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Minimization of power losses in hybrid electric vehicles in view of the prolonging of battery life

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ABSTRACT

Hybrid Electric Vehicles (HEVs) are becoming more popular than pure electric ones, nowadays. This is because of their better performance, economic advantages and higher operating range. However, their potential advantages extremely depend on their system design, most importantly their battery system design. Batteries' life requirements as well as the cost of replacing them at the end of their life period, currently limit manufacturers to bring HEVs into play, even though their fuel economy reduces their everyday cost considerably. Generally, inappropriate discharge/charge patterns would result in loss in batteries' life. In the present study, an optimization based control strategy has been proposed for the series HEVs in order to maximize the efficiency of the power-train while minimizing the loss. A genetic algorithm is implemented to optimally evaluate the control algorithm's parameters. The approach is then compared to two main control strategies, namely thermostatic control strategy and power follower control strategy. The computational procedure of the genetic algorithm is discussed, and a simulation study based on a model of a series hybrid electric vehicle is given to validate the genetic algorithm results.

1. Introduction

Hybrid Electric Vehicles (HEVs) have great capabilities as new alternative means of transportation. The advantages of HEVs over the conventional vehicles are mainly improved fuel economy and reduced emissions. In a series HEV, traction force is provided only by an electric motor. The driving power for this motor comes from a bidirectional storage system (e.g., battery, flywheel, or ultra-capacitor) and an engine-generator set (Genset). Now, the question is how to distribute the required power for the electric motor between the batteries and the Genset. The answer is provided by the control strategy that is being adopted. A control strategy is an algorithm regulating the operation of the drive-train. It takes data from the vehicle (e.g., speed, acceleration and grade) and makes decisions to turn on/off certain components or to increase/decrease their power output [1].

Not many approaches exist in literature for the control strategy of series HEVs. Different methods of optimal control have been used in these papers to minimize the fuel consumption or emission. Among them, we can refer to Refs. [2,3]. Other studies, e.g., Refs. [4,5], have considered the internal battery losses empirically or as an average value.

Nevertheless, the batteries performance and life length have not been addressed in most proposed algorithms. In order to reduce the costs associated with loss of life cycle in batteries, their charge/discharge patterns have to be managed. For this purpose, it has been recommended to avoid deep discharging and frequent charging, since this will cause the batteries life to deteriorate dramatically. The main objective of this paper is to propose an algorithm by which the demanded power (from the main vehicle controller) gets distributed between the batteries and the Genset in such a way that the batteries' life losses are as low as possible. Besides, in the proposed control strategy, the factors reducing the battery life such as deep discharge and frequent charging are avoided. This looks like solving an optimization problem for minimizing of the fuel consumption with the battery life expectation constraint. The method will be verified by simulation.

The vehicle under-study which is used for current investigations is the O457 bus which has been converted to a series hybrid vehicle at Vehicle, Fuel and Environment (VFE) Research Institute at University of Tehran.

The proposed algorithm relies on parameters that characterize the driving schedule and is also flexible to unexpected changes in the driving situation. The layout of this paper is as follows. In Section 2, the series HEV model and power losses due to each com-

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Nomenclature

SoC	battery state of charge
DoD	battery depth of discharge
R_i	battery internal resistance (Ω)
I_b	battery current (A)
P_b	battery power (W)
U_b	battery voltage (V)
U_0	initial capacitor voltage (V)
P_d	drive power (W)
$P_{e/g}$	Genset power (W)
$P^*_{e/g}$	desired Genset power (W)
a_0, a_1, a_2	parameters of Genset efficiency curve
D_R	DOD for which rated cycle life was determined
C_R	rated ampere-hours capacity at rated discharge current I_R (Ah)
L_R	cycle life at rated DOD, D_R and discharge current I_R (Ah)
D_A, C_A	actual value of D_R and C_R
u_0, u_1, u_2	parameters of cell cycle life curve
L_{time}	life time (s)
d_{actual}	actual absolute discharge
d_{eff}	effective discharge
P_{eff}	effective discharge power (W)
$P_{b/loss}$	power losses of battery (W)
P_{bus}	bus power (W)
H_{SoC}	higher value of SoC
L_{SoC}	lower value of SoC
t_{moff}	shortest allowed duration of engine off time
P_{off}	power below which engine is shut off if the batteries are charged

Greek symbols

η_{gen}	efficiency of generator
η_{ICE}	efficiency of ICE
Γ_R	rated charge life (Ah)

ponent have been introduced. The optimization problem definition and control algorithm have been explained in Section 3. In Section 4, results from the developed control strategy have been compared to the common control strategy. Conclusions are presented in Section 5.

2. System components

The series HEV power-train is composed of an engine/generator set (Genset), an electric traction motor with a power converter, and a battery pack with an appropriate controller. In addition, there is a central controller that manages the interaction between these components, as shown in Fig. 1. The output of the generator is connected to an electric power bus through a Power Conditioner (PC). The battery pack serves as the bidirectional electrochemical energy source which is connected to the bus by means of a power electronic converter (DC/DC converter). The electric power bus is also connected to the controller of the electric traction motor. The traction motor can be controlled either as a motor or a generator, and either in forward or reverse motion.

To study the optimization algorithm by which the parameters of the control strategy are determined, the model of a series hybrid electric vehicle was built. This model enables us to calculate the flow of power among different components of the drive-train. Accuracy of the model is of course the main concern, but as long as consistent behavior is seen, a few percents of error in the fuel consumption or battery losses are tolerated.

2.1. Genset

The Genset provides one part of the power that is required by the electric traction motor for propulsion. As proposed in Ref. [4], the convex second degree polynomial of Genset's power can represent the efficiency curves at different speeds, as follows (Fig. 2):

$$\eta_{ICE} = a_0 + a_1 P_{e/g} + a_2 P_{e/g}^2 \tag{1}$$

where $P_{e/g}$ is the mechanical power on the Genset output shaft and η_{ICE} denotes the Internal Combustion Engine (ICE) thermal efficiency. The generator efficiency map is depicted in Fig. 3. The reference engine speed is obtained from the efficiency/power map to optimize the efficiency at the requested power. Then the ICE controller regulates the engine shaft speed to follow the reference value, as shown in Fig. 4.

2.2. Battery pack

The battery pack is an energy source just like a fuel tank. However, its high cost, low energy storage density and shorter life often

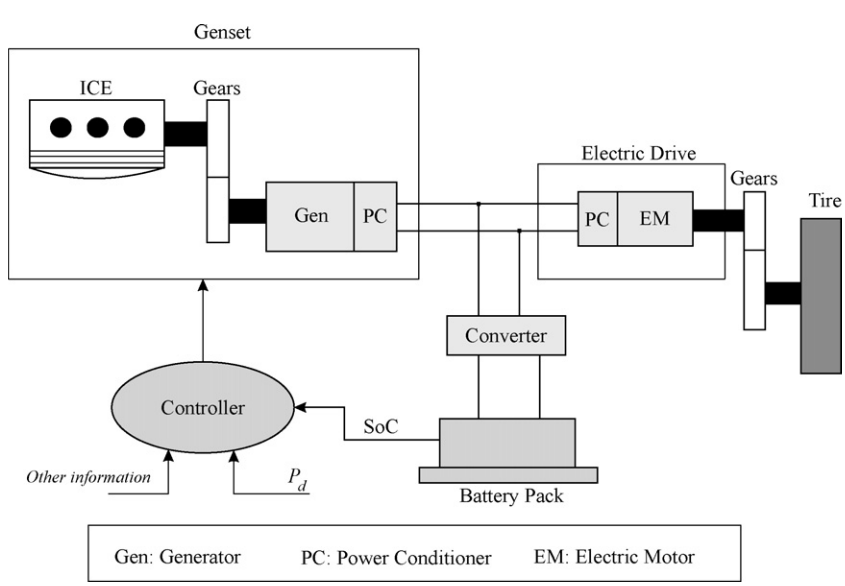

Fig. 1. General arrangement of a series HEV.

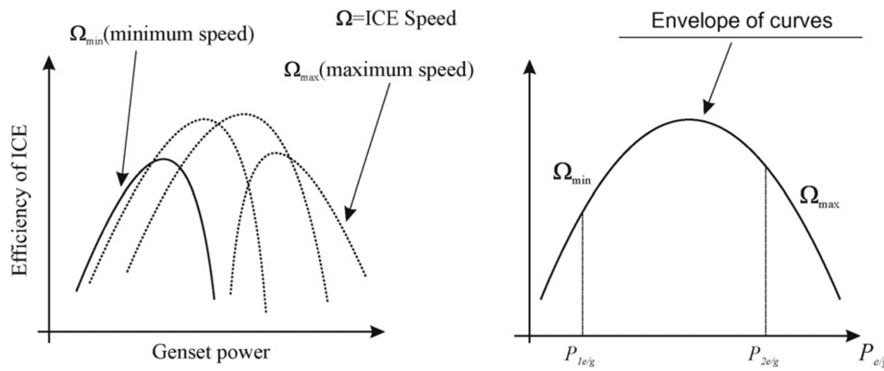

Fig. 2. Qualitative efficiency of the ICE. The specific consumption curves, obtained from the engine efficiency maps have the qualitative behavior of the left graph, one curve for each rotational speed. To ensure the best efficiency for each value of the desired power of Genset, the ICE should vary its speed so as to follow the envelope of such curves, as shown in the right graph.

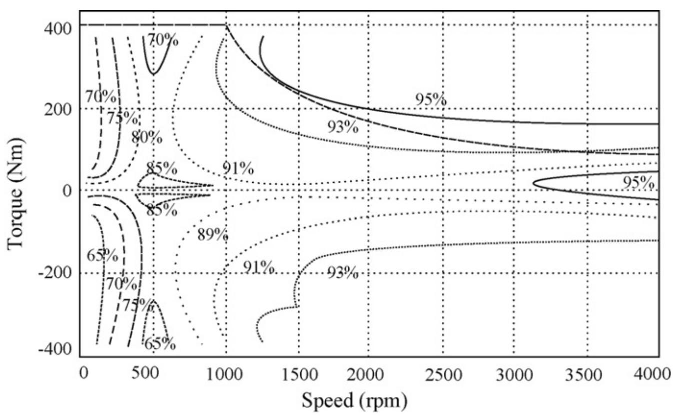

Fig. 3. Efficiency map of the generator.

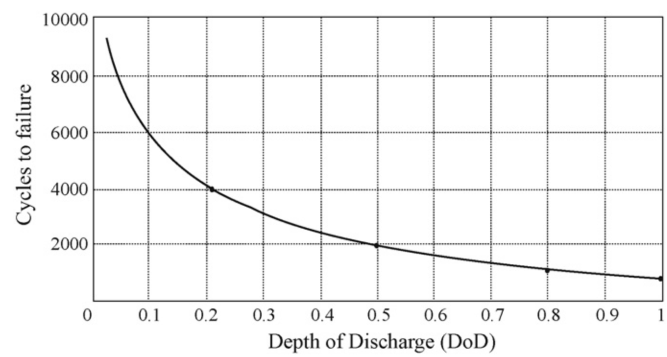

Fig. 5. Best fit curve to battery manufacturer's cycle life data.

makes the battery pack the weakest chain ring in the drive-train [6].

Batteries are expensive items. The cost for a certain storage capacity can vary from 100 to 900 $\$\,\mathrm{kW}^{-1}\,\mathrm{h}^{-1}$ or even higher [7]. Unlike the fuel tank, batteries might not last for the whole life span of the vehicle and their condition usually deteriorates over their life as well. The life of a battery is measured in cycles or years for cyclic applications (like in HEVs). The cycle life of batteries is between 300 and 1500 full cycles, depending on the battery type.

In order to prolong batteries' life, different factors of their operation can be taken into account. However, the first step towards achieving this goal is to implement a proper life prediction method for them. The method used in this paper is similar to the method reported in Ref. [6]. Each battery cell has a finite life as measured by the sum of the effective ampere-hour during its useful life. When the cumulative effective ampere-hour (the total of the individual effective ampere-hour corresponding to a series of discharge events) equal the rated charge life of the cell, the cell will reach its useful life. The rated charge life, Γ_R, of a cell is defined as:

$$\Gamma_R = L_R D_R C_R \tag{2}$$

where, C_R is the rated Ampere-hour capacity at rated discharge current I_R. Besides, D_R stands for the Depth of Discharge (DoD) for which rated cycle life was determined, and L_R represents the cycle life at rated DoD, D_R and discharge current I_R.

The actual charge life (cumulative effective ampere-hour) of a cell, is a function of its DoD. To determine this relationship, the

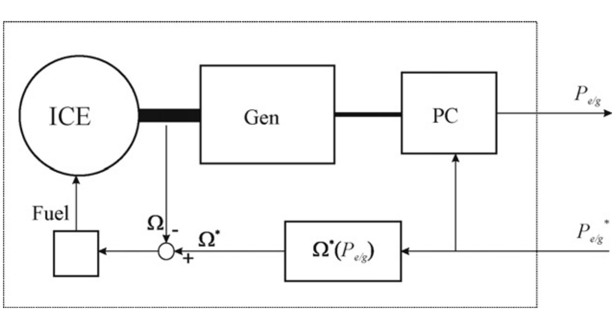

Fig. 4. Control arrangement to adjust the shaft speed to the requested output power. The ICE should operate so that it follows the minimum consumption curve by varying its rotational speed between the minimum and maximum allowed when following the required power $P^{*}_{e/g}$.

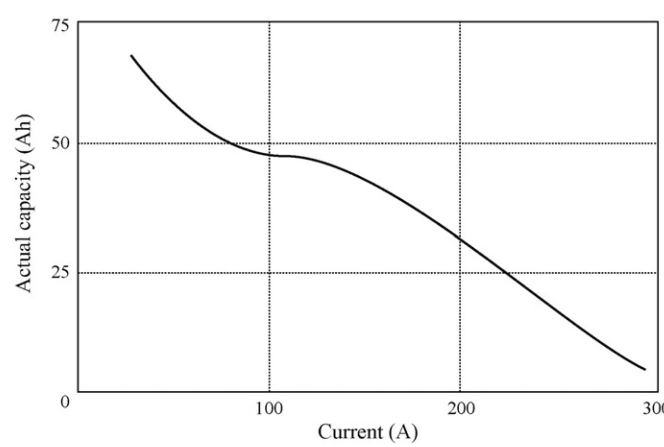

Fig. 6. Actual capacity versus discharge current for a 68 Ah valve regulated lead acid battery.

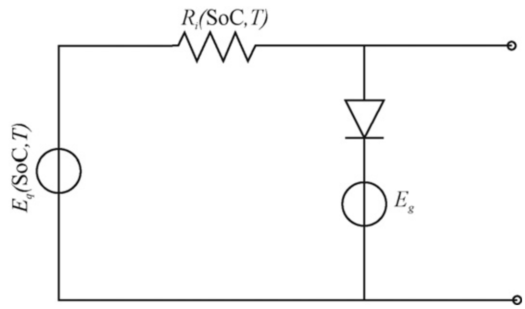

Fig. 7. Battery equivalent circuit utilized in the paper for modeling of the energy storage system.

following equation is proposed:

$$L = u_2\left(\frac{D_R}{D}\right)^{u_0} e^{u_1(1-(D/D_R))} \tag{3}$$

Fig. 5, shows the best fitted curve to a set of four data points: cycle life versus DoD which can be provided by the manufacturer of a lead-acid battery, based on Eq. (3). For the provided battery, the parameters in Eq. (3) are obtained as $u_0 = 0.1$, $u_1 = 1.69$ and $u_2 = 765$.

It is assumed that for a given actual discharge, the effective discharge d_{eff}, will increase with discharge rate and can be roughly expressed by the following function:

$$d_{eff} = \frac{C_R}{C_A} d_{actual} \tag{4}$$

in which, C_A can be obtained easily from the manufacturer's data such as the one shown in Fig. 6.

The effects of discharge rates are combined simply by multiplying the factors expressed in Eqs. (3) and (4).

$$d_{eff} = \left(\frac{D_A}{D_R}\right)^{u_0} e^{u_1((D_A/D_R)-1)} \frac{C_R}{C_A} d_{actual} \tag{5}$$

It should be noted that Eq. (5) expresses the effective discharge for a single discharge of specific magnitude and rate. A life prediction for a cell subjected to an irregular pattern of charge–discharge cycles requires the summation of the effective discharges from a series of discharge events.

The discharge profile can be obtained by actually monitoring of the battery current on an operating system, or by modeling battery's usage on a proposed system. The prescribed series of n discharge events will correspond to a certain time period (T) of system's operation. The life time (L_{time}) of the cell under the specified usage pattern is then given by:

$$L_{time} = \frac{\Gamma_R}{\Gamma_{eff}/T} = \frac{L_R D_R C_R}{\sum_{i=1}^{n} d_{eff}} T \tag{6}$$

In order to formulate the battery losses that reduce its life, the following equation can be employed:

$$P_{eff} = \left(\frac{C_R}{C_A}\right)^{1-u_0} \left(\frac{C_R}{C_A} - 1\right)^{u_0} e^{-u_1(C_A/C_R)} R I_b^2 \tag{7}$$

Table 1
Relevant battery data used in simulation of the HEV.

Battery rated capacity (C_R)	68 Ah
Battery internal resistance R	0.5 mΩ
Rated DOD	0.8
Number of battery module	54
Cycle life curve: u_0	0.19
Cycle life curve: u_1	1.69
Cycle life curve: u_2	765
Efficiency curve: a_0	0.3520
Efficiency curve: a_1	0.0025 kW^{-1}
Efficiency curve: a_2	−0.0001 kW^{-2}

Table 2
Description of control strategy parameters used in optimization.

Optimization variable	Description
H_{SoC}	Highest desired battery SoC
L_{SoC}	Lowest desired battery SoC
P_{off}	Power below which engine is shut off if the batteries are charged
P_{ch}	Power applied to engine to charge the batteries
t_{moff}	Shortest allowed duration of engine off time

Therefore, the total power losses of the battery are obtained as:

$$P_{b/loss} = R I_b^2 + P_{eff} = (1 + M) R I_b^2 \tag{8}$$

where,

$$M = \left(\frac{C_R}{C_A}\right)^{1-u_0} \left(\frac{C_R}{C_A} - 1\right)^{u_0} e^{-u_1(C_A/C_R)} \tag{9}$$

and, RI_b^2 is the losses caused by internal resistance and P_{eff} is the battery losses reducing the battery life.

A dynamical model for the lead-acid battery should be obtained for the purpose of minimization [8]. Battery modeling is of major concern in the overall HEV model development. Studies have been made to model the power output for batteries in various approaches [9,10]. A simple model represented in Fig. 7, as an equivalent electrical circuit, is considered for modeling of the battery. Battery parameters which are used for modeling are depicted in Table 1. This model has successfully been used for lead-acid batteries [9].

It should be noted that both the internal resistance and the electromotive force are not constants during the charge/discharge processes and vary as a function of the State of Charge (SoC) and electrolyte temperature. For simplicity, these dependencies are assumed to be linear.

3. Evolutionary design of the control strategy

Genetic algorithm (GA) used in this paper as the evolutionary algorithm is motivated by the mechanism of natural selection, a biological process in which fitter individuals have higher ability to survive during evolution.

The principles of multi-objective optimization are different from that of a single-objective optimization. The main goal in a single-objective optimization is to find the global optimal solution. However, in a multi-objective optimization problem, there

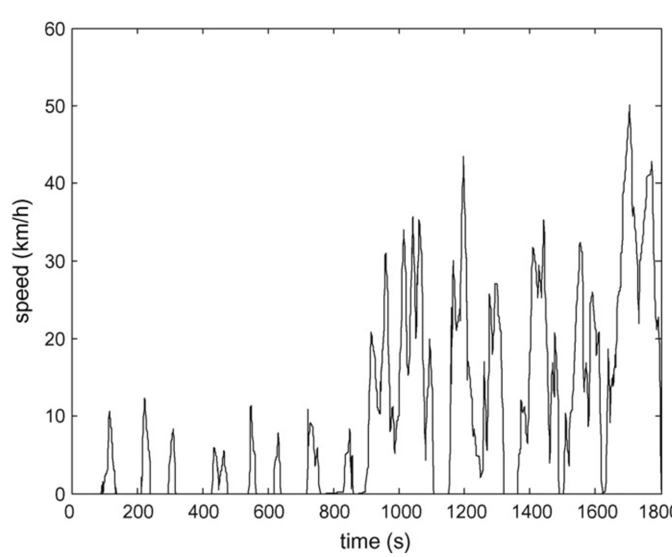

Fig. 8. Tehran city bus driving schedule used in simulation for testing the algorithm.

Table 3
Relevant vehicle and component data used in series hybrid electric vehicle model.

Vehicle	Vehicle mass: 9100 kg 27 × 70 kg (according to SAE 931788) Front area: 7.23 m^2 Rolling resistance coef.: 0.008 Aerodynamic coef.: 0.79
Engine	6.8 L CI, 170 kW/2200 rpm
Electric motor	Rated power: 170 kW Max. power: 300 kW Max. torque: 1000 Nm at 500 A Peak efficiency: 94.1%
PM Generator	Rated power: 105 kW Max. power: 160 kW Max. torque: 450 Nm at 250 A Peak efficiency: 95.2%

is more than one objective function, each of which may have a different individual optimal solution. If there is sufficient difference in the optimal solutions corresponding to different objectives, the objective functions are often known as being conflicting to each other. Multi-objective optimization with such conflicting objective functions gives rise to a set of optimal solutions, instead of one optimal solution. The reason for the optimality of many solutions is that no solution can be considered to be better than the other with respect to all objective functions. These optimal solutions have a special name—Pareto-optimal solutions.

It is clear that the concept of optimality in multi-objective optimization deals with a number (or a set) of solutions, instead of one solution. Based on the above discussions, the conditions for a solution to become dominated with respect to another solution and then present conditions for a set of solutions to become a Pareto-optimal set are defined.

Let us assume that the set of variables x_i, $i = 1,\ldots, M$, is a set of decision variables for a multi-objective optimization problem. In order to measure the decency of a certain solution, some criteria for evaluating the solution quality should be defined. These criteria are expressed as a set of functions $f_1(x),\ldots, f_j(x),\ldots, f_P(x)$ of the decision variables, which are called objective functions. Oftentimes, some of them are contradicting with others. The constraints specify the feasible region X in which any point x defines a feasible solution. It is impossible that all of the $f_j(x)$, $j = 1,\ldots, P$ values have an optimum in X at a common point x. Certain criteria should be developed to determine an optimal solution in this circumstance. One interpretation of the term optimum in the multi-objective optimization scenarios is the Pareto-optimality, which are highly associated with the concept of dominance. A solution x_1 dominates a solution x_2 if and only if the two following conditions are satisfied at the same time: firstly, x_1 is no worse than x_2 in all objective evaluations, i.e., $f_j(x_1) \le f_j(x_2)$ for all $j = 1,\ldots, P$. Secondly, x_1 is strictly better than x_2 in at least one objective, i.e., $f_j(x_1) < f_j(x_2)$ for at least one $j \in \{1,\ldots, P\}$. As a result, in a set of Pareto-optimal solutions, there is no solution which dominates another with respect to all the design objectives involved. It should be noted that multi-objective optimization needs a decision-making process as there is not a single solution but a set of non-dominated solutions from which the best should be chosen. That is, the major two tasks of multi-objective optimization are to obtain a representative set of non-dominated solutions and then select a suitable solution from this set based on the specific criterion. In this study, the standard GA algorithm is improved and extended to handle the target application, which is essentially a multi-variable problem.

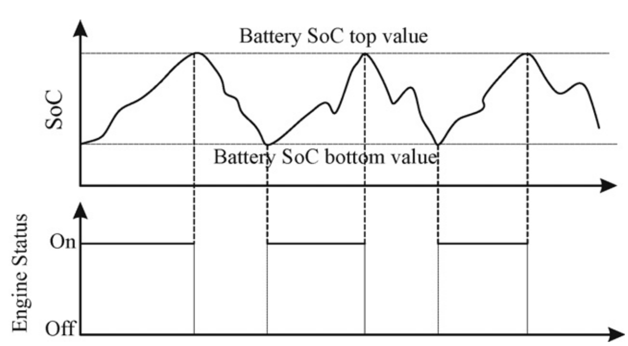

Fig. 9. Illustration of thermostat control strategy. When the SoC of the battery reaches its preset top line, the Genset is turned off and will be turned on when the SoC of the battery reaches its bottom line.

Table 4
Comparison of main parameters obtained from optimization and equivalent value of them in thermostatic control strategy.

Parameters	Developed control strategy	Thermostatic
H_{SoC}	0.915	0.8
L_{SoC}	0.35	0.3
P_{off}	35 kW	75 kW
P_{ch}	28 kW	0
t_{moff}	355	∞

Table 5
Minimum requirements of road performance based on previous version of O457 city.

Max vehicle speed (km h^{-1})	110
Max vehicle speed at 6% grade (km h^{-1})	85
Time to accelerate from 0 to 100 km h^{-1} (s)	35

3.1. Problem formulation

Optimization objective is to reduce the losses of the system, which are reflected by four parameters including the power losses of ICE, generator, battery pack and the losses due to the battery life. According to the above formulation, the set of objective functions are chosen as:

$$f_1(x) = \left(\frac{C_R}{C_A}\right)^{1-u_0}\left(\frac{C_R}{C_A} - 1\right)^{u_0} e^{-u_1(C_A/C_R)} R I_b^2 \tag{10}$$

$$f_2(x) = \frac{1 - \eta_{ICE}}{\eta_{ICE}} P_{e/g} \tag{11}$$

$$f_3(x) = (1 - \eta_{gen}) P_{e/g} \tag{12}$$

$$f_4(x) = R I_b^2 \tag{13}$$

It should be mentioned that due to the direct dependence of the electric traction motor's torque and speed on the driver commands and road conditions, the power losses due to the components can be ignored.

3.2. Archiving

The major function of the archive is to store a historical record of the non-dominated solutions found along the heuristic search process. The archive interacts with the generational population at each iteration so as to absorb superior current non-dominated solutions

Table 6
Comparison of the results for the developed and thermostatic control strategy.

	Fuel consumption (l 100 km^{-1})	Battery energy losses (kJ)	Battery life time (no. of cycles)[a]
Developed controller	65.4	897	1843
Thermostat control	71.5	1352	1360

[a] This means that how many cycles batteries can work before failure of health.

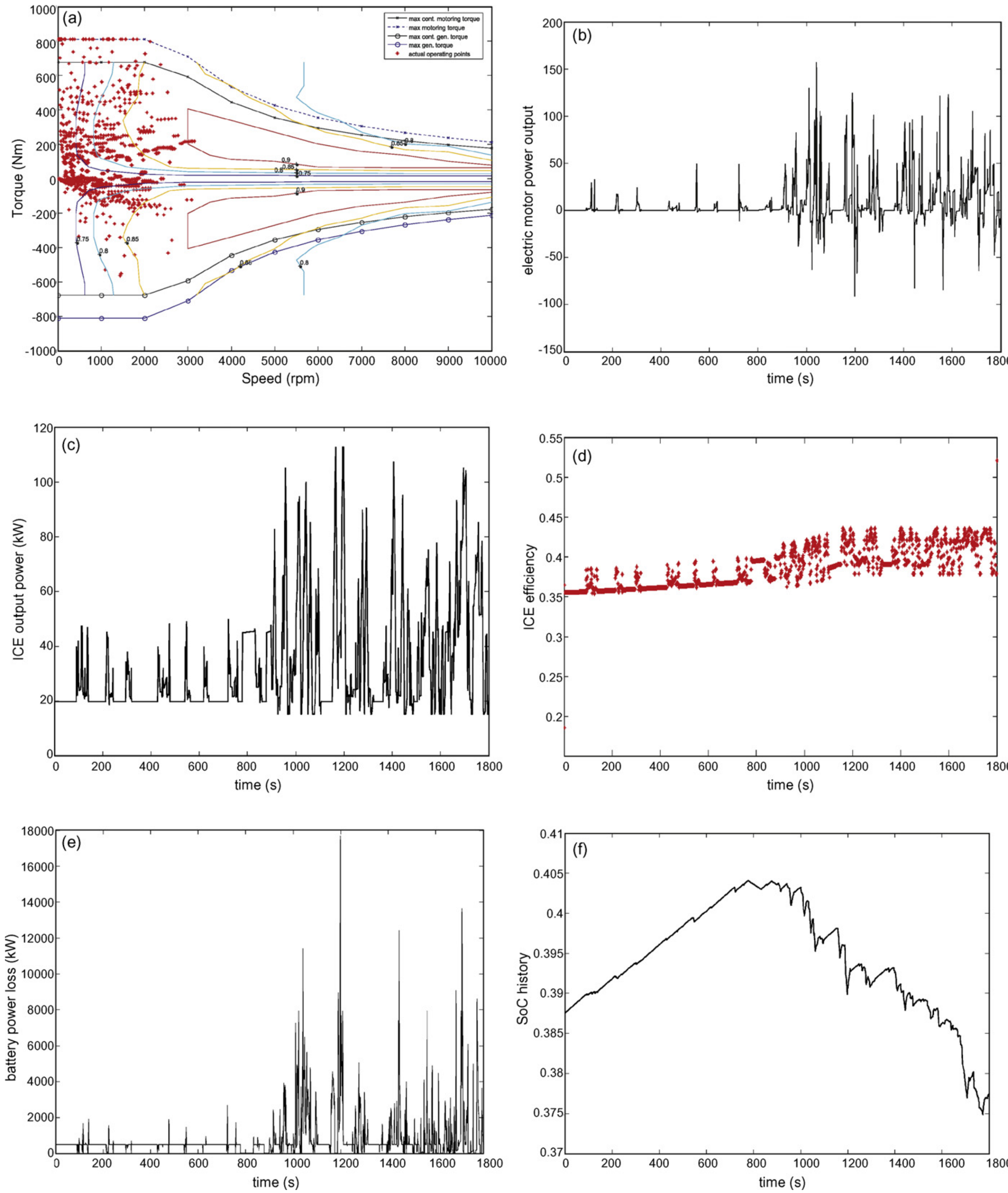

Fig. 10. Tehran city bus driving cycle test results using developed control strategy. (a) Efficiency map of the electric motor. (b) Electric motor output power. (c) ICE output power. (d) ICE efficiency history. (e) Battery power loss. (f) SoC history.

and eliminate inferior solutions currently stored in the archive. The non-dominated solutions obtained at every iteration in the generational population are compared with the contents of archive in a one-per-one basis. A candidate solution can be added to the archive if it meets any of the following four conditions:

- There is no solution currently stored in the archive;
- The archive is not full and the candidate solution is not dominated by or equal to any solution currently stored;
- The candidate solution dominates any existing solution in the archive;

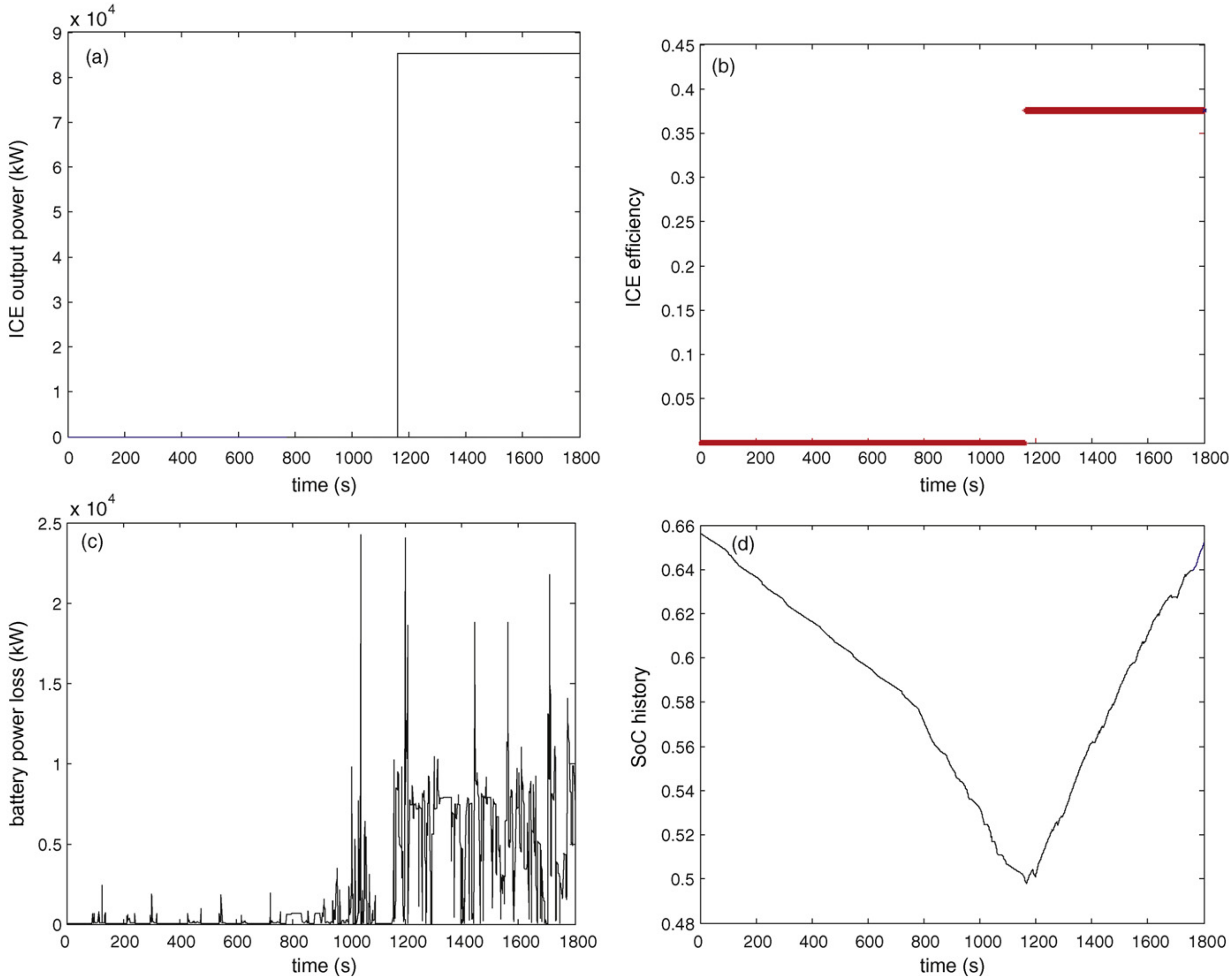

Fig. 11. Tehran city bus driving cycle test results based on thermostatic controller. (a) ICE output power. (b) ICE efficiency history. (c) Battery power loss. (d) SoC history.

- The archive is full but the candidate solution is non-dominated and is in a sparser region than at least one solution currently stored.

During the heuristic multi-objective optimization process, the multi-objective optimization algorithm is attempting to build up a discrete picture of a possibly continuous Pareto front. Therefore it is often desired to distribute the solutions as diversely as possible on the discovered tradeoff curve. Furthermore, the uniformity among the distributed solutions is also crucial so as to achieve consistent and smooth transition among the solution points (when searching for the preferred solution based on the particular requirements of the target problem). Therefore, to accomplish these challenges, it is necessary to preserve the diversity of the solutions distribution during the optimization process.

3.3. Encoding scheme

It is significant to select the appropriate optimal variables for the optimization process. The simplest way to implement a control strategy for the power management of an HEV is to propose a set of static thresholds, described in details in Table 2. The selected variables correlate closely with the fundamental vehicle operation.

In adopting GAs to the scheduling problem such as one dealt in this paper, each chromosome represents a candidate solution consisting of the following genes:

$$(H_{\mathrm{SoC}},\ L_{\mathrm{SoC}},\ P_{\mathrm{off}},\ P_{\mathrm{ch}},\ t_{\mathrm{moff}}) \tag{13}$$

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

4. Performance simulation

In order to help with the simulation, design, and analysis of the designed power-train, certain typical driving schedules have been developed. These driving schedules represent typical traffic conditions for a particular range of time. The optimization process is operated using Tehran transit bus driving cycle shown in Fig. 8 [11]. The total test time for this cycle is 1800 s, the average speed is 9.61 km h^{-1} and the maximum speed is 50.11 km h^{-1}. The distance driven is approximately 4.81 km.

After watchful tuning, the settings of GA parameters in the simulation are as follows: number of generations is 432, population size is 170, crossover probability is 87%, and mutation probability is 1.5%.

In order to investigate the advantages, the developed control strategy was implemented in Hybrid Electric Vehicle FEed-foRwarD SIMulator (HEV-FERDSIM), developed in VFE research institute [12]. The simulation parameters for vehicle used and its components are listed in Table 3. The battery SoC correction procedure is used to correct the fuel economy for the case in which the initial and the final battery SoC are not the same [12].

An optimized control strategy called thermostatic (engine-on–off) is used for comparison, illustrated in Fig. 9. The operation of the engine/generator is totally controlled by the SoC of the battery pack. When the SoC of the batteries reaches its predetermined high value, the engine/generator is turned off and the vehicle is driven only by the battery pack. On the other hand, when the SoC of the batteries reaches its predetermined low value, the engine/generator is turned on. The battery pack charges by the engine/generator. Thus, the engine can always operate within its optimal region.

The control strategy parameters obtained through the GA optimization are shown in Table 4, in addition to thermostatic control strategy parameters. It should be noted that some design parameters are not directly derived from the optimization, but are calculated from other design parameters. Each control strategy must be able to drive the mentioned transit bus, in such a way that the minimum requirements of performance (i.e., Table 5), are satisfied.

Table 6 presents fuel consumption, battery energy losses and battery life time for the developed and thermostatic controllers. As it can be seen, not only the fuel consumption is decreased when using the developed controller, but also the battery energy losses and life are improved considerably.

Simulation results of the vehicle under the prescribed controller policy are shown in Fig. 10. The electric motor operating points and power output are presented in Fig. 10(a) and (b), respectively. The ICE power output and its efficiency points during the cycle are depicted in Fig. 10(c) and (d), respectively. As can be seen, the operating points in Fig. 10(d) are close to the optimal region, which indicates that the ICE has been operating close to maximum possible efficiency.

The battery power losses and SoC history during the cycle are shown in Fig. 10(e) and (f). It can be concluded that lower variation of battery SoC during the cycle is the main reason of increasing of the battery life.

In the case of using thermostatic controller in the simulation, the battery power losses, SoC history, power output and efficiency are shown in Fig. 11(a–d), respectively. As can be seen, the ICE is turned off most of the time and battery is fully discharged. Therefore, the battery power losses increase in comparison to the developed controller losses.

5. Conclusions

A general control strategy for series HEVs has been proposed in order to optimize power-train efficiency based on the minimization of the losses reducing battery life. As long as ICE efficiency is high enough, there will be no need for charging or discharging the batteries which is an inefficient process. This control strategy has been evaluated in detail by means of validated simulations of an HEV. Since the simulations have been performed based on an existing vehicle, the intention of the authors is to make experimental validations of the proposed techniques in the next step. Because of its great importance in the vehicle control and its inherent complexity, more study is required to address challenging technical issues of the algorithm and the whole control strategy.

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References

[1] M. Ehsani, Y. Gao, S.E. Gay, A. Emadi, Modern Electric Hybrid Electric and Fuel Cell Vehicles, CRC Press, 2005.
[2] B. Huang, X. Shi, Y. Xu, IEEE Cong. Evolut. Comput. (2004) 1989–1994.
[3] M. Gokasan, S. Bogosyan, D.J. Goering, IEEE Trans. Power Electron. 21 (3) (2006) 779–790.
[4] S. Barsali, M. Ceraolo, A. Possenti, IEEE Trans. Energy Convers. 17 (2002) 260–266.
[5] S. Barsali, C. Miulli, A. Possenti, IEEE Trans. Energy Convers. 19 (1) (2004) 187–195.
[6] S. Drouilhet, B.L. Johnson, Proceedings of the AIAA Aerospace Science Meeting and Exhibition, Reno, Nevada, 1997.
[7] J. Larminie, J. Lowry, Electric Vehicle Technology Explained, John Wiley & Sons Ltd., 2003.
[8] M. Hemmingsson, A Power-flow Control Strategy to Minimize Energy Losses in Hybrid Electric Vehicles, Master thesis. Department of Industrial Electrical Engineering and Automation Lund Institute of Technology, Lund, Sweden, 1999.
[9] N. Abolhassani Monfared, N. Gharib, H. Moqtaderi, M. Hejabi, M. Amiri, F. Torabi, A. Mosahebi, J. Power Sources 158 (2) (2006) 932–935.
[10] B. Thomas, W.B. Gu, J. Anstrom, C.Y. Wang, D.A. Streit, Proceedings of the 17th International Electric Vehicle Symposium, October, Montreal, 2003.
[11] M. Montazeri-Gh, Development of minibus and bus driving cycle for city of Tehran (collaboration with AVL-MTC), research program in Iran University of Science & Technology, 2005.
[12] M. Amiri, V. Esfahanian, M.R. Hairi-Yazdi, M. Esfahanian, A.M. Fazeli, A. Nabi, J. Math. Comp. Model. Dyn. Sys. (2008), doi:10.1080/13873950802532294.