Plug-in Hybrid Electric Vehicle Control Strategy Parameter Optimization

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Abstract

Plug-in Hybrid Electric Vehicles (PHEVs) offer a great opportunity to significantly reduce petroleum consumption. The fuel economy of PHEV is highly dependent on All-Electric-Range (AER) and control strategy. Previous studies have shown that in addition to parameters influencing Hybrid Electric Vehicles (HEVs), control strategies of PHEVs are also influenced by the trip distance. This additional parameter makes it even more difficult to tune the parameters that minimize fuel consumption manually. This study uses a pre-transmission parallel PHEV model developed with the Powertrain System Analysis Toolkit (PSAT). A non derivative based algorithm called DIRECT (for DIvided RECTangles), is used to optimize the main control strategy parameters. The fuel economy and main performance criteria of the PHEVs are compared for the initial design and final optimal design. An optimal control solution resulting from an extensive search of the entire design space can provide physical insight into the PHEV operation.

Keywords: Plug-in Hybrid Electric Vehicles, Control Strategy, Simulation, Optimization.

1. Introduction

For the past couple of years, the U.S. Department of Energy (DOE) has spent considerable effort on research and development of Plug-in Hybrid Electric Vehicle (PHEV) technology, because of the potential fuel displacement the technology offers. DOE's PHEV R&D Plan [1], which was launched with the aim of reducing the dependence on foreign oil by diversifying the sources for automobile fuels, describes the different activities required to achieve its goals. DOE will use Argonne National Laboratory's (Argonne's) Powertrain System Analysis Toolkit (PSAT) to guide its analysis activities, stating that "Argonne's PSAT will be used to design and evaluate a series of PHEVs with various 'primary electric' ranges, considering all-electric and charge-depleting strategies".

PSAT [2, 3] is designed to serve as a single tool that can be used to meet the requirements of automotive engineering throughout the development process, from modeling to control. One of the most important characteristics of PSAT is that it is a forward-looking model — that is PSAT allows users to model real-world conditions by using real commands. For this reason, PSAT is called a command-based or driver-driven model. Written in Matlab/Simulink/Stateflow [4], the software allows the simulation of a wide range of vehicle applications, including light- (two- and four-wheel-drive), medium-, and heavy-duty vehicles. In 2004, PSAT, the primary vehicle simulation tool to support the DOE's Office of Energy

Efficiency and Renewable Energy (EERE) FreedomCAR and Vehicle Technologies Program [5], received an R&D100 Award, which highlights the 100 best products and technologies newly available for commercial use from all over the world.

One of the primary outcomes of the vehicle analysis is to define the component performance goals and requirements for R&D/solicitations. PSAT has been used to set the battery technical target [6, 7], that was used to develop the United States Advanced Battery Consortium (USABC) PHEV Request for Proposal [8]. In addition to parameters that influence the control strategy (such as battery State-of-Charge or drive cycle) of HEVs, several studies have demonstrated the impact of driving distance on fuel displacement for PHEVs [9]. This additional parameter makes it even more difficult to tune the parameters that minimize fuel consumption manually.

Numerous optimization algorithms are available, and they can be categorized in different ways; for example, there is the local optimization algorithm versus the global optimization algorithm, the deterministic optimization algorithm versus the stochastic optimization algorithm or the gradient-based algorithm versus the derivative-free algorithm. Making the proper selection of an optimization algorithm for the application of hybrid powertrain design is not obvious. In this paper, the DIRECT (for DIvided RECTangles) algorithm has been selected on the basis of previous work performed by the University of Michigan [10].

This paper will focus on the optimization of the parameters of a pre-transmission parallel PHEV with a 10 miles All Electric Range (AER). After describing the vehicle and its control strategy logic, we will evaluate the impact of the drive cycle and distance of several key parameters of the control.

2. Vehicle Description

The vehicle class used for the simulation is a midsize SUV, since this platform was used to define the USABC short-term battery requirements. The components selected, shown in Table 1, are the ones that have been implemented in Argonne's Mobile Advanced Automotive Testbed (MATT). MATT [11] is a rolling chassis used to evaluate component technology in a vehicle system context. The control strategy developed on the basis of the optimization results will ultimately be implemented and tested on hardware.

Table 1: Main Specifications of the Vehicle

Component	Specifications
Engine	2.2 L, 100 kW Ford Duratec
Electric machine	60 kW PM electric machine
Battery	Li-ion, 75kW, 23Ah
Transmission	5-speed automatic transmission
	Ratio: [3.22, 2.41, 1.55, 1, 0.75]
Frontal Area	2.76 m^2
Final Drive Ratio	3.58
Drag Coefficient	0.395
Rolling Resist.	0.008 (plus speed related term)
Wheel radius	0.33 m
Vehicle Mass	1823kg

In this study, the battery equations were derived to calculate the impedance of a plug-in hybrid vehicle battery. Developing the equations to express the battery resistance of a PHEV battery is more complex than developing them for a standard hybrid vehicle because the plug-in battery may be charged and discharged during vehicle operation for periods lasting several minutes. Ideally, the equations should be able to reproduce the measured voltage curves for a complete discharge and charge at constant current, as well as the battery resistance under conditions of rapidly changing currents.

Current and voltage data taken at Argonne were available for a cell fabricated by SAFT, Inc. The data for the cell measured at Argonne were for a 3-h discharge at constant current and for Hybrid Pulse Power Characterization (HPPC) tests [11]. These data were fit to an electronic simulation model with two time constants (Figure 1) of the form:

$$\frac{(OCV - V_L)}{I_L} = R_0 + R_{p1} \times \frac{I_{p1}}{I_L} + R_{p2} \times \frac{I_{p2}}{I_L} \tag{1}$$

In this relationship, OCV and VL are the open circuit and load voltages, respectively; R_0, R_{p1}, and R_{p2} are the ohmic resistance and the polarization impedances; and I_{p1}/I_L and I_{p2}/I_L are the ratios of the polarization currents to the load current. The polarization currents are determined by integration of the equation

$$\frac{dI_p}{dt} = \frac{(I_L - I_p)}{\tau} \tag{2}$$

for each of the polarization impedances, where τ_1 and τ_2 are time constants, as in an earlier study that also used two polarization impedances and in the DOE's PNGV Lumped Parameter Model, which was a similar model with one polarization impedance. The parameters in the equation (OCV, R_0, R_{p1}, R_{p2}) were selected to match the measured data for both the 3-h discharge and the HPPC data for the entire range of the discharge, and these parameters were presented in the form of a lookup table with values from 0% to 100% state of charge at 10% intervals (τ_1 and τ_2 were held constant over the entire discharge).

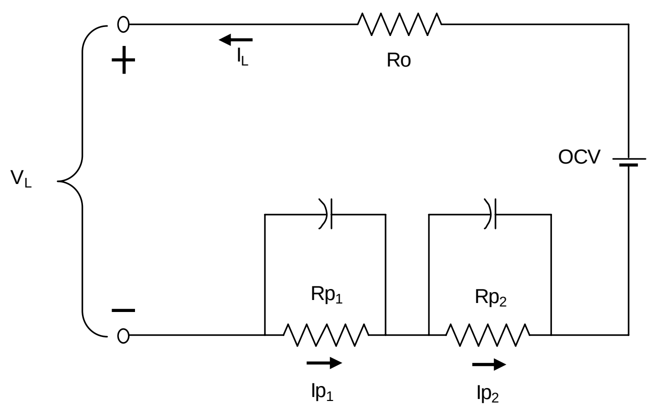

Figure 1 Battery Electric Circuit Model

As shown in Figure 2, the configuration selected is a pre-transmission parallel hybrid, which is very similar to the one used in the DaimlerChrysler Sprinter Van [12].

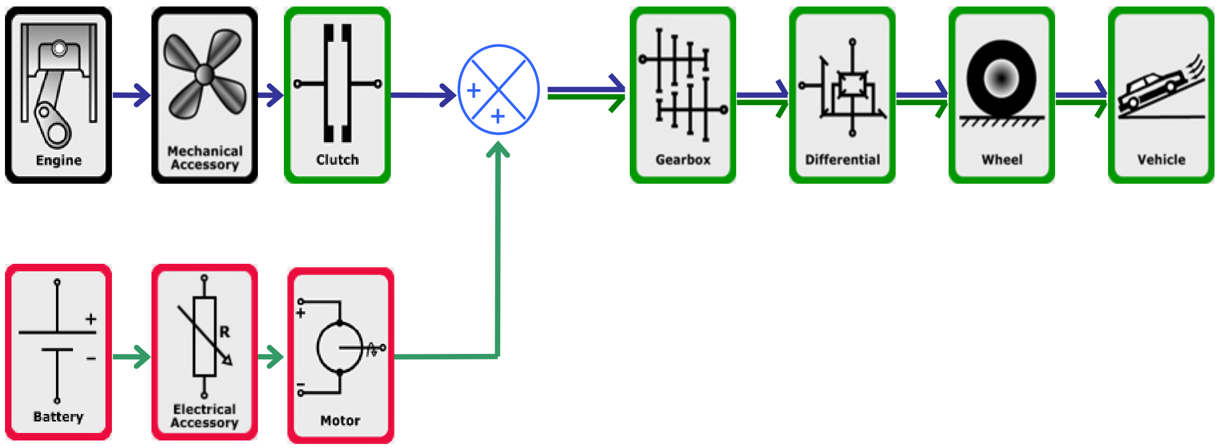

Figure 2: Configuration Selected – Pre-Transmission Parallel HEV

3. Control Strategy Algorithm

The control strategy can be separated into two distinct modes, as shown in Figure 3:

- Charge Depleting (CD) mode: Vehicle operation on the electric drive, engine subsystem or both with a net decrease in battery state-of-charge.
- Charge-Sustaining (CS) mode: Vehicle operation on the electric drive, engine subsystem or both with a 'constant' battery state-of-charge (i.e., within a narrow range), which is similar to those in HEVs that are in current production.

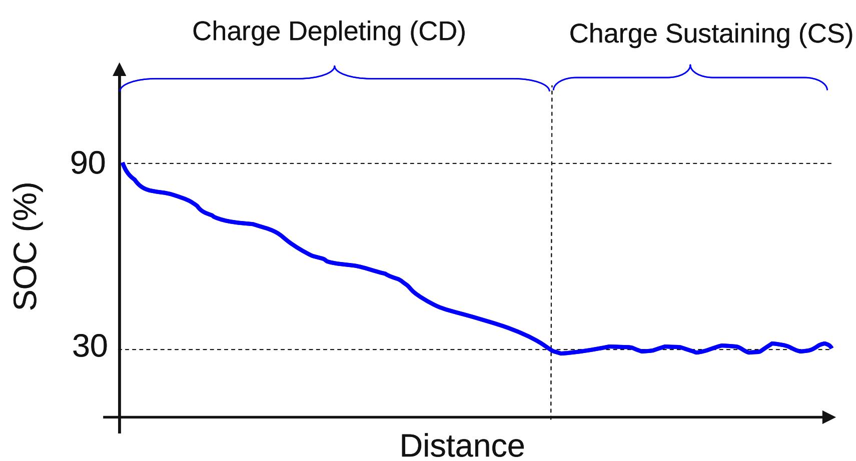

Figure 3: Control Strategy SOC Behavior

The first critical part of the control strategy logic is related to the engine ON/OFF logic. As Figure 4 shows, the engine ON logic is based on three main conditions:

- The requested power is above a threshold.
- The battery SOC is lower than a threshold.
- The electric motor cannot provide the requested wheel torque.

In addition to these parameters, additional logic is included to ensure proper drive quality by maintaining the engine ON or OFF during a certain duration. In addition, to avoid unintended engine ON events resulting from spikes in power demand, the requested power has to be above the threshold for a pre-defined duration. The engine OFF logic condition is similar to that of the engine ON. Both power thresholds used to start or turn off the engine as well as determine the minimum duration of each event have been selected as input parameters of the optimization problem.

To be able to regulate the battery SOC, especially during the charge depleting mode, the power demand that is used to determine the engine ON/OFF logic is the sum of the requested power at the wheel plus an additional power that depends on battery SOC. This power can be positive or negative depending on the value of the current SOC compared to the target.

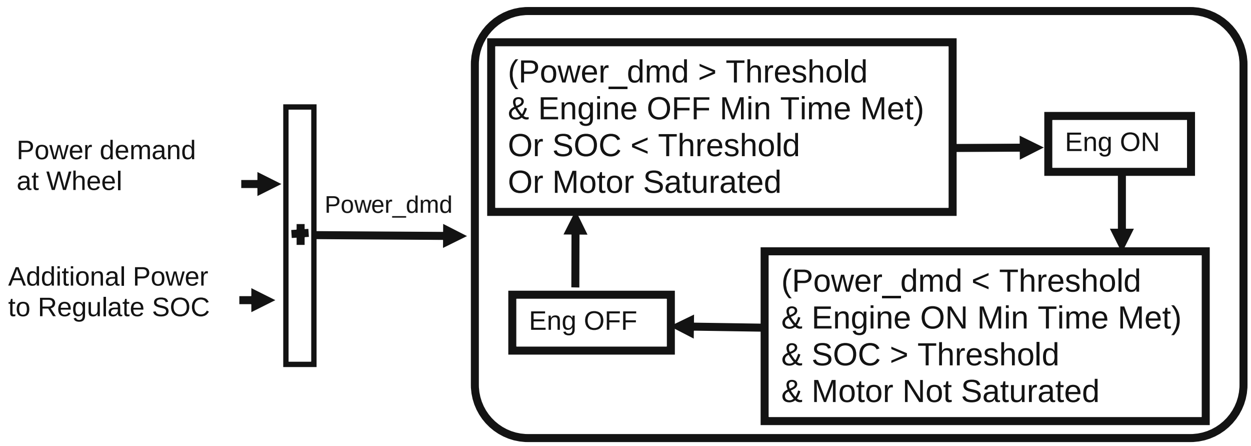

Figure 4: Simplified Engine ON/OFF Logic

Figure 5 shows the different parameters used to define the additional power to regulate the SOC in greater detail. The SOC target has been set when the vehicle is considered entering the charge sustaining mode (30% SOC). Both *ess_percent_pwr_discharged* and *ess_percent_pwr_charged* have been selected as input parameters to the optimization problem.

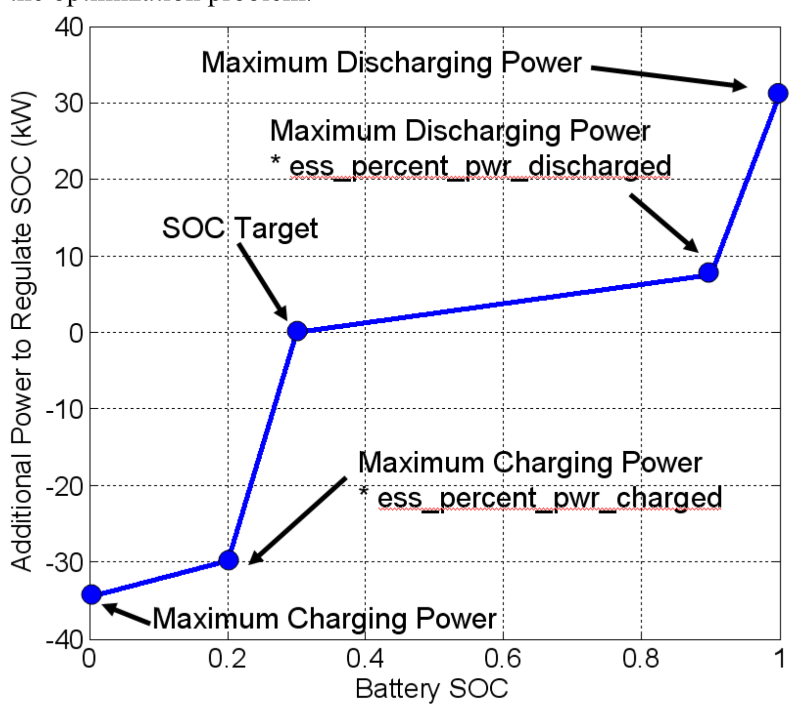

Figure 5: Example of additional Power to Regulate SOC

In electric only mode, the vehicle is propelled by the electric machine. When the engine is ON, it is operated close to its best efficiency curve, depending on the vehicle power request and the battery SOC status. Table 2 summarizes the selected control parameters used as part of the optimization process.

Table 2: Control Parameter List

Parameter	Unit	Min	Max	Description
eng_pwr_wh_above_turn_on	W	5000	30000	Power above which the engine is turned ON
eng_pwr_wh_below_turn_off	W	500	25000	Power below which the engine is turned OFF
eng_time_min_stay_on	sec	1	10	Minimum time the engine stays ON
eng_time_min_stay_off	sec	1	10	Minimum time the engine stays OFF
ess_percent_pwr_discharged	%	20	100	Percentage of maximum battery discharging power at high SOC
ess_percent_pwr_charged	%	20	100	Percentage of maximum battery charging power at low SOC

4. Principles and Procedure of DIRECT

The fuel economy of a plug-in HEV depends on many design parameters such as component sizes and control strategy parameters. This optimization objective response function in the multi-dimensional design space is multi-modal (involving many local minima), and could be noisy and discontinuous. Gradient based algorithms such as Sequential Quadratic Programming (SQP) use the derivative information to find the local minima. The major disadvantage of local optimizers is that they do not search the entire design space and cannot find the global minimum. Derivative-free algorithms such as DIRECT [13], Simulated Annealing (SA) [14], Genetic Algorithm (GA) [15], and Particle Swarm Optimization (PSO) [16] do not rely on the derivatives and can therefore work exceptionally well when the objective function is noisy and discontinuous. Derivative-free methods are often the best global algorithms because they must often sample a large portion of the design space to be successful. A comparison of the gradient-based and the derivative-free algorithms for the optimization of hybrid electric vehicle is given in [17]. Here, the global optimization algorithm, DIRECT, is used.

DIRECT is a sampling algorithm, developed by Donald R. Jones [13]. This global optimization algorithm is a modification of the standard Lipschitzian approach that eliminates the need to specify the Lipschitz constant. Lipschitz constant is a weighing parameter that decides the emphasis on the global and the local search. The use of the Lipschitz constant is eliminated in by searching all possible values for the Lipchitz constant, thus putting a balanced emphasis on both the global and local search.

The algorithm begins by scaling the design box to an *n*-dimensional unit hypercube. DIRECT initiates its search by evaluating the objective function at the center point of the hypercube. DIRECT then divides the potentially optimal hyper-rectangles by sampling the longest coordinate directions of the hyper-rectangle. The sampling is done such that each sampled point becomes the center of its own *n*-dimensional rectangle or box. This division continues until termination (i.e., when a pre-specified iteration limit is reached) or when convergence is achieved. The division of rectangles in the first three iterations of a two dimensional problem is illustrated in Figure 6, where *d* represents the center to vertex distance, and each center point is labeled with a numeral for identifying the rectangles.

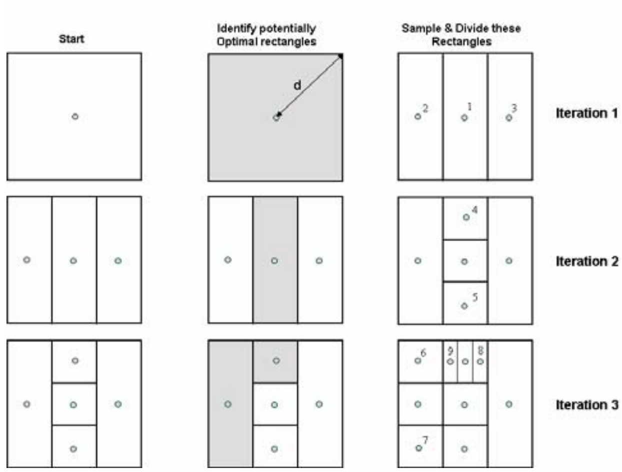

Figure 6: The First Three Iterations of the DIRECT Algorithm

In the first iteration, the unit hypercube is trisected into three rectangles. The objective function value is evaluated at the center points of the three resultant rectangles. The objective function values are plotted against the center – vertex distance as shown in Figure 7 (a). Then the rectangle with the lowest objective value in each column of dots, which represent the design points, is selected as the optimal rectangle. In the first iteration there is only one column of dots; therefore rectangle 1 is selected as the optimal rectangle and trisected in the second iteration. Similarly in the second iteration, rectangle 4 and rectangle 2 have the lowest objective function values as shown in Figure 7 (b). These two rectangles are selected as potential optimal rectangles and trisected in the third iteration. This process is continued until the maximum number of function evaluations is exhausted or the objective value converges.

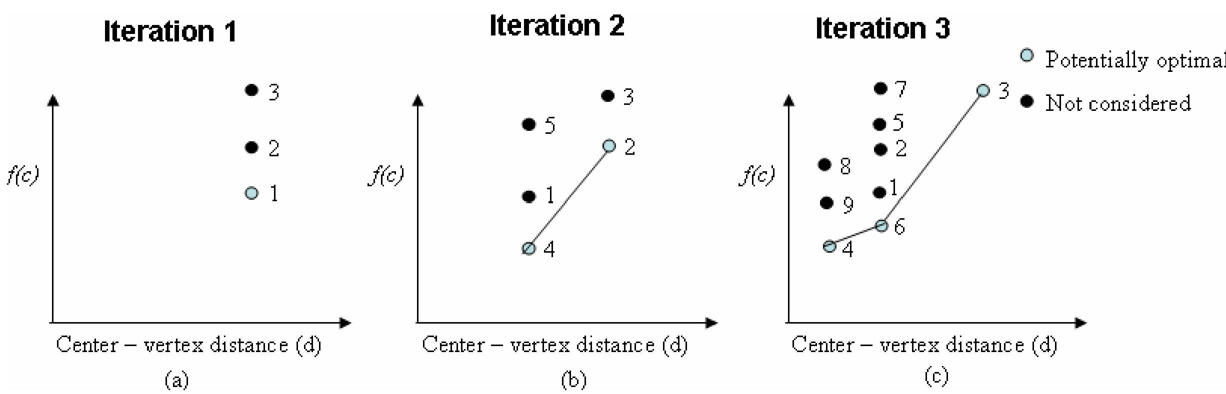

Figure 7: Rectangles Selected by DIRECT for Further Subdivision

5. Optimization Results

The algorithm optimized the fuel economy, and has been exercised on two driving cycles, the Urban Driving Dynamometer Driving Schedule (UDDS) and the highway drive cycle (HWFET). To assess the impact of distance, each cycle has been repeated 2, 4, 6 and 8 times.

Table 3: Drive Cycle Characteristics

	Unit	UDDS	HWFET
Duration	sec	1372	764
Distance	km/miles	11.92/7.45	16.38/10.24
Average speed	mph	19.5	48.26
Average acceleration	m/s^2	0.5	0.19

5.1 Parameter Control Values

Some of the parameters have a higher impact than other on the outcome of the results. Based on the correlation coefficients between the inputs and the fuel economy values, the parameters with the highest impact are the power threshold to turn the engine ON (*eng_pwr_wh_above_turn_on*) and the time the engine is maintained ON (*eng_time_min_stay_on*). Conversely, those with the lowest impact are the power threshold to turn the engine OFF (*eng_pwr_wh_above_turn_on*) and the percentage of maximum battery charging power at low SOC (*ess_percent_pwr_charged*).

To simplify the analysis, only the UDDS drive cycle will be considered in the following paragraphs. Table 4 shows the optimization results of the UDDS standard drive cycle. As the table shows, both power thresholds related to the engine tend to decrease with increasing distance. This result can be explained by the fact that the engine should be turned ON more often for longer distances than for shorter ones. Figure 8 demonstrates that point, comparing the engine power on the UDDS when the cycle is repeated 2 and 8 times. Even if the engine is used at similar operating conditions (i.e., efficiency is fairly constant around 32%, independently of the distance), it turns ON less often during a short distance cycle (2.2% on the UDDS*2 vs. 11.6% on the UDDS*8 during the first cycle).

Table 4: Optimized Parameters for UDDS Drive Cycle

		2 UDDS	4 UDDS	6 UDDS	8 UDDS
eng_pwr_wh_above_turn_on	W	17500	16265	15820	15340
eng_pwr_wh_below_turn_off	W	12750	8515	8313	7608
eng_time_min_stay_on	sec	1.5	1.05	1.018	1.018
eng_time_min_stay_off	sec	1.5	1.16	2.129	1.055
ess_pwr_chg_at_target	%	0.244	0.79	0.926	0.863
ess_pwr_dis_at_target	%	0.6	0.215	0.2	0.205

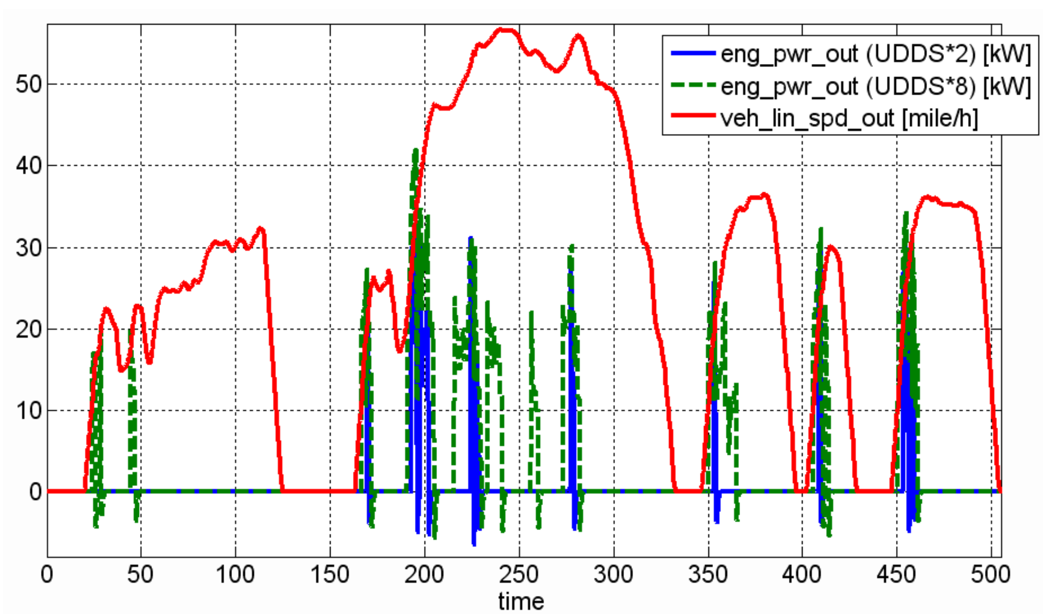

Figure 8: Engine Power for 2 and 8 UDDS

In order to assess the impact of the parameters, we will consider different options:

- Same distance, different parameters.
- Same parameter, different distances.
- Same parameter, different cycles.

5.2 Influence of Different Parameters on Distance

In order to evaluate the impact of parameters on the fuel economy, the same trip was run with the optimized parameters of the different drive cycle distances. For instance, Figure 9 shows the vehicle simulated on 2 UDDS (total distance of 23.7 km) with the parameter values optimized for 2, 4, 6 and 8 UDDS drive cycles. The ratios are in respect to the 2xUDDS results.

Figure 9 shows that, for a short distance (23.7km), there is a significant difference in fuel consumption between the set of parameters obtained for 2 UDDS and the others. The longer the distance to optimize, the less difference there is in fuel consumption. Figure 10 reinforces this point by showing the same information for 6 successive UDDS drive cycles. In addition, the difference between the parameter values generated for 2 UDDS is not as stringent. The results generated for 4 and 8 UDDS are similar to the results for 6 UDDS.

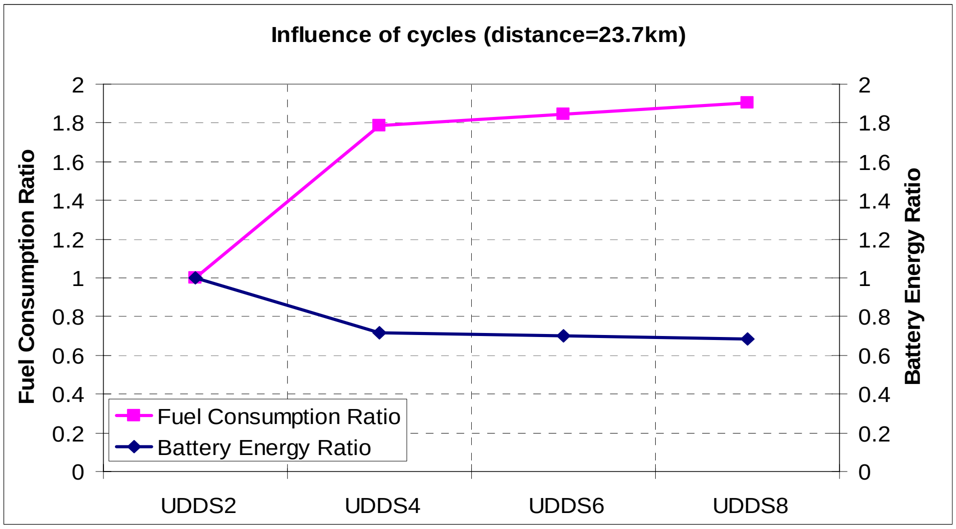

Figure 9: Fuel Consumption and Battery Energy Ratios on 2*UDDS

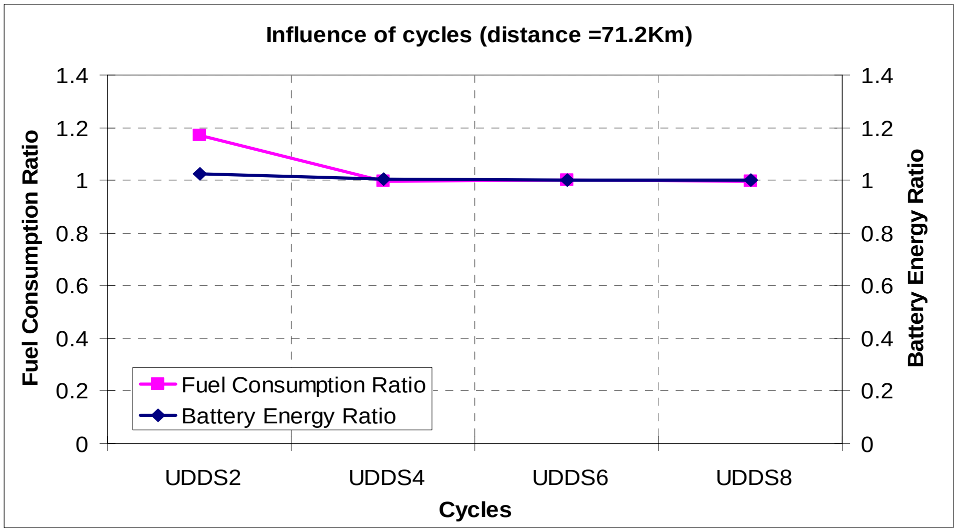

Figure 10: Fuel Consumption and Battery Energy Ratios on 6*UDDS

On the basis of the information above, at least two sets of parameters should be used to properly control the vehicle: one set for short distances and one for long distances. However, this approach is valid only when one knows the trip distance in advance.

5.3 Influence of Different Distances on Parameters

In order to evaluate the impact of drive cycle distance on the fuel economy, different trips were run with each set of optimum parameters. Figure 11 shows the vehicle simulated on 2, 4, 6 and 8 UDDS using the parameter values optimized for 2 UDDS.

Figure 11 shows the fuel consumption and battery energy ratios for several distances (2, 4, 6, and 8 UDDS) based on optimum parameters defined for 2 UDDS. One notices a ratio of almost 4 for increased distances. This value is much higher than the one generated with optimum parameters defined for 6 UDDS as shown in Figure 12. This behavior is similar when considering 4 and 8 UDDS.

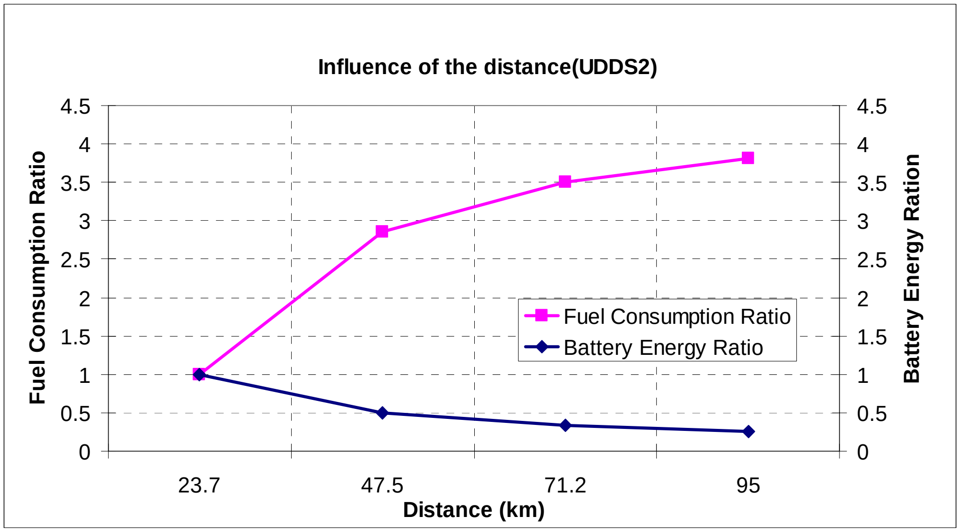

Figure 11: Fuel Consumption and Battery Energy Ratios on Different Distances Based on Optimized Parameters from 2*UDDS

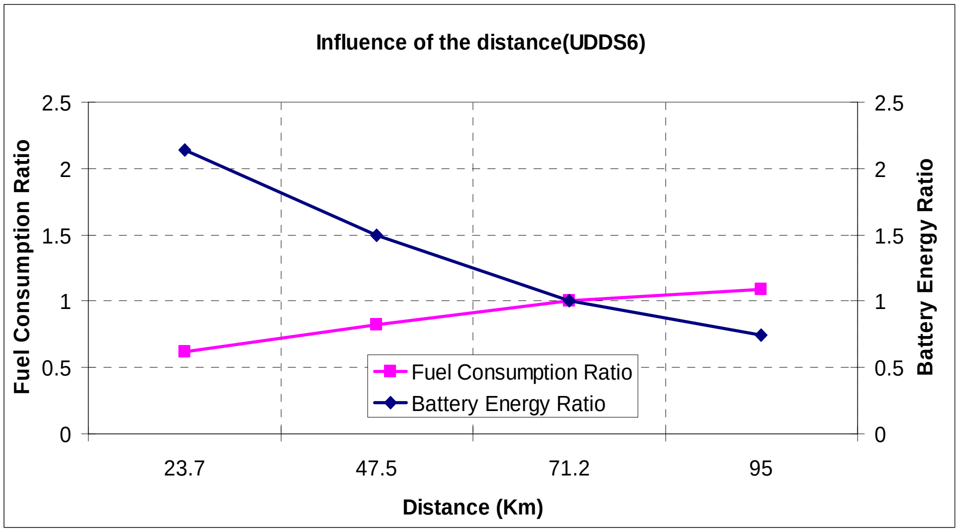

Figure 12: Fuel Consumption and Battery Energy Ratios on Different Distances Based on Optimized Parameters from 6*UDDS

Figure 11 and 12 demonstrates that optimizing for a short distance but driving a longer one lead to higher losses in fuel economy than optimizing for a longer distance and driving a shorter one.

5.4 Selection of the Best Single Set of Parameters

To select a single set of parameters, we considered the average as well as the spread of the fuel economy from two different points of view:

- Same distance with parameters optimized for different ones (2, 4, 6 and 8 UDDS).
- Different distances with parameters optimized on only one (2, 4, 6 or 8 UDDS).

In our case, the lower the spread, the better the parameter selection is.

Figure 13 shows the average and spread of each set of runs and optimum parameters for UDDS. As one notices, independently of the distance the parameters were optimized on, driving a short distance will always bring the best fuel economy. In addition, driving an equal number of short and long distances will lead to similar average fuel economy. The longer the driving distance, the less important which distance was used to optimize the parameters (Red spread smaller for 4, 6 and 8 UDDS than for 2). Finally, if the parameters are optimized on a short distance but longer distances are driven, the fuel economy will fluctuate more and can get higher than optimizing on a long distance and driving a short one.

As a result, selecting a single set of parameters will depend on the average driving distance and will consequently be different from one drive to another. Considering the high sensitivity to distance of the parameters based on 2 UDDS, the parameters from the 4 UDDS appear to be the best compromise if only one set can be selected. Knowing the trip distance is critical for maximize fuel displacement through GPS or additional algorithms.

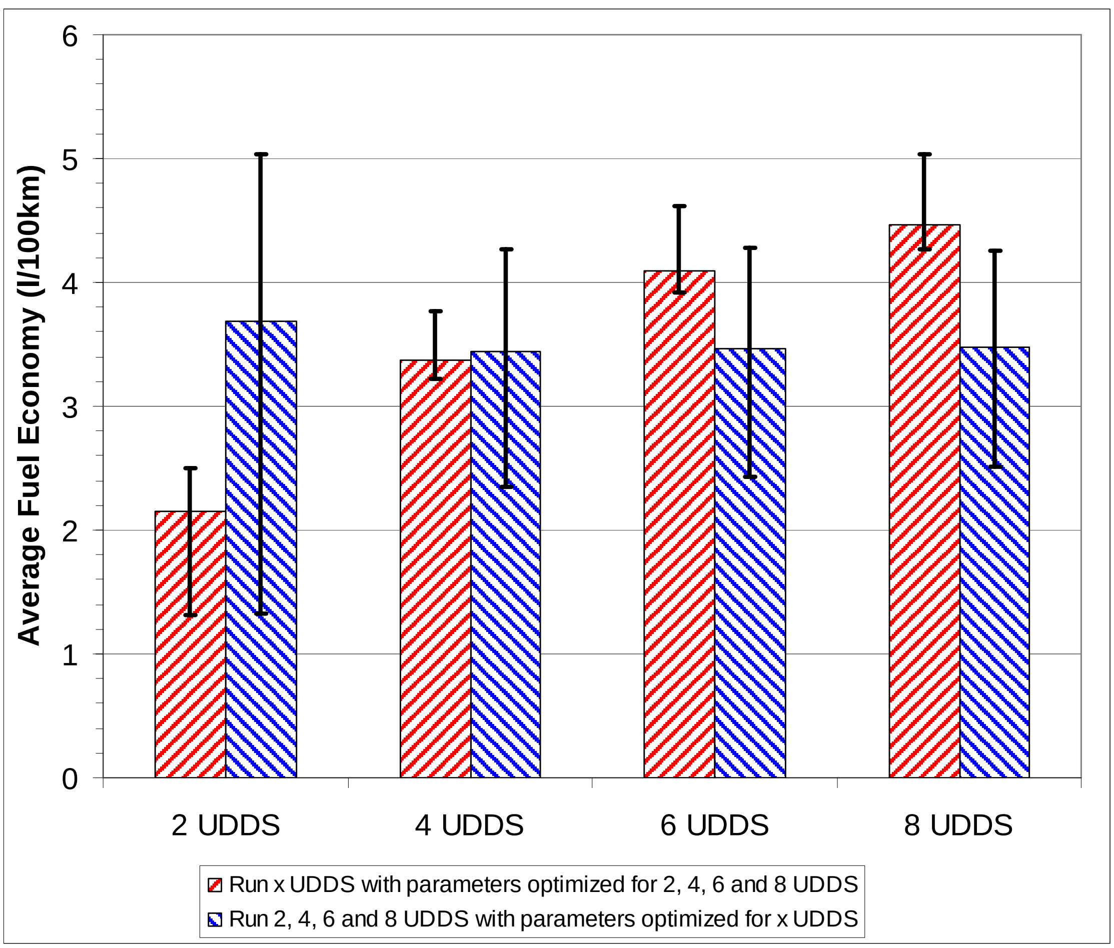

Figure 13: Average and Spread of Each Set of Runs and Optimum Parameters for UDDS

5.5 Impact of Drive Cycle Characteristic

Table 5 shows the optimization results of the HWFET standard drive cycle. As the table shows, in contrast to the UDDS, the power threshold related to the engine ON tends to remain fairly constant with distance.

Table 5: Optimized Parameters for HWFET Drive Cycle

		2 HWFET	4 HWFET	6 HWFET	8 HWFET
eng_pwr_wh_above_turn_on	W	16780	17809	17500	15648
eng_pwr_wh_below_turn_off	W	13153	13052	12750	10028
eng_time_min_stay_on	sec	1.241	2.055	1.5	1.16
eng_time_min_stay_off	sec	2.166	3.5	2.5	3.5
ess_pwr_chg_at_target	%	0.462	0.6	0.86	0.51
ess_pwr_dis_at_target	%	0.205	0.215	0.24	0.33

Figure 14 shows the fuel economy ratio evolution of the different drive cycles considered. For each curve, the reference (ratio of one) is set for the cycle that has been initially optimized. In this figure, each set of optimum parameters is run for every other distance. The figure shows that the sensitivity of the parameters on the UDDS is about the same than for the HWFET, except for the short optimized distance where UDDS is a lot more sensible to driving distance.

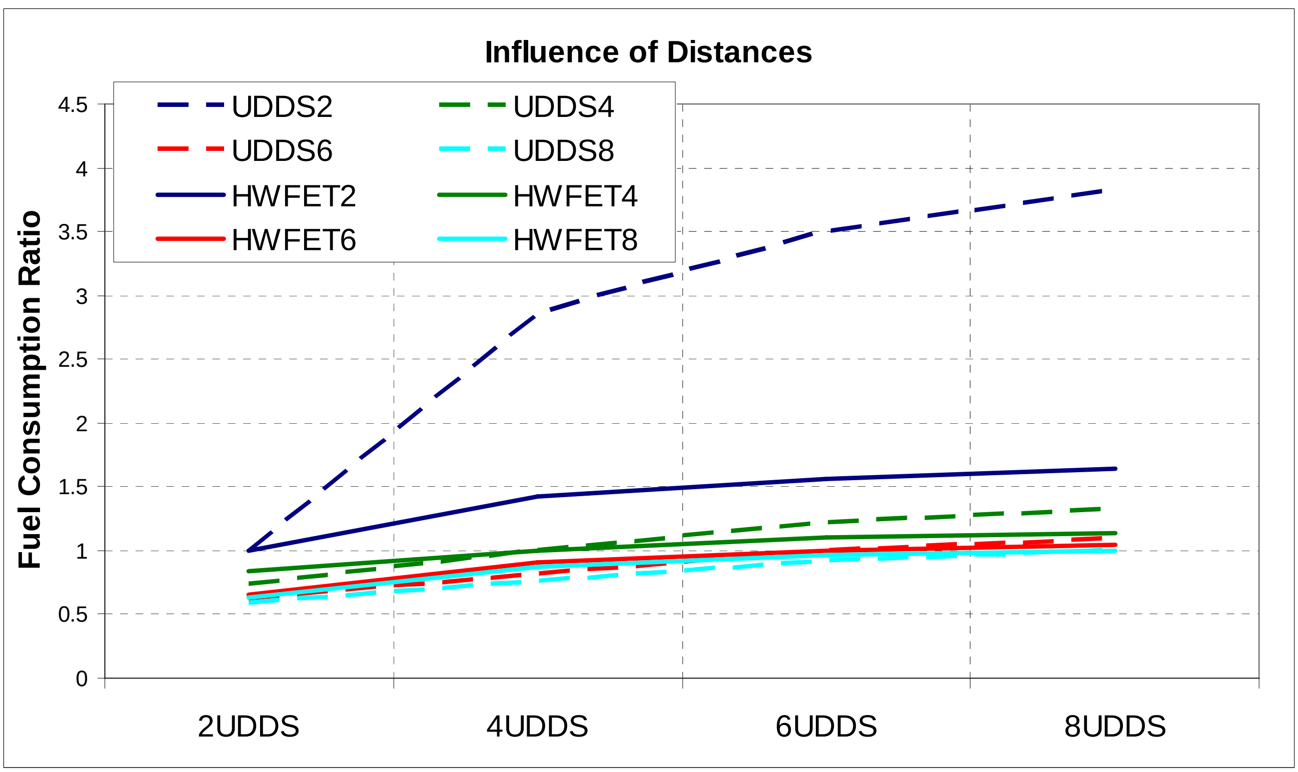

Figure 14: Fuel Economy Ratio Evolution for UDDS and HWFET

5.6 Comparison between Heuristic and Global Optimization

Previous studies based on the global optimization algorithm [9] have shown that the optimal pathway was based on maximizing the charge depleting operating conditions, meaning that the minimum SOC was reached only at the end of the trip. Figure 15 shows the battery SOC from the optimum parameters defined using DIRECT for several UDDS (2, 4, 6 and 8). As the figure shows, a significant portion of the trip is performed in charge sustaining mode.

Several explanations can account for these results, including the following:

- There is a limitation on the initial control strategy logic.
- There is a need for a larger number of simulations (currently limited at 1,000).
- The study minimized the number of parameters to be optimized.

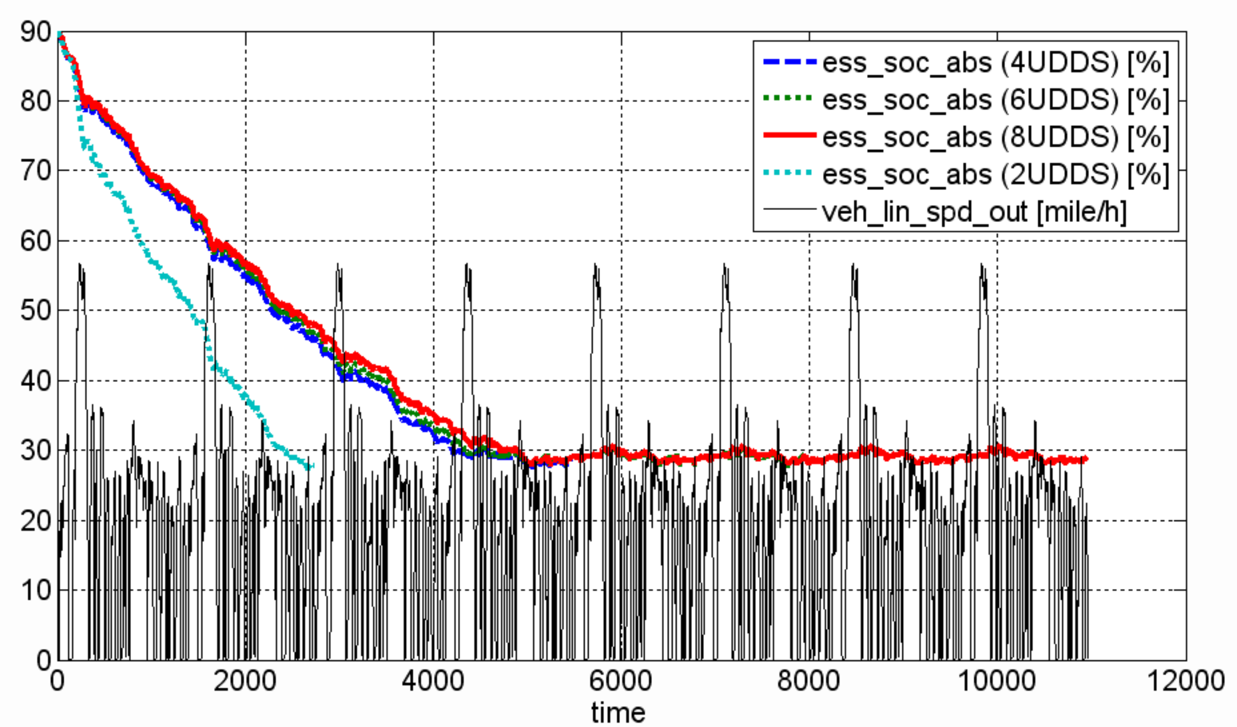

Figure 15: SOC Evolution for several UDDS

6. Conclusions

A non-derivative based algorithm, DIRECT, was used to optimize the main parameters of a pre-defined control strategy algorithm. Different sets of parameters were generated for several drive cycles and distances. Their impact on distance and driving cycle were analyzed.

The results demonstrate the need to have different control parameters depending on distance and drive cycle. Since none of the trip characteristics might be known at the outset, if only one parameter is used, the best compromise for fuel economy average and variance is achieved with the parameters defined for medium distances.

Future work will focus on defining the parameters for additional drive cycles as well as developing algorithms to recognize trip characteristics and distance. The initial control strategy logic will also be revisited based on outputs from the global optimization algorithm.

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