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## Simultaneous Optimization for Hybrid Electric Vehicle Parameters Based on Multi-Objective Genetic Algorithms

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**Abstract:** Compared to conventional vehicles Hybrid Electric Vehicles (HEVs) provide fairly high fuel economy with lower emissions. To enhance HEV performance in terms of fuel economy and emissions, and ensure user satisfaction with driving performance, the need for simultaneous optimization for the main parameters of powertrain components and control system is inevitable. However, this problem is challenging due to the large amount of coupling design parameters, conflicting design objectives and nonlinear constraints. Considering the defect of the methods which convert multi-objective optimization problems into single-objective ones, a comprehensive methodology based on the non-dominated sorting genetic algorithms II (NSGA II) to achieve parameter optimization for powertrain components and control system simultaneously and successfully find the Pareto-optimal solutions set is presented in this paper. A case simulation is carried out and simulated by ADVISOR, The simulation results show that this method can produce many Pareto-optimal solutions and a satisfactory solution can be selected by decision-makers according to their requirements. The results demonstrate the effectiveness of the algorithms proposed in this paper.

**Keywords:** hybrid electric vehicles; simultaneous optimization; multi-objective genetic algorithms; Pareto optimal solution

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## 1. Introduction

Consumer demand for more environmentally friendly and fuel efficient vehicles has been increasing in response to growing concerns about a clean environment and saving energy. Hybrid electric vehicles have been widely recognized as the most promising next generation vehicle technology to offer high energy utilization efficiency and very low emissions.

The optimization design of HEVs aims at improving fuel economy and decreasing emissions subject to user satisfaction with their drivability [1–3]. However, hybrid electric vehicles are complex electromechanical systems involving hundreds of design parameters. A successful HEV design requires optimal sizing of its key mechanical and electrical components. In addition, for more HEV efficiency, optimal management of the energy flow (control strategy) is required. Therefore, in the design process of a HEV, there is a large variety of design variable choices, including HEV configuration, key mechanical and electrical components sizes and control parameters that must be considered.

HEVs have a number of design variables as well as multiple design objectives which are conflicting. Additionally, many design constraints must also be fulfilled simultaneously. Moreover, the sizes of powertrain components and control system parameters are coupled and have simultaneous impacts on the performance of the vehicle. The effects of these design parameters on the objectives are non-monotonic. Therefore, the optimization of a HEV can be formulated as a multi-objective constrained nonlinear optimization problem.

Considering the importance of this practical issue, a literature review reveals a rather limited number of works on the topic. The optimization algorithms developed to solve HEV optimization in the recent literature can be roughly classified into two categories: gradient-based algorithms and derivative-free methods.

Gradient-based algorithms, such as sequential quadratic programming (SQP), use the derivative information to solve this problem [4,5]. The major disadvantage of these methods is that they are weak at global optimization. Meanwhile, these search techniques require strong assumptions for the objective function, such as continuity, differentiability, satisfaction of the Lipschitz condition *etc.*, which cannot be trivially assumed for this problem.

Derivative-free methods, such as genetic algorithms [6–11] or particle swarm optimization [12–14] have been proven to be a suitable approach to solve the HEV design optimization problem. However, most of these methods convert the multi-objective optimization problem into a single objective optimization problem by allocating weights to each of the objective functions (*a priori* methods). In this category, the initial multi-objective problem is transformed into a mono-objective problem by aggregating all objectives (weighted sum) or considering one objective as the main objective and other ones as constraints. The common drawback of these methods is that a single solution is obtained after optimization. To find another solution, the user has to restart an optimization run with new problem formulation by modifying the weight coefficients or by expressing other priorities. In addition the Pareto front is in general not homogeneous, convex or even continuous and the non dominated solutions may be grouped in the same region so that the designer choice is limited. On the other hand, most of the previous research efforts studied the optimization of powertrain component sizing or control system parameters individually. However, the powertrain component and control system

parameters are coupled, thus, it is difficult to find a global optimum for the design parameters. Therefore, it is necessary to study the simultaneous optimization of powertrain and control system parameters of HEVs.

Various computer programs, such as ADVISOR [15], PSAT [16] *etc.* are available for the analysis of HEVs. These tools have some built-in optimization features, including the ability to automatically size the powertrain components subject to user-selectable performance constraints. Additionally, they can be used to select suitable controller parameters to maximize the fuel economy and minimize emissions, however, both functions are not accessible simultaneously from the graphical user interface.

The main objective of this research was to develop a comprehensive methodology based on the non-dominated sorting genetic algorithms II, which can simultaneously achieve parameter optimization for powertrain and control system and find the Pareto-optimal solutions set successfully. Organization of this paper is as follows. In Section 2 the optimization problem of HEV is stated. In Section 3 the non-dominated sorting algorithms used in this paper are explained in detail. A case simulation is carried out and the simulation results are analyzed in Section 4. The conclusions are given in Section 5.

## 2. HEV Parameter Optimization Problem Formulation

### 2.1. Statement of Multi-Objectives Optimization

Most practical problems require the simultaneous optimization of multiple, often competing objectives, based on some given criteria. The mathematical description of such multi-objective optimization problems is as follows [17,18]:

$$\begin{cases} \min_{X \in \Omega} F(X) = [f_1(X), f_2(X), \dots, f_m(X)] \\ \text{s.t. } g_j(X) > 0 \quad j = 1, 2, \dots, n \end{cases} \quad (1)$$

where  $X = (x_1, x_2, \dots, x_N)$  is a variable vector in a real and N-dimensional space,  $\Omega$  is the feasible solution space. There are m objective functions and n constraint functions.

In general, the objective functions are competing and conflictive, and there is no global optimization solution for all of these objective functions, but a set of alternative solutions exists. These solutions are called Pareto-optimal solutions. The Pareto-optimal solution can be defined as follows:

Definition 1: For decision vector  $X^* \in \Omega$ , if there does not exist any other decision vector  $X \in \Omega$  in the solution space, which can make the two following inequalities be satisfied simultaneously:

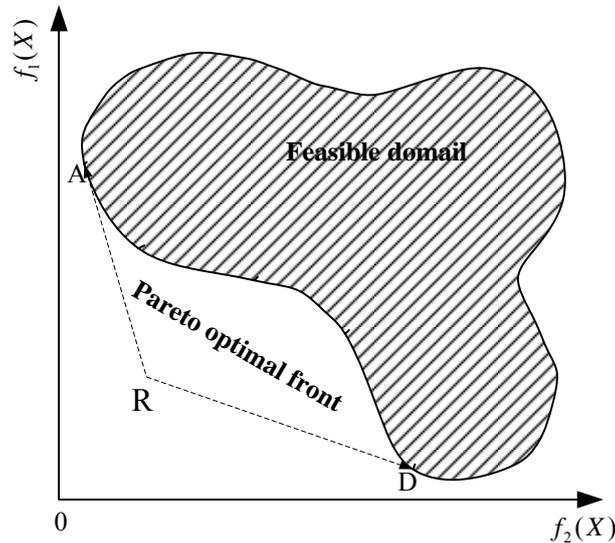
$$f_i(X) \leq f_i(X^*) \quad i = 1, 2, \dots, m \quad (2)$$

$$f_j(X) < f_j(X^*) \quad j \in \{1, 2, \dots, m\} \quad (3)$$

then,  $X^*$  is called a non-dominated solution, or a Pareto-optimal solution of the multi-objective optimization problem. All of these solutions constitute the Pareto-optimal solutions set. No other solutions in the search space are superior with respect to all the objectives involved in the Pareto-optimal solutions set, and any improvement in one of the objectives inevitably leads to the deterioration of at least one of the other objectives. The objective functions representation of the Pareto optimal set is the Pareto optimal front (POF, Figure 1). Searching the Pareto-optimal solutions

set for the multi-objective optimization problem is the most important task in the optimization algorithm research.

**Figure 1.** Pareto optimal front.



## 2.2. Objective of HEV Optimization

The design optimization for HEV powertrain components and control system parameters aims at improving fuel economy and reducing the emissions (CO, HC, NO<sub>x</sub>) without sacrificing its performance, which can be described as follows:

$$\begin{cases} \min_{X \in \Omega} F(X) = [Fuel(X), CO(X), HC(X), NO_x(X)] \\ \text{s.t. } g_j(X) > 0 \quad j = 1, 2, \dots, n \end{cases} \quad (4)$$

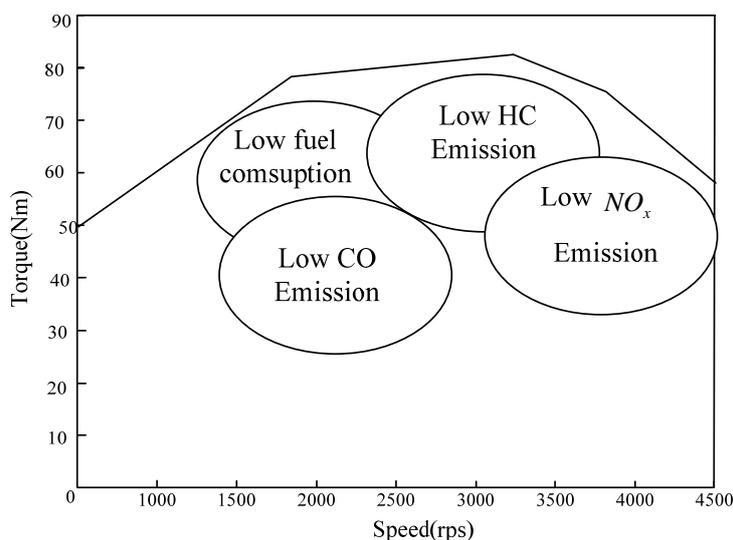
where  $X$  is the variable vector which includes the powertrain component and control system parameters of the HEV,  $\Omega$  is the feasible solution space, the constraints are governed by  $g_j(X) > 0 \quad j = 1, 2, \dots, n$ , which are the requirements related to the drivability performance (maximum speed, acceleration and gradeability, etc.) of the vehicle. Therefore, parameter optimization of HEV is a typical multi-objective optimization problem.

As mentioned previously, the optimization of HEV is aimed at several simultaneous targets such as minimization of FC and exhaust emissions (HC, CO and NO<sub>x</sub>). The work process of the engine is complex, and the fuel economy and HC, CO, and NO<sub>x</sub> emissions are decided by the engine speed and torque. However, the relationship between [FC, HC, CO, NO<sub>x</sub>] and [engine speed, torque] cannot be described by any specific analytic functions. The relationship is obtained by experiments and graphed. In the same time, these aspects are often in conflict with each other. The diagram of the typical operation points of an internal combustion engine (ICE) is shown in Figure 2. It can be seen clearly from this figure that the minimum FC does not necessarily result in the minimum emissions, implying the need for a tradeoff solution.

### 2.3. Optimization of the Powertrain and Control Strategy Parameters

Optimization of the vehicle involves hundreds of design variables, and it is difficult to optimize all of these variables. In this study only the key powertrain component and control system parameters that have significant impacts on the performance of the vehicle are taken as consideration.

**Figure 2.** Operating points for an IC engine.



The main components of HEV include the ICE, the electric motor (EM), the battery and the transmission. The sizes of these components have crucial effects on the integrative performance optimization of HEV. This study is basically limited to four design variables but can be extended to a larger number of variables. The descriptions of these design variables are given in Table 1.

**Table 1.** Key parameters of the powertrain components.

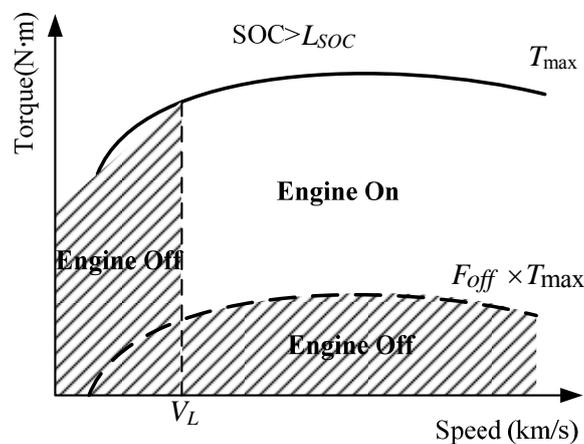
Variable	Description
$P_{ICE}$	Peak power of ICE
$P_{EM}$	Rating power of EM
$C_{bat}$	Capacity of the battery
Fd	Final reduction ratio

The control strategy has a significant impact on the performance and fuel economy of a vehicle. In this paper, the electric assist control strategy (EACS) is utilized. This strategy is charge sustaining, which means that the battery is never to be charged by the ICE when the SOC is up a certain point ( $H_{soc}$ ) and never be discharged when the SOC is below a certain point ( $L_{soc}$ ) [19,20]. In this strategy, the main energy provider is the ICE and the electric motor is used as an assistant. EACS employs the electric motor when the ICE either does not operate efficiently or the requested power is beyond its maximum deliverable torque. On the other hand, when the battery state of charge (SOC) is low, the engine will provide excess torque to be used by the motor to charge the batteries (the motor functions as a generator). The EACS methodology is illustrated in Figures 3 and 4. As shown in these Figures, the engine is turned off in some cases. In these cases, the electric motor takes on the responsibility to

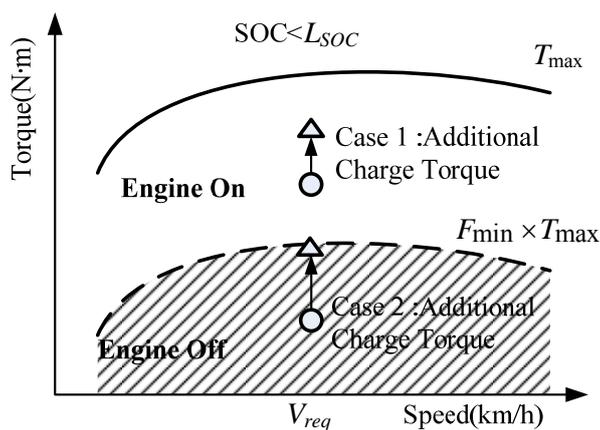
supply the whole required torque. As shown in Figure 3, when the SOC is higher than its limit ( $H_{SOC}$ ), if the required speed is less than a certain value, the engine will turn off. This specific speed is called the electric launch speed ( $V_L$ ). Furthermore, if the required torque is less than a cutoff torque ( $F_{min} \times T_{max}$ ) that is referred to as “off-torque fraction”, the engine will also turn off.

Figure 4 illustrates the case when the battery SOC is lower than its low limit ( $L_{SOC}$ ). In this case, an additional torque ( $T_{chg}$ ) is required from the engine to charge the battery. This additional charging torque is proportional to the difference between SOC and the average of  $L_{SOC}$  and  $H_{SOC}$ . Engine charging torque is only requested when the engine is on. The engine torque is prevented from being below a certain fraction of the maximum engine torque ( $F_{min} \times T_{max}$ ) that is referred to as “min-torque fraction”. This strategy is designed to prevent the engine from operating at an inefficient low torque condition.

**Figure 3.** Electric assist control ( $SOC \geq L_{SOC}$ ).



**Figure 4.** Electric assist control ( $SOC < L_{SOC}$ ).



The use of this control strategy requires the tuning a set of static thresholds, since they influence the vehicle achievement in terms of environmental impact (fuel economy, emissions) and road performance (acceleration times, gradeability, etc.) in a non-trivial manner. Therefore, an optimization problem is formulated and solved in this study to determine the optimal control parameters. Table 2 describes the variables that are usually defined for an EACS.

**Table 2.** Main variables of the control strategy.

Name	Description
$H_{SOC}$	Highest desired battery SOC
$L_{SOC}$	Lowest desired battery SOC;
$V_L$	Vehicle speed threshold, below this speed the ICE turn off
$F_{off}$	The minimum torque fraction of ICE turn-off
$T_{chg}$	The minimum torque of charge
$F_{min}$	Torque fraction of charge

#### 2.4. Constraints of the Optimization Problem

Vehicle performance constraints are imposed on the design problem to ensure the performance requirements of the vehicle are met. In this study the performance requirements were taken from those set out by the U.S. Consortium for Automotive Research for the Partnership for a New Generation of Vehicles (PNGV) [21]. These constraints are defined as the drivability requirements of the vehicle and the SOC difference between initial and final stages:

$$t_1 \leq 12 \text{ s for } 0\text{--}60 \text{ mph} \quad (5)$$

$$t_2 \leq 5.3 \text{ s for } 40\text{--}60 \text{ mph} \quad (6)$$

$$t_3 \leq 23.4 \text{ s for } 0\text{--}85 \text{ mph} \quad (7)$$

$$\text{Time from } 0 \text{ to } 137 \text{ km/h} \leq 23.4 \text{ s} \quad (8)$$

$$\text{The gradeability at } 55 \text{ mph for } 1200 \text{ s Grad} \geq 6.5\% \quad (9)$$

$$\text{Maximum speed: } \geq 137 \text{ km/h} \quad (10)$$

$$\text{Maximum acceleration: } > 0.5 \text{ g} \quad (11)$$

$$\text{Distance in } 5 \text{ s: } > 42.7 \text{ m} \quad (12)$$

$$\Delta SOC \leq 0.5\% \quad (13)$$

### 3. Optimization Based on Non-Dominated Sorting Genetic Algorithm

Genetic algorithms are stochastic global search techniques which mimic the process of natural biologic evaluation (survival of the fittest). They have been shown to be an effective strategy to solve complex engineering optimization problems characterized by non-linear, multimodal and non-convex objective functions. Over the past decade, many genetic algorithms have been developed to solve multi-objective optimization problems because they have the ability to find multiple Pareto-optimal solutions in one simulation run [22–24]. In this study the non-dominated sorting genetic algorithms II are used to solve this problem. The major processes of this algorithm are as follows:

Step 0: (Coding) The starting point in applying genetic algorithms to solve an optimization problem is to choose a chromosome representation to describe each individual in the population. Each chromosome represents a candidate solution which consists of the following genes:

$$X = (P_{ICE}, P_{EM}, C_{bat}, Fd, H_{SOC}, L_{SOC}, V_L, F_{off}, T_{chg}, F_{min}) \quad (14)$$

Each element in the chromosome is coded using a floating-point number.

Step 1: (Initialization): Generate initial population in the feasible space.

Step 2: (Crossover): Single crossover point operator is utilized in this paper.

Step 3: (Mutation): Mutation operator with a predetermined mutation probability is applied in this study.

Step 4: (Elitist Strategy): To maintain the best solutions appearing in the explorative process, the parent and offspring populations are combined and a combined population with size  $2N$  is formed. Then the selection operator is used on this combined population.

Step 5: (Evaluation): Calculate the values of the objective functions for the generated individuals.

Step 6: (Non-dominated sorting): This process can rank all members of the population. In a first stage, all individuals in the non-dominated solutions are found and are ranked level 1. In order to find the next non-dominated front, the solutions of the first level are temporarily eliminated and the non-dominated solutions in the remainder population are rank level 2; the above procedure is repeated until all the individuals are ranked in a non-dominated level and each solution is assigned a fitness equal to its non-dominated level.

Step 7: (Crowding-distance computation): To maintain the diversity of the population and the explorative power of the NSGA II, a niche technique based on the crowding-distance of the nearest neighbors to each solution is applied in this algorithm. Firstly, the population is sorted according to each objective function value in ascending order of magnitude. Thereafter, for each objective function, the solutions with the smallest and largest function values are assigned an infinite distance value. All other intermediate solutions are assigned a crowding-distance value equal to the absolute normalized difference in the function value of these two adjacent solutions:

$$d_{i,j}(f_k) = |f_k(X_i) - f_k(X_j)| \quad (15)$$

This calculation is continued with other objective functions and the overall crowding-distance value is the sum of these individual distance values:

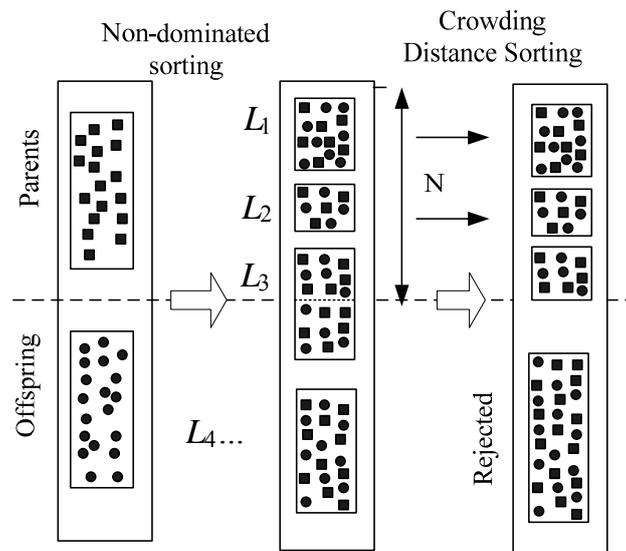
$$d_{i,j} = \sum_{k=1}^n d_{i,j}(f_k) \quad (16)$$

Step 8: (Selection): The best  $N$  solutions should be selected from the combination population with size  $2N$  according to the non-dominated level and crowding-distance. Firstly, all of the  $2N$  individuals are sorted according to their non-dominated level in ascending order. Secondly, the individuals that have the same non-dominated level are sorted with respect to their crowding-distance in descending order. Finally, the top  $N$  individuals are selected as the next generation population. The selecting procedure is shown in Figure 5.

Step 9: (Termination test): If the pre-specified stopping condition is not satisfied, return to step 2.

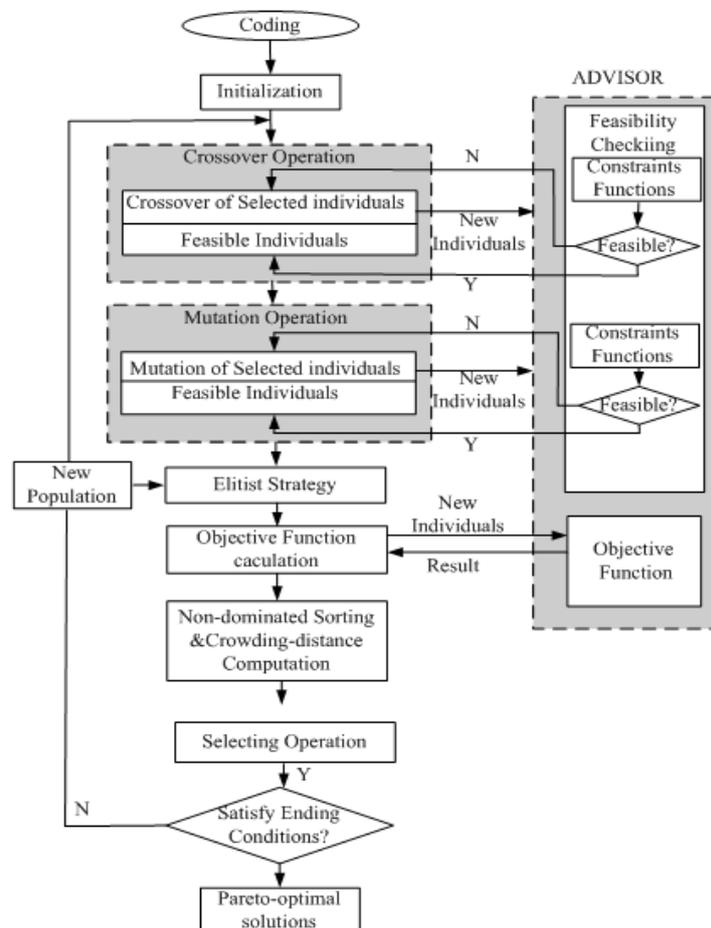
ADvanced VehIcle SimulatOR (ADVISOR) was developed by the U.S. National Renewable Energy Laboratory (NREL) for rapid analysis of the performance and fuel economy of conventional, electric, and hybrid vehicles [25]. ADVISOR provides a backbone for the detailed simulation and analysis of user defined drivetrain components and algorithms from which to take full advantage of the modeling flexibility of simulation and analytic power of MATLAB.

Figure 5. Selection procedure of NSGA II.



The fuel consumption and exhaust emissions of the vehicle are obtained with the ADVISOR software. As shown in Figure 6, the NSGA II modifies the parameters of the specified base PHEV, and calls for ADVISOR to run a drive cycle test, then, the evaluations of the objective values including fuel consumption and exhaust emissions can be obtained.

Figure 6. The iterative process of the NSGA.



Like the objective functions, the dynamic performance of the vehicle is evaluated in the ADVISOR acceleration test and the grade test so as to evaluate the constraints shown in inequalities (5) to (13). For the sake of saving simulation time, if the individual can't satisfy any one of the constraints, the simulation for objective functions is cancelled. In order to eliminate the effect of energy from the battery on fuel consumption, it is necessary to run the simulation several times starting with different initial SOC values until the  $\Delta$ SOC becomes negligible (within  $[0.5\% + 0.5\%]$ ) in ADVISOR.

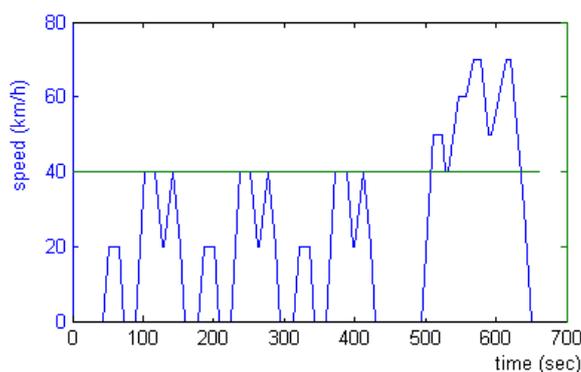
#### 4. Case Simulation

To validate the effectiveness of this approach proposed in this paper, a case simulation was carried out. The vehicle "PARALLEL\_defaults\_in" which is available in the ADVISOR 2002 software is chosen as the baseline vehicle and the CYC-1015 mode driving cycle is used for the optimization simulation. The configuration of this vehicle is given in Table 3 and the speed profile of the bCYC-1015 driving cycle is shown in Figure 7.

**Table 3.** Initial powertrain value of design variables.

Design Variable	Initial Value
Calculated mass	1350 kg
Transmission	5-speed manual transmission
Aerodynamic drag coefficient	0.335
Vehicle front area:	2 m <sup>2</sup>
Peak power of ICE	41 kW
Rating power of EM	75 kW
Capacity of the battery	26 Ah
Final reduction ratio	3.28

**Figure 7.** Speed profile of the CYC-1015 drive cycle.



The non-dominated sorting genetic algorithm II proposed in this paper is utilized to solve the HEV optimization problem and the Pareto-optimal solutions set is obtained. The settings of the genetic algorithms are as follows: population size is 200, number of generations is 2000, crossover probability is 0.9 and mutation probability is 0.01. In order to facilitate the comparison of the optimization results, the initial design variables and the optimum design variables are given in Table 4. The drivability, fuel economy and emissions indices corresponding to these variables are also tabulated in Table 4 (only eight groups of the objective functions are listed for brevity sake).

**Table 4.** Fuel consumption and emission of the HEV before and after the optimization.

Items		Unit	1	2	3	4	5	6	7	8	Initial Value
Variables	$P_{ICE}$	Kw	41	37	35	35	33	39	40	31	41
	$P_{EM}$	Kw	60	58	59	60	57	56	60	56	75
	$C_{bat}$		24	23	20	24	21	22	23	19	25
	$H_{SOC}$		0.75	0.81	0.82	0.80	0.82	0.8	0.8	0.84	0.7
	$L_{SOC}$		0.4	0.4	0.6	0.6	0.6	0.6	0.37	0.6	0.6
	$F_{off}$		0.15	0.12	0.1	0.18	0.1	0.13	0.12	0.22	0
	$F_{min}$		0.45	0.6	0.5	0.5	0.45	0.52	0.6	0.6	0.4
	$T_{chg}$	N·m	20	15	19	17	18	16	12	17	15.25
	$V_L$	Km/h	12	11	18	15	15	10	8	15	0
	Fd		3.46	3.93	3.82	3.92	3.60	3.61	3.56	3.9	3.28
Constraint	$t_1$	S	9.7	9.8	9.9	9.7	10	9	10.2	10.3	9
	$t_2$	S	5	5	4.9	4.8	5.2	4.5	5.3	5.1	4.5
	$t_3$	S	20.3	20.7	21.7	21.1	21.2	18.2	21.6	22.9	18.4
	Grad	%	20.6	19.6	20.4	20.4	19.3	20.9	20	18.8	21.5
	$\Delta soc$	%	-0.4	-0.3	-0.2	-0.3	-0.4	-0.3	-0.04	-0.4	-0.1
Objective	Fuel	L/100 km	6.3	6.2	6.0	6.0	5.9	6.2	6.4	5.9	7.5
	CO	g/km	1.958	2.371	2.493	2.228	2.989	2.361	2.100	3.179	2.601
	HC	g/km	0.374	0.350	0.324	0.330	0.306	0.372	0.365	0.291	0.401
	NO <sub>x</sub>	g/km	0.339	0.330	0.319	0.326	0.289	0.328	0.337	0.273	0.357

It can be seen that the range of fuel economy and emissions indices after optimization are as follows:

Fuel: [5.9, 6.5] (L/100km)

CO: [1.960, 3.179] (g/km)

HC: [0.291, 0.374] (g/km)

NO<sub>x</sub>: [0.289, 0.329] (g/km)

and the indices of the initial configuration are:

Fuel: 7.5L/100 km, CO: 2.601 g/km, HC: 0.401 g/km, NO<sub>x</sub>: 0.357 g/km.

The optimization results indicate that peak power of the internal combustion engine, rating power of the electric motor and number of the battery modules was reduced significantly. The drivability can be improved by optimizing the parameters of the control system though the sizing of the main powertrain components is decreased (such as case 1). A comparison of fuel economy and emission before and after optimization reveals that most of the solutions can increase the fuel economy and reduce the emission of CO, HC, NO<sub>x</sub> in the solutions set (such as in cases 1, 2, 3, 4, 6 and 7). However, there are some exceptional cases (such as cases 5 and 8), in which the improvement of fuel economy and reduction of HC, NO<sub>x</sub> leads to a deterioration of CO emissions, thus shows how the objective functions are competing and conflicting

## 5. Conclusions

Concurrent optimization of the powertrain and control system parameters of a HEV is formulated as a constrained nonlinear multi-objective optimization problem in this paper. Multi-objective genetic algorithms are employed to solve the Pareto-optimal solutions set of this problem. This set can provide a wide range of choices for powertrain and control system variable parameters simultaneously. To validate the effectiveness of this approach, a case simulation is carried out and ADVISOR is utilized to simulate the performance of the vehicle. The simulation results demonstrate that the proposed approach can improve fuel economy and reduce emissions without sacrificing the performance of the HEV.

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