple crossover and the binary mutation are considered for this study.

In this study, the population of genetic algorithm is initialized with 50 randomly selected components from the entire solution space and the maximum number of generation is set to 150 as after 100 generations there is small improvement of results.

3.4 Driving patterns

Driving patterns could be varied from driver to driver, but in a broader sense could be classified into conservative, normal and aggressive. All the three types of driving patterns can exist in both urban and highway. For this study, driving patterns are classified into above discussed categories based on drive cycles parameters [18] and shown in Tables 2 and 3. The ECE15, the FTP and the LA92 are selected as conservative, normal and aggressive urban driving patterns respectively. The EUDC, the HWFET and the US06 are selected as conservative, normal and aggressive highway driving patterns respectively.

The FE is evaluated for all the driving patterns as listed in Tables 2 and 3 and the cumulative FE is used for the method 2. For this study, all the driving patterns are given equal weight of preference.

Table 2: Classification of urban driving patterns

Parameters, (unit)	Urban		
	Conserva-tive	Normal	Aggre-ssive
	ECE15	FTP-75	LA92
% of driving time accelerating	35.3	41.8	46.7
% of driving time decelerating	32.0	35.2	40.5
Maximum speed, kph	50.07	91.09	107.35

Table 3: Classification of highway driving patterns

Parameters, (unit)	Highway		
	Conserva-tive	Normal	Aggre-ssive
	EUDC	HWFET	US06
% of driving time accelerating	32.6	34.6	37.1
% of driving time decelerating	13.4	27.5	36.7
Maximum speed, kph	120.09	96.32	128.91

Where,

% of driving time accelerating =

$$\frac{\textit{Drive time spent accelerating}}{\textit{Driving time}}100$$

% of driving time decelerating =

$$\frac{\textit{Drive time spent decelerating}}{\textit{Driving time}}100$$

Drive time spent accelerating =

$$\begin{cases} t_2 - t_1 & (a_1 > acc\_threshold) \\ 0 & (else) \end{cases} + \sum_{i=2}^{n} \begin{cases} t_i - t_{i-1} & (a_i > acc\_threshold) \\ 0 & (else) \end{cases}$$

Drive time spent decelerating =

$$\begin{cases} t_2 - t_1 & (a_1 < -acc\_threshold) \\ 0 & (else) \end{cases} + \sum_{i=2}^{n} \begin{cases} t_i - t_{i-1} & (a_i < -acc\_threshold) \\ 0 & (else) \end{cases}$$

Driving time,

$$T_{drive} = T_{total} - T_{stop}$$

Total time,

$$T_{total} = (t_2 - t_1) + \sum_{i=2}^{n} (t_i - t_{i-1})$$

Standing time,

$$T_{stop} = \begin{cases} t_2 - t_1 & (v_1 = 0 \,\&\, a_1 = 0) \\ 0 & (else) \end{cases} + \sum_{i=2}^{n} \begin{cases} t_i - t_{i-1} & (v_i = 0 \,\&\, a_i = 0) \\ 0 & (else) \end{cases}$$

$t = time$

$v = speed$

$a = acceleration$

4 Results and discussions

All three design parameters - the IC engine power (P_{IC}), the electric motor power (P_{EM}) and the battery capacity (C_B) are optimized as per the method 2 using all the six driving patterns as shown in Tables 2 and 3. To compare the method 2 with the method 1, all the design parameters are also optimized for each of the most widely used conservative driving NEDC, aggressive urban driving LA92 and normal highway driving HWFET as per the method 1.

Comparison of the optimum component sizes between the method 1 and the method 2 are shown in Table 4. Results in Table 4 show that the optimum component sizes for the NEDC, the LA92 and the HWFET are different when optimization is done based on the method 1. The optimum components of one driving pattern are not the optimum for other driving patterns. As different sets of optimum components are found, the designer has to make decision about the choice of the components for any application. In other words, the choice of optimum component becomes designer dependent. On the other hand, the method 2 finds only one optimum size of the IC engine, the electric motor and the battery for a range of driving patterns which cover conservative, normal and aggeressive driving. Therefore, for the method 1, designer has to decide which design to choose from the available three different optimum designs but for the method 2, designer has only one choice. Hence, in case of the method 2 the component size optimization over a range of driving patterns becomes designer independent.

The optimum components based on each of the three driving patterns - NEDC, LA92 and HWFET are evaluated on one conservative driving NEDC, one aggressive urban driving LA92, one normal highway driving HWFET and one real world driving combining the ARTEMIS-urban and the ARTEMIS-highway to find the variation in FE over the four driving patterns. The optimum components based on the method 2 are also evaluated for the same four driving patterns as discussed before. The FE of the optimum components based on the NEDC driving pattern are 89.9 mpg, 39.0 mpg, 109.5 mpg and 38.8 mpg when evaluated on the NEDC, the LA92, the HWFET and the ARTEMIS driving patterns respectively. Similarly, the optimum components based on the LA92, the HWFET and the method 2 are also evaluated on the NEDC, the LA92, the HWFET and the ARTEMIS driving patterns. The comparative results of FE are shown in Table 5.

The average FE of the optimum components of the method 2 is comparable to that of the optimum components for each of the other three driving patterns - NEDC, LA92 and HWFET.

The overall variation in FE of the optimum components based on the NEDC and the HWFET are 64.6% and 66.6% respectively. The optimum components based on the LA92 shows 53.4% variation in FE. The optimum engine size for the LA92 is 60.5% and 19.7% higher as compared to that of the NEDC and the HWFET respectively. And the optimum battery size for the LA92 is 72.6% and 4 times higher as compared to that of the NEDC and the HWFET respectively.

Table 4: Comparison of optimum component sizes between methods 1 and 2

Components	Optimum sizes			
	Method 1 (Conventional methodology)			Method 2 (Proposed methodology – combination of 6 driving patterns)
	NEDC	LA92	HWFET	
P_{IC}, kW	31.1	49.9	41.7	40.4
P_{EM}, kW	29.7	29.9	26.3	29.8
C_B, Ah	5.34	9.22	1.8	7.95

Table 5: Comparison of fuel economy over different driving patterns

Driving patterns	Fuel economy (FE), mpg			
	Method 1 (Conventional methodology)			Method 2 (Proposed methodology)
	NEDC	LA92	HWFET	
NEDC	89.9	66.4	64.9	69.2
LA92	39.0	50.4	40.6	49.9
HWFET	109.5	97.0	111.7	102.9
ARTEMIS (urban + highway)	38.8	45.2	37.3	43.5
% Overall variation in FE, [(max–min)/max]	64.6	53.4	66.6	57.7
Average of FE	69.3	64.8	63.6	66.4
Standard deviation of FE	36.0	23.3	34.3	26.7

So, the overall vehicle weight and cost would increase for the LA92 based design compared to the NEDC and the HWFET based designs. The variation in FE for the method 2 is 57.7%. The optimum components based on the method 2 reduces around 11% and 13% variation in FE as compared to the optimum components based on the NEDC and the HWFET driving pattern respectively. But, the variation in FE for the method 2 is 8% higher as compared to the LA92 based optimum components.

Similarly, the standard deviation of FE for the method 2 is 26.7 that is around 26% and 22% lower than that of the NEDC and the HWFET respectively and 14% higher as compared to that of the LA92 based optimum components.

The advantage of the method 2 over the method 1 in case of the LA92 is that it reduces the IC engine and the battery sizes by around 19% and 14% respectively as compared to that of the LA92. This would reduce the overall vehicle weight as well as the cost.

Results in Table 5 show that for the method 1, the best design for the maximum FE is the HWFET based design for the HWFET driving pattern and the best design for the minimum variation in FE is the LA92 based design. But no optimum designs lead to that of the method 2 which produces lower variation in FE with reduced component sizes.

The decision making based on the method 1 is required more time, as each driving pattern needs to be investigated. But for the method 2 only one evaluation is required. Therefore, the decision making for the selection of the optimum components becomes easy and less time consuming.

As the method 2 demonstrates its potential to reduce the variation in FE for the electric assist supervisory control strategy which is deterministic rule based, it could be inferred that the method 2

could be applicable for any other detreministic rule based supervisory control strategy under similar conditions. The fuzzy rule based supervisory control strategies are expected to work better with the method 2 as the fuzzy logic is better suited for handling uncertainty of different driving patterns.
As the method 2 considers a range of different driving patterns and hybrid electric vehicles are subjected to different driving patterns irrespective of architectures, the method 2 could be equally applicable to other HEV architectures also.

5 Conclusions

In this paper, a methodology to select component sizes optimized simultaneously for a range of driving patterns has been proposed. The proposed methodology has considered six different driving patterns consist of conservative, normal and aggressive driving for both urban and highway.
The component size optimization has become designer independent as the proposed methodology has provided a single set of optimum components instead of multiple sets of optimum components over a range of driving patterns.
The proposed methodology has reduced the variation in FE with reduced component sizes over a range of different driving patterns as compared to the conventional methodology.
The proposed methodology is easy and less time consuming as compared to the conventional methodology while selecting optimum components over a range of driving patterns.

6 Future works

Exhaust emissions and component cost have an influence on component size optimization. Vehicle exhaust emissions and cost of components will be considered in further studies to enhance the proposed methodology.

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