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# Study of Control Strategy Parameters and Component Sizing in Hybrid Electric Vehicles Using Particle Swarm Optimization

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**Abstract**

This paper studies the effect of different control strategy parameters on fuel economy for hybrid electric vehicles. The parameters with significant effect as well as the key component sizing are used in the optimization algorithm to reduce fuel consumption. The optimization algorithm applied in this paper is the PSO algorithm with a proposed approximation approach. The approximation approach is an interpolation method used to generate search-space in the early optimization stage to improve the computational efficiency. Simulations are carried out in Powertrain System Analysis Toolkit (PSAT). The results show that the computational load of the optimization algorithm is greatly reduced for both parallel and series HEVs. This method could be further applied to investigate the optimized parameters for different driving cycles. In this paper, three driving cycles are applied: 2 NEDC, 4 NEDC, and 6 NEDC. The optimized parameters from each of these three driving cycles are used to calculate the fuel economy for all the three driving cycles. Comparing the average and the standard deviation of fuel economy, it is suggested that the parameters optimized from the driving cycle with longer distance provide a better result. This study could be further investigated on the relation between optimized parameters and characteristics of driving cycles to achieve an interactive control strategy parameter advising system in the future.

*Keywords: HEV (hybrid electric vehicle), optimization, efficiency, energy consumption, simulation*

## 1 Introduction

Transportation consumes a large portion of the world's total primary energy and produces a huge amount of exhaust emissions. The energy conversion is highly inefficient in the vehicles powered by the conventional (IC) internal combustion engine. Hybrid electric vehicle (HEV) is an alternative that mixes the strength of the IC engine and battery as the power source to propel the vehicle.

To achieve high energy efficiency for HEVs, many studies have been done under the topic of HEV performance optimization. The most popular aspects are the optimization of fuel economy and exhaust emissions. Traditional optimization methods have been applied to optimize powertrain sizing for less fuel consumption and exhaust emissions [1]. These methods have the requirements of continuity, differentiability and

Lipshitz conditions on the objective function [2]. In contrast, meta-heuristic optimization algorithms, such as particle swarm optimization (PSO), evolutionary algorithm (EA) and parallel chaos optimization algorithm (PCOA) have been used for the optimization of component sizing and control strategy. Wu *et al.* [2] used a PSO-based methodology for parameter optimization to reduce fuel economy, exhaust emissions, and costs of HEV. This multi-objective optimization was converted into a single-objective optimization problem using a goal-attainment method. Galdi *et al.* [3] and Piccolo *et al.* [4] used genetic algorithms to optimize component sizing and control strategy parameters, respectively. The parameter optimization of a series HEV was studied in [5] by evolutionary algorithms. The multi-objective optimization method was used to provide a set of trade-off optimal solutions between the fuel economy and emissions. In [6], PCOA was used for the optimization of PHEV (Plug-in Hybrid Electric Vehicle) component sizing.

In optimization algorithms, the selection of optimization parameters plays a crucial role in improving fuel economy. This paper studies the effect of different control strategy parameters for optimization on fuel economy. The parameters with significant effect as well as component sizing ($P_{eng}$ and $P_{motor}$) are selected as optimization parameters in the PSO algorithm. An approximation method is applied to accelerate the generation of the search-space in the early optimization stage. Moreover, this paper also investigates the relation between optimized parameters and driving cycles. Instead of using pre-defined parameters, this work may make it possible to adjust control strategy parameters during real-time driving for better fuel economy in the future work.

## 2 Proposed Method

The framework of the proposed work is shown in Figure 1. Powertrain System Analysis Toolkit (PSAT) is used in this paper to calculate the fuel economy for the defined drivetrain configuration and parameters. The parameters that have important effect on the value of fuel economy are selected as the optimization parameters in the optimization algorithm. The optimization algorithm is carried out to find out the optimum parameters. This work attempts to find out an efficient way for improving fuel economy.

The configurations of the parallel HEV (P-HEV) and the series HEV (S-HEV) built in PSAT are shown in Figure 2. The main specifications of the vehicle are listed in Table 1.

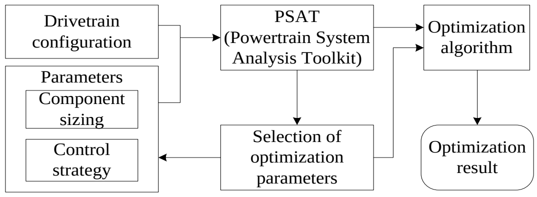
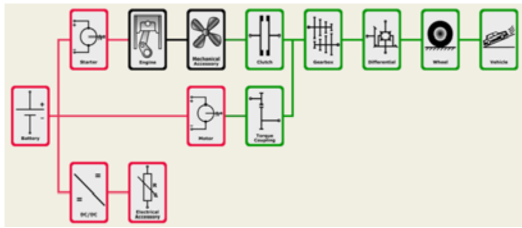
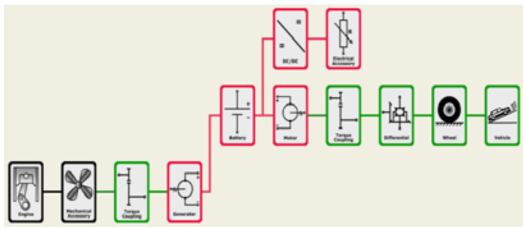



Figure 1: Framework of proposed work



(a) Parallel HEV configuration



(b) Series HEV configuration

Figure 2: Two configurations of HEVs in PSAT

Table 1: Main specifications of HEV

| | |
|---|---|
| Vehicle name | Ford explorer |
| Vehicle body mass | 1220 kg |
| Vehicle cargo mass | 136 kg |
| Frontal area | 2.46 m$^2$ |
| Fraction of weight to front wheels | 0.47 |
| Vehicle wheel base | 2.889 m |
| Drag coefficient | 0.41 |
| Battery type | Li-ion |
| Number of battery modules | 25 |
| Cell number | 75 |
| Capacity | 6 Ah |
| Mass of one cell | 0.37824 kg |
| Mass per wheel | 30 kg |
| Maximum braking torque | 2000 Nm |
| Inertia per wheel | 1 kg·m$^2$ |
| Wheel radius | 0.34865 m |
| 0$^{th}$ order coefficient of rolling resistance polynomial | 0.009 |
| 1$^{st}$ order coefficient of rolling resistance polynomial | 0.00012 |

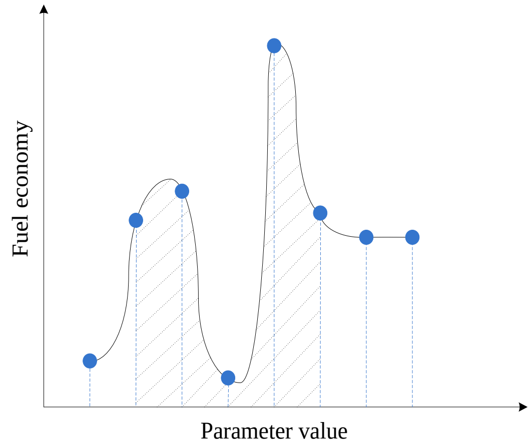
The fuel economy for different parameter values is calculated from PSAT. The objective of the optimization algorithm is to find out the values of the optimization parameters that provide the largest fuel economy. PSO algorithm developed by Kennedy and Eberhart [7] is applied in this paper. In this algorithm, each particle keeps tracking its personal best solution *pbest*; meanwhile, *gbest* is tracked as the best solution so far by any particle. The movement of each particle is related to its current position, current velocity, the distance from *pbest* and the distance from *gbest*. PSO accelerates each particle toward the locations of its *pbest* and *gbest* by adjusting the velocity with a random weighted acceleration, as expressed in the following equations.

$$V_i^{k+1} = wV_i^k + c_1 r_{1i}^k (pbest_i^k - X_i^k) + c_2 r_{2i}^k (gbest^k - X_i^k) \quad (1)$$

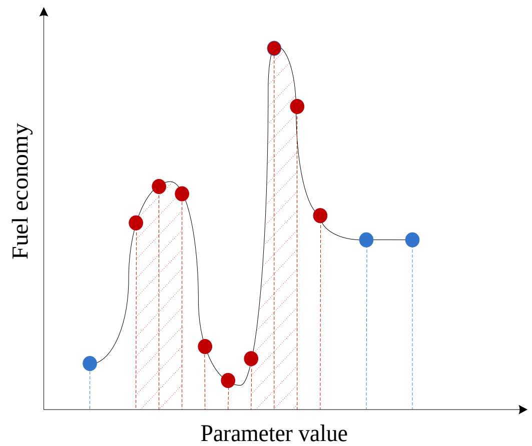
$$X_i^{k+1} = X_i^k + V_i^{k+1} \quad (2)$$

where $V_i^k$ is the velocity of particle *i* at iteration *k*, *w* is inertia weight, $c_1$ and $c_2$ are two positive constants, and $r_{1i}^k$ and $r_{2i}^k$ are two uniformly distributed random numbers between 0 and 1. Further, $pbest_i^k$ is the location of the $i^{th}$ particle's personal best solution up to iteration *k*, $gbest^k$ is the location of the population's best solution up to iteration *k*, and $X_i^k$ is the position vector of the $i^{th}$ particle at iteration *k*.

Since the calculation of fuel economy from PSAT involves heavy computational load, the optimization, especially for the multi-dimensional search-space, is quite time-consuming. To accelerate this process, a rough search-space is generated in the early optimization stage. For the sake of explanation, one dimensional search-space is used as shown in Figure 3. A rough mesh is generated between the lower bound and upper bound of the optimization parameter. In Step 1, the fuel economy for each mesh point is calculated from PSAT as the nodes shown in Figure 3(a). The fuel economy for the other parameter values in between is calculated by interpolation instead of using PSAT to reduce computational costs. Using this estimated search-space, PSO is applied to find the potential region where the optimum parameter (the one with the maximal fuel economy) may exist. In this example, the potential region is the one with shadow in Figure 3(a). The boundary of this region defines the upper and lower bond of the search-space in Step 2 as shown in Figure 3(b). In Step 2, the interpolation is done with a finer mesh. Finally, a small region or several small regions will be obtained and used in the normal PSO algorithm.




(a) Step 1




(b) Step 2

Figure 3: Illustration of interpolation method

The optimization parameters studied in this paper are the parameters in control strategy and component sizing, such as $SOC_{max}$, $SOC_{min}$, $P_{Eoff}$, $P_{Eon}$, $t_{off}$, $Target_{SOC}$, and $K_p$ in control strategy, as well as $P_{eng}$ and $P_{motor}$ in component sizing. The parameter descriptions are listed in Table 2. The framework of the proposed optimization work is shown in Figure 4. It starts with investigating the effect of each control strategy parameter on fuel economy. The parameters have significant effect and the component sizing parameters are used as the optimization parameters in the PSO algorithm with the approximation method. Similarly, this parameter optimization process is carried out with various driving cycles.

Table 2: Descriptions of optimization parameters

| Parameter | Unite | Description |
|---|---|---|
| $SOC_{max}$ | % | SOC above which the engine is turned off |
| $SOC_{min}$ | % | SOC below which the engine is turned on |
| $P_{Eoff}$ | kW | Max power for the engine to turn off |
| $P_{Eon}$ | kW | Min power for the engine to turn on |
| $t_{off}$ | s | Once off, minimum time for the engine to stay off |
| $Target_{SOC}$ | % | SOC charge map target point |
| $K_p$ | --- | Regulation of the engine speed when recharge the battery |
| $P_{eng}$ | kW | Peak engine power |
| $P_{motor}$ | kW | Peak motor power |

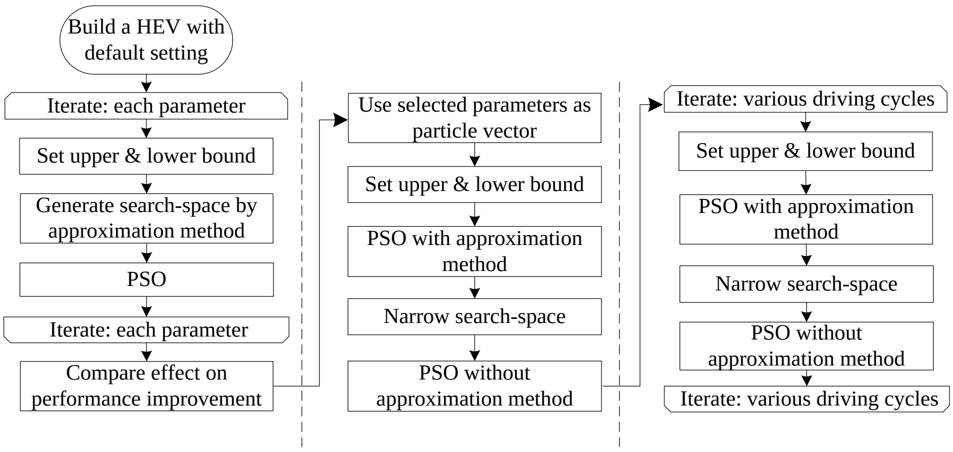



Figure 4: Proposed optimization framework

## 3 Results

To study the effect of each parameter on the fuel economy, only one parameter is studied at each time. All other parameters are kept at the default value. As shown in Figure 5, the NEDC is repeated four times as the driving cycle. Simulations are carried out for P-HEV and S-HEV. The simulation results in Figure 6 show the range of fuel economy for each of the seven control strategy parameters in the P-HEV. The fuel economy of the default setting is defined as the benchmark 100% to compare the improvement of the fuel economy by each control strategy parameter. The simulation results indicate that the value of fuel economy varies in a wide range if $SOC_{max}$ is changed. In contrast, the effect of $SOC_{min}$ is not as important as the one of $SOC_{max}$ and the other control strategy parameters for P-HEV.

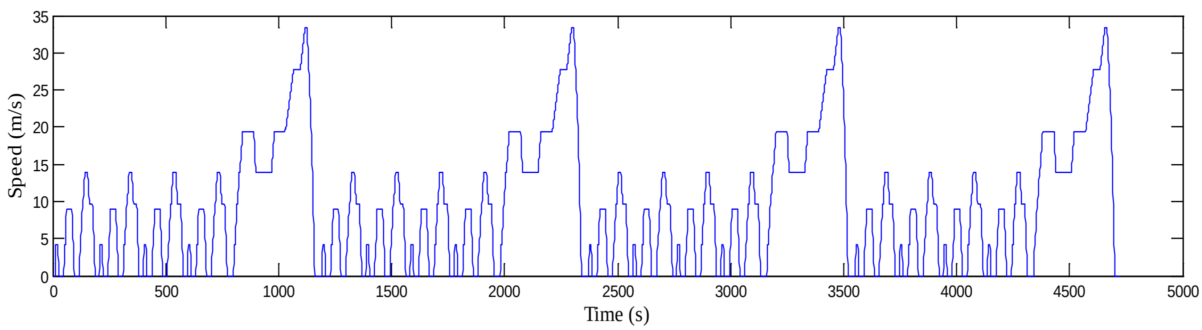



Figure 5: 4 NEDC driving cycle

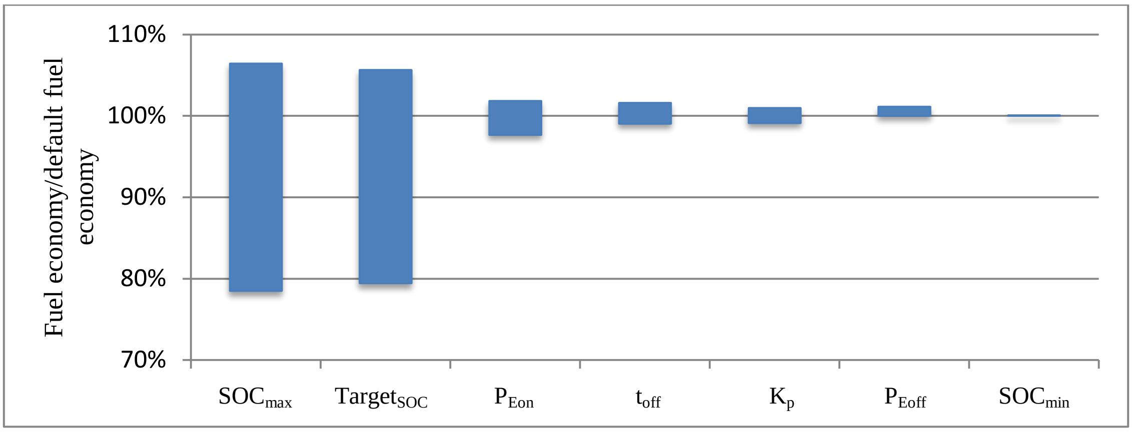
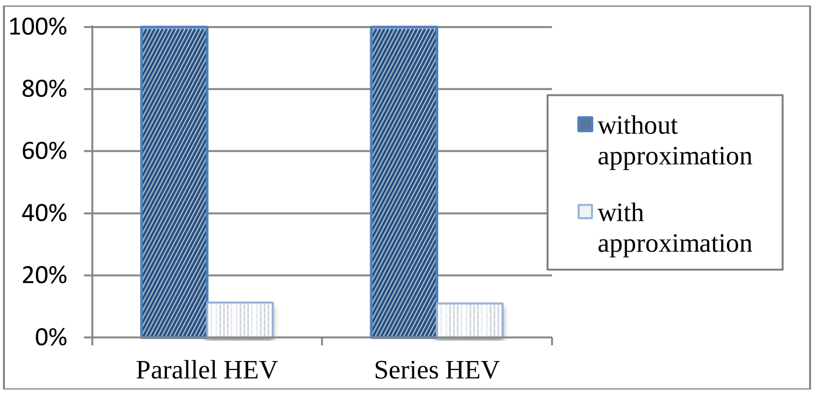


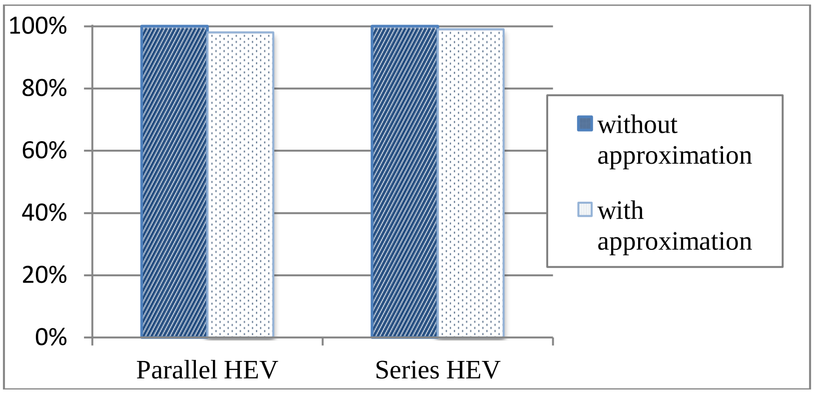

Figure 6: Effect of control strategy parameters on fuel economy for P-HEV

A better optimization result (fuel economy) could be achieved if the parameters with high impact on fuel economy are all selected for the optimization algorithm. From the simulation result shown in Figure 6, the control strategy parameters $SOC_{max}$, $Target_{SOC}$, $P_{Eon}$, and $t_{off}$ are selected. The optimization parameter vector in this paper is [$SOC_{max}$, $Target_{SOC}$, $P_{Eon}$, $t_{off}$, $P_{eng}$, $P_{motor}$]. However, the generation of the search-space for PSO would have to go through heavy computation, especially for the multi-dimensional space. To reduce the computational load, an approximation method is used to generate a rough search-space with the interpolation method in the early optimization stage. The optimized results with/without the approximation method for one dimensional case are compared in Figures 7(a) and 7(b). In normal approach without approximation, the computational load is defined as 100% and its optimal fuel economy is used as the reference for comparison. The results in Figure 7(a) show that the computational load is significantly reduced in both P-HEV and S-HEV by using the approximation method; moreover, this approximation does not cause large errors in fuel economy as shown in Figure 7(b).

Similarly, the simulation is carried out to obtain the optimum parameters for various driving cycles. The profile of the driving cycles with 2, 4, and 6 NEDC are shown in Figure 8. Table 3 summaries the specifications for these driving cycles. The optimum parameters from 2, 4, and 6 NEDC are used for these three driving cycles. Figure 9 represents the average and the standard deviation of the fuel economy in three driving cycles using the optimized parameters from 2 NEDC, 4 NEDC, and 6 NEDC, respectively. The results show that using the optimized parameters from 6 NEDC for the three driving cycles provides the largest average value and the smallest standard deviation in fuel economy. Using the optimized parameter from 2 NEDC for these three driving cycles achieves the smallest fuel economy and the largest standard deviation. Since the mainly difference among these three driving cycles is the distance, the results may suggest that using the parameters optimized by a longer distance for the driving cycles with various distances has a smaller deviation and a better average fuel economy.

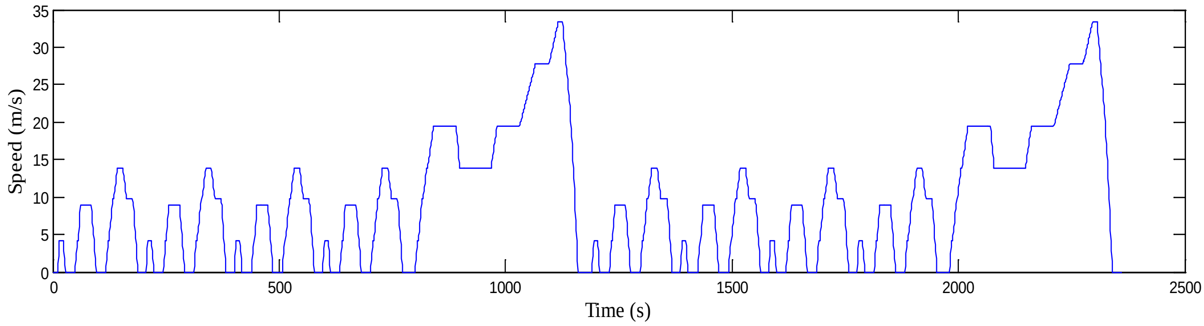



(a) Computational load

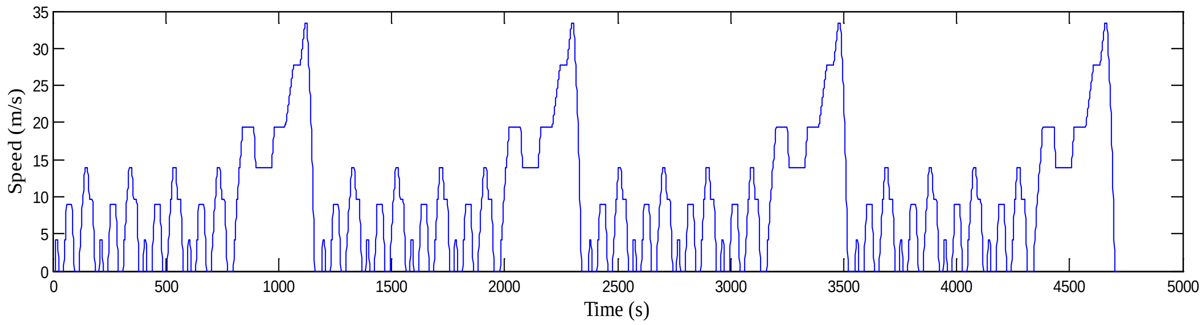



(b) Fuel economy

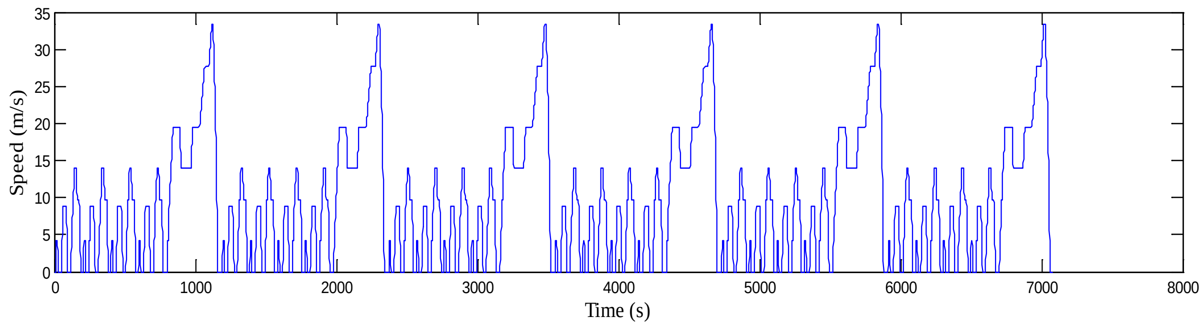
Figure 7: Study the efficiency of the approximation method for optimization




(a) Driving cycle with 2 NEDC




(b) Driving cycle with 4 NEDC




(c) Driving cycle with 6 NEDC

Figure 8: Profile of various driving cycles

Table 3: Specifications of various driving cycles

| | | 2 NEDC | 4 NEDC | 6 NEDC |
|---|---|---|---|---|
| Cycle time (s) | | 2361 | 4723 | 7085 |
| Distance (mile) | | 13.6866 | 27.3732 | 41.0598 |
| Speed (mile/h) | Maximum | 74.6 | 74.6 | 74.6 |
| | Average | 20.8601 | 20.8601 | 20.8601 |
| | Standard deviation | 19.23 | 19.23 | 19.23 |
| Acceleration ($m/s^2$) | Maximum | 1.0729 | 1.0729 | 1.0729 |
| | Average | 0.594 | 0.594 | 0.594 |
| | Standard deviation | 0.25222 | 0.25209 | 0.25205 |
| Deceleration ($m/s^2$) | Maximum | -1.4305 | -1.4305 | -1.4305 |
| | Average | -0.78881 | -0.78881 | -0.78881 |
| | Standard deviation | 0.21749 | 0.21734 | 0.21729 |
| Stop | Number | 26 | 52 | 78 |
| | Frequency (stop/mile) | 0.001180403 | 0.001180403 | 0.001180403 |
| | Duration (s) | 588 | 1176 | 1764 |
| | Percent of cycle (%) | 24.904701 | 24.899428 | 24.897671 |

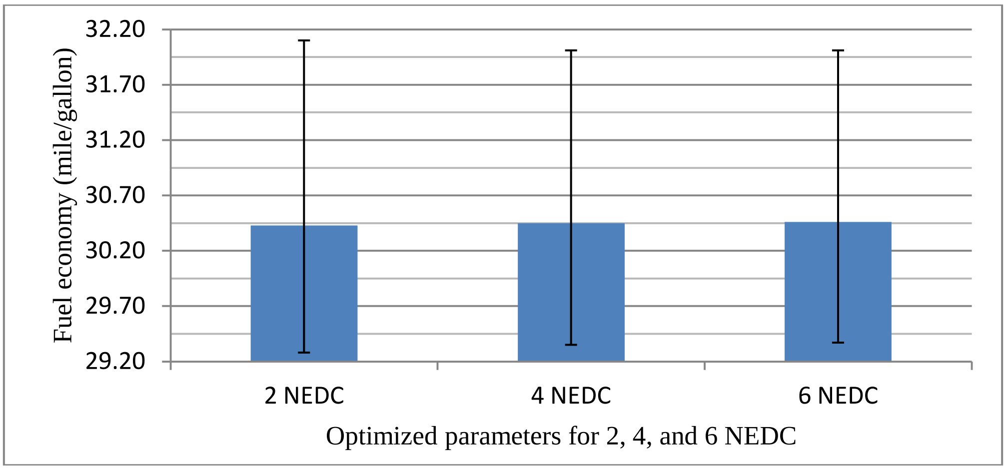



Figure 9: Fuel economy for various driving cycles

In this paper, UDDS is also used as the driving cycle to compare with the results from NEDC. It is found that the values of some optimum parameters in UDDS are quite different from the ones obtained using NEDC as the driving cycle. This may be due to the fact that more characteristics of the driving cycle, besides the driving distance, are different. In the future work, the relation between the optimized parameters and the characteristics of driving cycles (such as average speed, idle duration, stop frequency, acceleration and deceleration) will be investigated. This could help to devise a dynamic control strategy for different driving cycles. Thus, good fuel economy could be expected for the condition without pre-defined/predictive driving cycles.

Furthermore, the optimization objective in this paper is to maximize fuel economy. The optimization parameters include component sizing and control strategy parameters. In control strategy, the fuel economy is related to the battery performance on charging and discharging. The charging and discharging cycles, depth of discharge, and driving frequency all have an impact on battery's life time and durability. In view of the component availability and price, it may be necessary to further consider the price-performance trade-off for key components. The optimization may take the above discussed factors (fuel economy, battery life time, component performance, and component cost) into consideration by using the cost to build up the relation with these factors. The relation of the costs with the battery life time and component sizing can be found in [8-9].

# 4 Conclusions

This paper studies the effect of different control strategy parameters and component sizing on fuel economy of HEVs. The ones with significant effects ($SOC_{max}$, $Target_{SOC}$, $P_{Eon}$, $t_{off}$, $P_{eng}$, and $P_{motor}$) are used in the PSO algorithm with the proposed approximation method to reduce the computational load of the optimization algorithm. The optimized parameters for different driving cycles are investigated. The simulation results imply that using the optimized parameters from a longer distance for the driving cycles with various distances achieves a better result in fuel economy. The further investigation on the relation between the optimized parameters and the characteristics of driving cycles has the potential to design a dynamic advising system for control strategy parameters. This system may provide good performance on the driving cycles without prediction.

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# References

[1] K. Wipke et al., *Optimizing energy management strategy and degree of hybridization for a hydrogen fuel cell SUV*, International Electric Vehicle Symposium EVS18, Berlin, Germany, 2001

[2] J. Wu et al., *PSO algorithm-based parameter optimization for HEV powertrain and its control strategy*, International Journal of Automotive Technology, ISSN 1976-3832, 9(2008), 53-69

[3] V. Galdi et al., *A genetic-based methodology for hybrid electric vehicles sizing*, Soft Computing – A Fusion of Foundations, Methodologies and Applications, ISSN 1433-7479, 5(2001), 451-457

[4] A. Piccolo et al., *Optimization of energy flow management in hybrid electric vehicle via genetic algorithms*, IEEE/ASME International Conference on Advanced Intelligent Mechatronics Proceedings, Como, Italy, ISBN 0-7803-6736-7, 1(2001), 434-439

[5] B. Zhang et al., *Multi-objective parameter optimization of a series hybrid electric vehicle using evolutionary algorithms*, Vehicle Power and Propulsion Conference VPPC'09, ISBN 978-1-4244-2600-3, (2009), 921-925

[6] X. Wu et al., *Component sizing optimization of plug-in hybrid electric vehicles*, Applied Energy, ISSN 0306-2619, 88(2011), 799-804

[7] J. Kennedy et al., *Particle swarm optimization*, Proceedings of IEEE International Conference on Neural Networks, ISBN 0-7803-2768-3, 4(1995), 1942-1948

[8] S. Golbuff, *Optimization of a plug-in hybrid electric vehicle*, MSc thesis, Georgia Institute of Technology, 2006

[9] R. Graham, *Comparing the benefits and impacts of hybrid electric vehicle options*, 1000349, Palo Alto, CA, Electric Power Research Institute, 2001

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