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Real-world investigation of a methodology for powertrain component sizing of hybrid electric vehicles

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Abstract

Hybrid electric vehicles (HEVs) have emerged as near term sustainable technologies to reduce fossil-fuel dependency. The variation in fuel economy (FE) due to the variation in driving patterns exists in hybrid electric vehicles (HEVs). Powertrain component size optimisation based on a methodology considering a range of driving patterns including different traffic conditions and driving styles simultaneously has previously demonstrated the potential to reduce variation in FE over standard legislative driving patterns. Though standard legislative driving patterns are useful for comparative study, there are evidences that legislative driving patterns are often considerably different from real-world driving. Therefore to ensure wide applicability, the methodology needed to be validated for real-world driving pattern. This paper applied the methodology for ten real world driving patterns over a predefined route consisting of urban and highway driving to investigate the applicability of the methodology in real world. The study was carried out using a series-parallel Toyota Prius HEV. A rule based supervisory control strategy was considered as the energy management. A genetic algorithm was considered as the optimisation method. The methodology demonstrated the potential to reduce variation in FE by up to 33% in real world driving.

Keywords: Component, Optimisation, Hybrid Electric Vehicle, Simulation, Real-world driving

1 Introduction

The decrease in fossil-fuel reserves has motivated automotive manufacturers to look for alternative technologies to reduce fuel dependency. Hybrid electric vehicles (HEVs), combining an internal combustion (IC) engine and electric motors are potential technologies for fuel economy (FE) improvement.

In spite of the potential to improve FE as compared to conventional vehicles (IC engine powered), variation in FE exists in HEVs due to variation in driving patterns [1], [2] along with other factors such as variation in atmospheric temperatures and operation of air-conditioning [3], [4]. Driving patterns are speed-time profiles of vehicles [5]. The importance of driving patterns is even higher in HEVs as evidence of higher variation in FE due to variation in driving patterns in HEVs as compared to conventional vehicles was found in existing literature [6], [7], [8], [9]. The variation in FE of an HEV could be up to 30% higher as compared to a conventional vehicle [9].

It was found in a previous study that variation in FE due to variation in driving patterns could be reduced when powertrain component sizes were optimised for FE considering a range of driving patterns of different traffic conditions and driving styles simultaneously [10]. In other words, variation in FE could be reduced when powertrain components are optimum over a range of driving patterns simultaneously (termed as “proposed methodology”), rather than over a single driving pattern (termed as “conventional methodology”) [10].

In the study [10], standard legislative driving patterns were categorised into urban and highway traffic conditions and each traffic condition was further classified into three driving styles – conservative, normal and aggressive and all categorised driving patterns were used simultaneously for the proposed methodology to find an optimum combination of powertrain components for optimum FE. The study considered one conservative urban driving – ECE15, one normal urban driving – FTP-75, one aggressive urban driving – LA92, one conservative highway driving – EUDC, one normal highway driving – HWFET, one aggressive highway driving – US06. For the conventional methodology, NEDC, LA92 and HWFET were considered separately to find an optimum combination of powertrain components. The proposed methodology provided a single optimum design over the range of six driving patterns and the conventional methodology provided three different optimum designs over the NEDC, LA92 and HWFET. Each optimum design of both the methodologies were evaluated for FE over three standard legislative driving patterns – NEDC, LA92, HWFET and a real-world driving – Artemis. The proposed methodology reduced variation in FE over the driving patterns as compared to the conventional methodology.

Standard legislative driving patterns were developed for the adherence of legislative norms by all vehicles. Though standard legislative driving patterns are useful for comparative study, there is evidence that standard legislative driving patterns are considerably different from real-world driving [11]. Though the proposed methodology demonstrated its potential to reduce variation in FE over standard driving patterns, the optimum design of the proposed methodology needs to be validated in real world driving patterns extensively to establish its applicability in practical application.

In the previous study [10], the objective was to develop the proposed methodology and this paper investigated the applicability of the methodology in real world driving.

In this paper, powertrain components were optimised for FE using both the proposed and conventional methodologies based on standard legislative driving patterns similar to the previous study [10]. After optimisation, optimum design of the proposed methodology was evaluated for ten driving patterns over a predefined route consisting of urban and highway driving as against that of the conventional methodology. Vehicle exhaust emissions and component cost were not considered for the study.

This paper is categorised into six sections. The first section is introduction. The second section briefly discusses the methodology of powertrain component size optimisation proposed in the previous study [10] followed by the discussion on the simulation set up for the study in the third section. The fourth section presents results and the fifth section concludes the study followed by future direction of work in the sixth section.

2 Methodology of component sizing

The “proposed methodology” (Method 2) of the optimisation of powertrain component sizes in the previous study considered a range of driving patterns of different traffic conditions and driving styles simultaneously, whereas the “conventional methodology” (Method 1) considered a single driving pattern to find a combination of powertrain component sizes for optimum FE [10]. In the proposed methodology, driving patterns were categorised into different traffic conditions and each traffic condition was further classified into different driving styles. All the categorised driving patterns were considered simultaneously during optimisation.

3 Simulation study

The simulation set up of the study is described in this section which is categorised into nine subsections. Each subsection is detailed next.

3.1 Vehicle configuration

The study considered a series-parallel Toyota Prius HEV. A simulation model of the vehicle from WARPSTAR, based on MATLAB/SIMULINK, was considered for the study [12]. The vehicle simulation model consisted 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

3.2 Design parameters

The Toyota Prius HEV had a spark ignition engine (1.5L) of 43 kW, a brushless DC motor of 30 kW, a generator of 15 kW and a battery of 6.0 Ah. These components were considered as the base components for optimum designs. The IC engine's maximum power (P_{IC}), generator's maximum power (P_G), motor's maximum power (P_M) and battery's maximum capacity (P_C) were considered as design parameters for the optimisation to get optimum FE. The range of the variations of each design parameter was kept within ±70% of the base component as listed in Table 1 to allow sufficient design space for the optimisation algorithm to find optimum components. With very restricted design space, the search for optimum components also becomes restricted. With infinite design space, the optimisation algorithm would take higher computational time to find optimum components. Though there could be argument about the justification of choosing the ranges of each parameter, the ranges were constant for both the methodologies and even if there were effects, the effects were same for both the methodologies. Therefore, the effect of the ranges on the comparative investigation was of little significance on the comparative results.

Table 1: Range of variations of each design parameter

Design parameters	Lower limit	Upper limit
P_{IC}, kW	12.9	73.1
P_{EM}, kW	9.0	51.0
P_G, kW	4.5	25.5
C_B, Ah	1.8	10.2

Different power ratings of the components during optimisation were achieved by linear scaling of the performance of the components of the Toyota Prius. The study assumed linear relationship for IC engine power and fuel consumption. In actual case it might not vary linearly and might affect the final FE values. However, in this study the aim was to compare two methodologies and hence, the absolute value of FE was of little relevance on the comparative results.

It was assumed linear relationship between torque and power of IC engine, generator and motor. Efficiencies of IC engine, generator and motor were assumed constant.
For battery, it was assumed linear relationship between battery capacity and current. Charging and discharging resistance of battery were assumed constant. Number of modules in a battery and number of cell in a module were assumed constant. For IC engine, generator and motor operating speed ranges were assumed constant for respective scaled components.

3.3 Problem formulation

The problem was formulated as a constraint optimisation problem where an optimum combination of the IC engine, generator, motor and battery needed to find for optimum FE without sacrificing vehicle performance. The problem was formulated as follows,

Minimise, $f(x), x \in X$
Satisfy, $h_i(x) \leq 0, i = 1, 2, \dots, N$
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
$h_i(x) \leq 0$ represents constraints
N is the number of constraints

3.4 Constraints

Acceleration, maximum speed and gradeability of the Toyota Prius were considered as constraints so that the performance of optimum components should not deteriorate as compared to the Toyota Prius HEV. These performance constraints were as follows and calculated as suggested in [13], [14].

- Acceleration (0~60 mph) :<13.4 seconds
- Maximum speed: > 113.3 mph
- Gradeability: >13.8% at 55 mph

Another constraint was the battery SOC which was considered in order to compare different designs for FE performance. In order to eliminate the influence of initial battery SOC on FE, the SOC correction has to be selected and hence the initial and final battery SOC on all driving patterns needs to be the same [15], [16], [17].
For this study, the constraint was

- Difference between the final battery SOC and the initial battery SOC: < 0.5%

3.5 Supervisory control strategy

A rule based electric assist charge sustaining supervisory control strategy was considered for energy management [18]. The control strategy consisted of the following rules

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

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

3.6 Optimisation method

A genetic algorithm (GA) was considered as optimisation method [19]. GA is good at finding global optimum. It requires neither any gradient information like derivative-based optimisation method nor solving equations like analytical-based optimisation methods. GA has proven its potential in finding a combination of powertrain components of HEVs for optimum FE [20], [21], [22].

The GA is a population based method and every individual of the population is a potential solution. Each individual of the population is an encoded string known as a chromosome that contains the decision variables known as genes. The method consists of selection, crossover and mutation operation. The 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. At first, higher fitness individuals are selected for next generation of population. Next, selected individuals go through crossover and mutation to generate new population for next generation. This process is continued until termination criterion is achieved.

The study considered single point crossover and the crossover probability was 0.9. The mutation probability was 0.15. The selection method used for the study was roulette wheel where the probability to choose a certain individual was proportional to its fitness [23]. Death penalty function was used to handle constraints [24], [25]. The population size was 40 and maximum number of generation was set to 200, as after 150 generations there was little improvements of results.

Since GA is stochastic in nature, each optimisation run does not produce same result and there is no simple method available to verify for a component size optimisation problem of HEVs whether the solution reaches global optimum. Therefore, each optimisation run was carried out 10 times and the optimum design with minimum FE value was presented as the result.

The study used model-in-loop approach [26] where an optimisation algorithm worked along with a vehicle simulation model. In each optimisation run, the optimisation method produced a new combination of powertrain components, and the FE of that combination of components was evaluated through a vehicle simulation model. Based on the FE value, the optimisation method produced a new combination of components and the procedure continued until the termination criterion was met.

3.7 Optimum designs

Powertrain components were optimised for optimum FE using both the proposed and conventional methodologies [10]. Standard legislative driving patterns were categorised into urban and highway traffic conditions and each traffic conditions were further classified into three driving styles – conservative, normal and aggressive. The study considered one normal urban driving – FTP-75, one aggressive urban driving – LA92, one normal highway driving – HWFET, one aggressive highway driving – US06 and one conservative driving – NEDC which consists of urban (ECE15) as well as highway (EUDC). Classification of driving patterns was done based on driving parameters [10], [27]. The Method 2 considered all the five driving patterns simultaneously, whereas the Method 1 considered each of the five driving patterns separately to find optimum powertrain component sizes.

3.8 Real-world driving patterns

Speed-time data of a conventional vehicle driven by ten drivers were considered as real world driving data. The vehicle was driven over a predefined route consisting of urban as well as highway driving. The ten driving patterns were termed as D1 to D10 respectively. D6 and D8 driving patterns are shown in Figures 1 and 2. The study assumed that vehicle speed-time profiles were independent of vehicle type. Though the data was collected from a conventional vehicle, with the assumption of independency of speed-time data from vehicle type, the vehicle's speed-time data could be considered as real world driving patterns for an initial study to validate the methodology (Method 2) in real world.

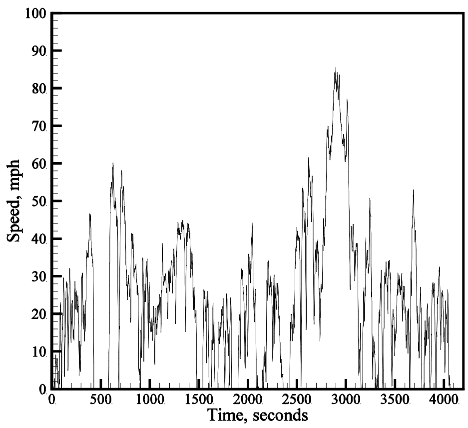

Figure 1: D6

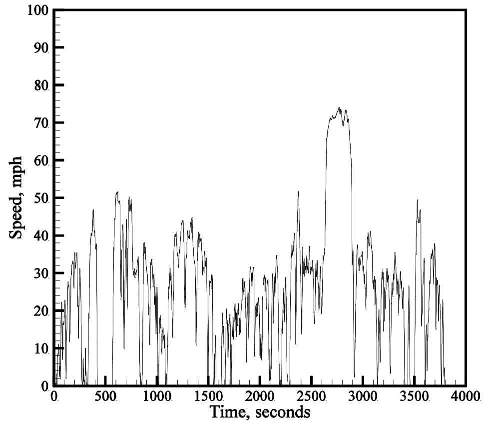

Figure 2: D8

3.9 FE evaluation

Each optimum design of both the methodologies was evaluated for FE over the ten driving patterns and the coefficient of variation of FE over the ten driving patterns was considered as the variation in FE of that optimum design. Coefficient of variation is the ratio of the standard deviation to the mean. For the comparison of FE of different designs over a driving pattern, the initial and final battery SOC were maintained within ±0.5% by adjusting the target SOC value of the supervisory control strategy. The adjustment of target SOC value was done through optimisation using GA.

4 Results and discussions

Four powertrain components – IC engine, generator, motor and battery were optimised as per the Method 1 and Method 2. The Method 1 produced five different sets of optimum design one for each driving pattern, whereas the Method 2 produced a single optimum design over the five driving patterns as shown in Table 2. The optimum designs based on the Method 1 over the NEDC, FTP, LA92, HWFET and US06 are termed as M1-NEDC, M1-FTP, M1-LA92, M1-HWFET and M1-US06 respectively. The optimum design of the Method 2 was termed as M2. The variations of IC engine, generator, motor and battery among the M1-NEDC, M1-FTP, M1-LA92, M1-HWFET and M1-US06 designs were 27.6%, 33.6%, 21.6% and 30.7% respectively.

Table 2: Comparison of optimum component sizes

Design parameters	Optimum size					
	Method 1					Method 2
	M1-NEDC	M1-FTP	M1-LA92	M1-HWFET	M1-US06	M2
IC engine, kW	35.1	37.9	36.3	29.3	40.5	44.9
Generator, kW	13.2	14.1	13.7	12.2	18.3	16.5
Motor, kW	39.9	39.5	44.4	44.3	34.8	30.5
Battery , Ah	6.2	8.9	8.7	7.3	8.7	7.7

Table 3: Comparison of FE over real-world driving

Driving patterns	FE, mpg (miles per gallon)					
	Method 1					Method 2
	M1-NEDC	M1-FTP	M1-LA92	M1-HWFET	M1-US06	M2
D1	48.6	50.7	49.1	47.1 (x)	52.3	55.4
D2	64.3	66.7	65.6	57.7	66.1	65.0
D3	48.7	51.7	50.4	47.5 (x)	52.0	51.0
D4	66.0	67.2	66.9	60.1	66.1	64.1
D5	54.5	56.6	55.9	50.1 (x)	57.0	57.4
D6	46.3	49.2	47.4	47.3 (x)	50.0	51.0
D7	58.9	60.6	60.4	53.5	59.9	58.8
D8	70.9	71.4	71.5	66.0	69.6	67.5
D9	59.9	62.6	62.2	52.9 (x)	61.9	60.9
D10	61.4	62.5	62.3	55.9	61.1	59.6
Average FE, mpg	57.9	59.9	59.2	53.8	59.6	59.1
Standard deviation of FE, mpg	7.8	7.2	7.8	5.9	6.3	5.3
FE variation, [coefficient of variation]	0.135	0.121	0.131	0.110	0.106	0.090
(x): failed to operate in charge sustaining mode						

Optimum designs based on both the methodologies were evaluated for FE over the ten driving patterns as shown in Table 3. All optimum designs except the M1-HWFET were able to operate in charge sustaining mode (i.e., final battery SOC was within ±0.5% of the initial battery SOC) over all driving patterns. The M1-HWFET was not able to operate in charge sustaining mode over D1, D3, D5, D6 and D9 driving patterns.

Average FE of the M1-NEDC, M1-FTP, M1-LA92, M1-HWFET and M1-US06 designs were 57.9 mpg, 59.9 mpg, 59.2 mpg, 53.8 mpg and 59.6 mpg respectively.

Average FE of the M2 design was 59.1 mpg i.e., the M2 design had average FE of 2.1% and 9.9%

higher as compared to the M1-NEDC and M1-HWFET designs respectively, but had 1.3%, 0.2% and 0.8% lower average FE as compared to the M1-FTP, M1-LA92 and M1-US06 designs respectively.

Standard deviations of FE of the M1-NEDC, M1-FTP, M1-LA92, M1-HWFET and M1-US06 designs were 7.8 mpg, 7.2 mpg, 7.8 mpg, 5.9 mpg and 6.3 mpg respectively, whereas the standard deviation of FE of the M2 design was 5.3 mpg.

The variation in FE of the M1-NEDC, M1-FTP, M1-LA92, M1-HWFET and M1-US06 designs were 0.135, 0.121, 0.131, 0.110 and 0.106 respectively, whereas the variation in FE of the M2 design was 0.090. Therefore, the M2 design had lower variation in FE by 33.3%, 25.6%, 31.3%, 18.2% and 15.1% as compared to the M1-NEDC, M1-FTP, M1-LA92, M1-HWFET and M1-US06 designs respectively.

The minimum FE value of the M2 design for the ten driving patterns was 51.0 mpg over the D3 and D6. The minimum FE values of the M1-HWFET were 47.1 mpg over the D1, whereas the minimum FE values of the M1-NEDC, M1-FTP, M1-LA92 and M1-US06 were 46.3 mpg, 49.2 mpg, 47.4 mpg and 50.0 mpg respectively over the D6. Therefore, the M2 design improved the minimum FE by 10.2%, 3.7%, 7.6%, 8.3% and 2.0% as compared to the M1-NEDC, M1-FTP, M1-LA92, M1-HWFET and M1-US06 designs respectively.

The above results clearly showed that the M2 design had lower variation in FE as compared to all optimum designs of the Method 1 and the reduction of variation in FE could be from 15.1% to up to 33.3%. Though the M2 design had 1.3%, 0.2% and 0.8% lower average FE as compared to the M1-FTP, M1-LA92 and M1-US06 designs respectively, the lower variation in FE of the M2 design by 25.6%, 31.3% and 15.1% as compared to the M1-FTP, M1-LA92 and M1-US06 made the M2 design potentially less sensitive to variation in driving patterns and higher minimum FE of the M2 design by 3.7%, 7.6% and 2.0% as compared to the M1-FTP, M1-LA92 and M1-US06 showed the potential improvement of the M2 design even under the condition of least FE. Therefore, even though the M2 design had marginally lower average FE as compared to the M1-FTP, M1-LA92 and M1-US06, the M2 design has the potential to have higher FE as compared to the M1-FTP, M1-LA92 and M1-US06 under varying driving patterns in the real-world.

5 Conclusions

The methodology of powertrain component sizing of HEVs based on a range of driving patterns has been investigated for ten real world driving patterns over a predefined route consisting of urban as well as highway driving. The methodology (Method 2) demonstrated the potential to reduce variation in FE by up to 33% with comparable average FE over ten real world driving patterns as compared to the conventional methodology (Method 1). The potential of the methodology (Method 2) to reduce variation in FE indicates its potential applicability in real world application.

6 Future work

Exhaust emissions and component cost will be considered along with FE. The proposed methodology will also be evaluated for simultaneous optimisation of powertrain components and supervisory control strategy parameters.

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