Research Article

Application of a Pheromone-Based Bees Algorithm for Simultaneous Optimisation of Key Component Sizes and Control Strategy for Hybrid Electric Vehicles

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Abstract

A Pheromone-Based Bees Algorithm (PBA) is employed to optimize the key component sizes and control strategy for parallel Hybrid Electric Vehicles (parallel HEVs) presented. The Basic Bees Algorithm (BBA) is an intelligent optimization tool mimicking the food foraging behavior of honey bees. In this research, however, a new version of BBA which uses pheromones, chemical substances secreted by bees and other insects into their environment, enabling them to communicate with other members of their own species, is applied. The PBA employs the pheromone to attract bees to explore the promising regions of the search space, and the parallel HEV configuration and an Electric Assist Control Strategy are used to formulate the research. The value of the key component size and control strategy parameters is adjusted according to PBA to obtain the minimization of weighted sum of Fuel Consumption (FC) and emissions while vehicle performance that satisfy the PNGV constraints. In this research, ADVISOR software has been used as the simulation tool, and driving cycles, FTP, ECE-EUDC and UDDS, are employed to evaluate FC, emissions and dynamic performances. Following a description of the algorithm, the paper shows the results obtained for the simultaneous optimization of key component sizes and control strategy for parallel Hybrid Electric Vehicles. The results prove that PBA is a strong algorithm for determining the optimal parameters of component sizes and control strategy resulting in improvement of FC and emissions without sacrificing vehicle performance. Compared to BBA, the new version, PBA, showed an improvement of about 25% in convergence speed with the nearly same results of optimization targets.

Keywords: Hybrid electric vehicles; Basic bees algorithm; Pheromone-based bees algorithm; Intelligent optimization; Parallel HEV control strategy

Introduction

Increasing concern about environmental issues, such as global warming and greenhouse gas emissions, as well as the predicted scarcity of oil supplies have made energy efficiency and reduced emissions a primary designing point for automobiles. HEVs have demonstrated improved fuel economy with lower emissions than conventional vehicles. Superior HEV performance in terms of higher fuel economy and lower emissions, with satisfaction of driving performance, necessitates a careful balance of key component sizes as well as control strategy parameter monitoring and tuning.

Optimal parameter value of component sizes and control strategy for HEVs have been studied previously [1-3]. The parametric optimization based on rule-based control was widely used in early studies whereas control concepts based on optimal theories such as Dynamic Programming (DP) or Pontryagin's Minimum Principle (PMP) [4,5] is more current. The optimal control parameters are obtained if the driving-cycle and vehicle performance such as fuel consumption, exhaust emission, and acceleration performance are known. In this case, the DP approach can find the global optimal solution [11-13]. However, DP has to use one more step, a post-processing step, such as neural networks to approximate the results of the optimal control pattern. Even then DP cannot cover all driving conditions. Hence, the real-time controller based on DP is effective only for the driving cycle that is used for rule extraction.

Another approach based on optimal control theory is PMP requiring less computing time than DP. While, control based on PMP can reduce the computational time for getting an optimal trajectory, it is a local optimal solution, not a global solution in general problems [7-9]. In addition, some other approaches have used for the optimization of HEV. Asians (1996) tried to find optimal input variables including the sizes of ICE, EM and battery pack. The optimization objective was to improve the FC when the driving performances were kept within the standard limits. However, they did not account for the exhaust emissions [13]. Montazeri (2006) used Genetic Algorithm (GA) to find optimal component sizes and control strategy. Their objective was to minimize a weighted sum of FC and emissions while the PNGV (the Partnership for a New Generation of Vehicles) performance requirements were considered as constraints [6]. Wu used Particle Swarm Optimization to achieve optimal parameters for both the powertrain and control strategy, and vehicle performances were also defined as constraints. This research aimed to reduce FC, emissions, and manufacturing costs of HEVs. To solve this problem, they used a single objective problem with a goal-attainment method to replace the original multi-objective optimization problem.

In 2012, Long, used a basic Bees Algorithm to optimize parallel HEV component sizes and control strategy. The parameters include three parameters of component size and six parameters of control

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strategy. In this paper, the number of parameters of control strategy is expanded to seven [14]. In order to enhance convergence speed, the component size and control strategy parameters of parallel HEVs are optimized simultaneously by using the new version of Bees Algorithm, the Pheromone-Based Bees Algorithm, to obtain the minimization of weighted sum of FC and emissions when the PNGV driving performances such as acceleration and grad-ability of parallel HEVs are maintained.

Parallel HEV component sizing and control strategy

The parallel HEV component sizing: The parallel HEV configuration is shown in (Figure 1). In this configuration, both ICE and EM are mechanically connected to the driving wheels. The EM plays the role of assisting the ICE in supplying the required power. The ICE can also drive the EM as a generator to charge the battery [15-17]. In this research, the ICE, EM and battery are treated as key components in the design process of parallel HEVs.

HEV control strategy: There are some control strategies that are proposed for parallel HEVs. The Electric Assist Control Strategy (EACS) has been used in this research. Using EACS, the main energy provider is ICE and the EM is used as ICE assistance. The EACS is described in (Figures 2-4) [8] and [2].

The EACS can use the EM in a variety of ways [10]:

1.   If the required speed is less than the electric launch speed (which is dependent on the SOC), the ICE could be turned off. In (Figure 4), above solid line the ICE is on and below solid line the vehicle attempts to run all electrically.

2.   If the SOC is higher than its low limit, the ICE could be turned off. If the requested speed is less than the launch speed and the SOC is higher than the low limit, the ICE will be turned off.

3.   If the required torque is less than a cutoff torque, $cs\_off\_trq\_frac$ fraction of the maximum torque T_{max}, the ICE could be turned off. If the requested torque is lower than this cutoff and the SOC is higher than the low limit, the ICE will be turned off.

4.   When the battery SOC is below cs_lo_soc, additional torque is required from the ICE to charge the battery. This additional charging torque is proportional to the difference between SOC and the average of cs_lo_soc and cs_hi_soc. This ICE torque is prevented from being below a certain fraction, $cs\_min\_trq\_frac$, of the maximum ICE torque T_{max} at the current operating speed. This is intended to prevent the ICE from operating at an inefficiently low torque.

Optimization targets: The HEV research objective is to minimize the weighted sum of FC and exhaust emissions (HC, CO and NO_x) while still satisfying charge sustaining requirement and driving performances. The PNGV passenger car constraints described in (Table 2) [19] are used as dynamic performance requirements to show that vehicle performance is not sacrificed during optimization.

The objective function is defined as follows:

$$G(x) = f_1 FC + f_2 HC + f_3 CO + f_4 NO_x \qquad (1)$$

Where, f_1 to f_4 are also defined as weighting factors used to investigate the effect of different objectives on the optimization results.

Bees algorithm for simultaneous optimization of component sizes and control strategy

Bees Algorithm mimics the food foraging behavior of a swarm of honey bees. This algorithm performs a type of neighborhood search

combined with random search.

Basic bees algorithm: The basic bee's algorithm is an intelligent optimization tool imitating the food foraging behavior of honey bees found in nature. In the natural environment bees are able to discover food sources using two kinds of search methods, namely, a global random search and a local search. The former consists of sending the bees at random around the hive. Once these bees, which are called the scout bees, discover potential food sources they return to their hive and start recruiting more bees to exploit those food sources which were discovered during the random search attempt. The bees waiting in the hive receive their instructions from the returning scout bees in the form of a waggle dance which gives them the following useful information: the location of the nearest food source, the quality of that food source, and the amount of energy needed to harvest the food. Logically, the better the food source and the closer to the hive the more numerous the recruited bees will be. The search performed by the recruited bees is similar to a local search. While some bees are recruited to conduct local search, a percentage of the bee population continues the global random search to look for other promising food sources. This ensures that the search continues cycle after cycle in an iterative manner until all the good food sources including the best food source in the vicinity of the hive are found. This is similar to an intelligent optimization process and can be formulated into an algorithmic form as in the basic Bees Algorithm [15].

Pheromone-based bees algorithm: In nature, the bees are known to secrete pheromones in a liquid form which is transmitted by coming into direct contact with it or as it is a vapor. The pheromones release chemical signals proportional to the amount which has been deposited by scout bees for marking potential food sources, marking their hive,
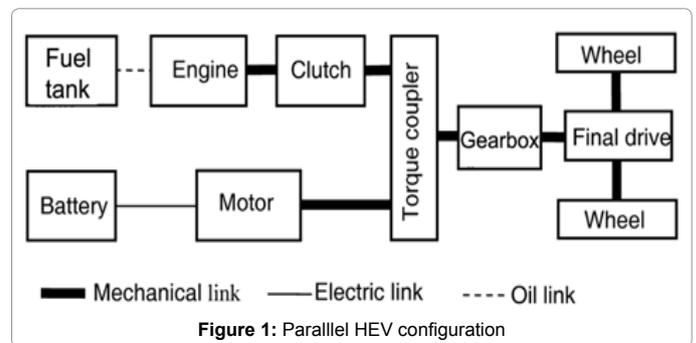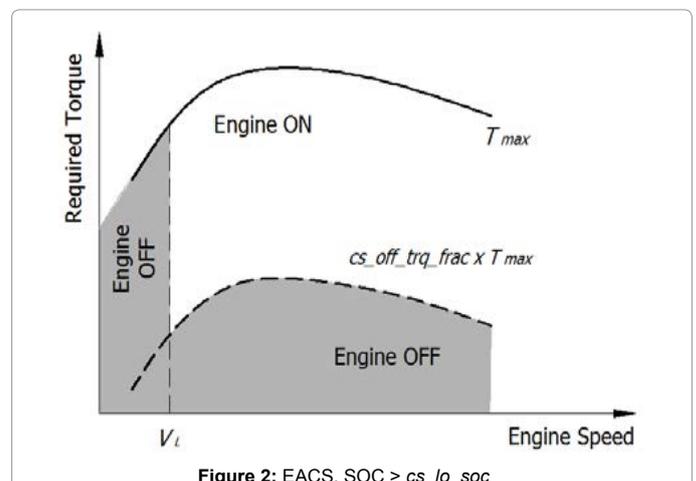

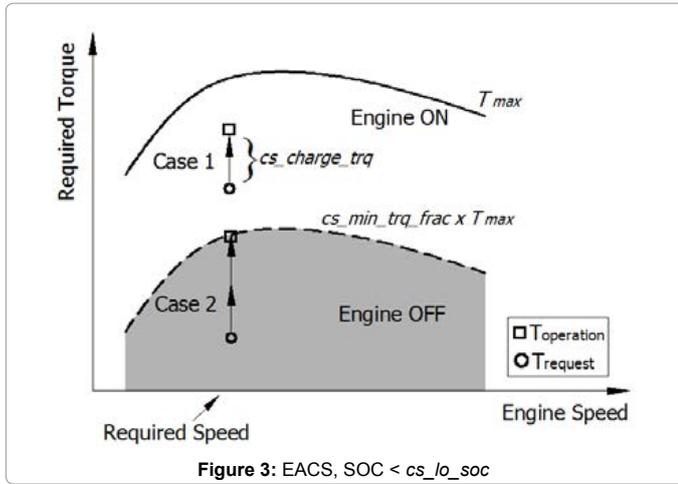**Figure 1:** Paralllel HEV configuration

Figure 2: EACS, SOC > cs_lo_soc
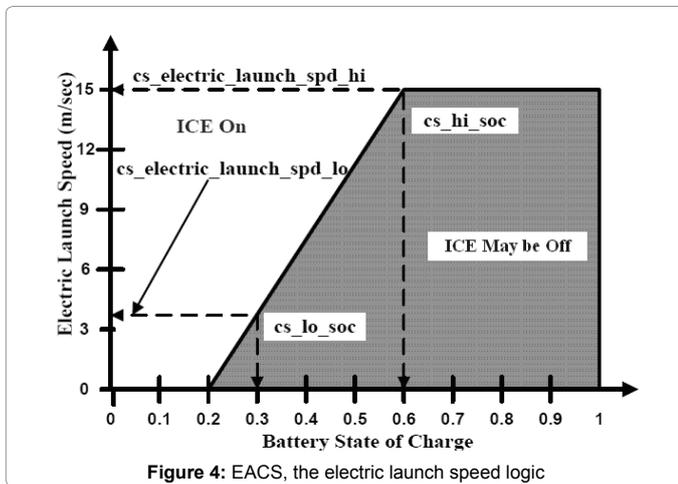
Figure 3: EACS, SOC < *cs_lo_soc*

Figure 4: EACS, the electric launch speed logic

scenting potential hive sites, and assembling or recruiting other bees. The scent arising from the secreted pheromones can intensify or diminish over time depending on the level of bee activity at that site. A strong scent will help to recruit bees in larger numbers to the food source while a mild scent will indicate the depletion of nectar in a previously marked food source.

In the Pheromone-Based Bees Algorithm the number of scout bees allocated for global random search is defined by parameter "n" and the number of bees assigned to search around the selected site "**e**" is defined by parameter "**m**". In order to facilitate the search within a sphere centered on the selected sites, the parameter "**n**$_{gh}$" is used to define the neighborhood size. In the Pheromone-Based Bees Algorithm, pheromones are used to recruit bees to search around each selected site. In every iteration, the bees deposit pheromones on the sites they are drawn to and the exact amount on a particular site depend on the quantity of pheromones already present on that site which is influenced by a decay rate, the fitness of that site, and the number of bees found on that site. The amount of pheromones found on a site will gradually evaporate to nothing, over time, if there is no bee activity there. Due to pheromone evaporation, the older the site, the less attractive it is (because it has been exploited and the nectar in it might have exhausted). As a consequence, the number of bees recruited to each site will be proportional to the quantity of pheromone already present on that site, and the fitness of that site. Thus the use of pheromones allows an automatic and dynamic recruitment of bees

across the search space. The pheromones are used to recruit bees to a particular site, uses not only the quality of that site, i.e. fitness, but also the amount of pheromone found on the site. The precise amount of pheromone accumulated on each site will be calculated in each iteration using a pheromone update equation which will show either an increase or decrease in its level [15].

The Pheromone-Based Bees Algorithm is shown as in Figure 5, and its parameters are described in Table 3.

The algorithm starts with the initial population of n scout bees to search randomly in the solution space. Then, the fitness of the scout bees associated with their respective sites is evaluated in step 2. However, only bees with the highest fitness are chosen as "selected bees" and sites visited by them are selected for neighborhood search in step 3. After that, in steps 4, 5 and 6, the algorithm will search in the neighborhood of the selected sites, the number of bees "m" recruited for each selected site depends on the pheromone deposited on that site. At the end of each neighborhood search, the bee having the highest fitness value associated with its visited patch is selected to form the next bee population

In order to avoid local optima, in step 7, the remaining bees (n-e) in the population have to search randomly around the solution space to find new potential sites. The iteration of these above steps will not be finished until a stopping criterion is met and the best bee of the last population is treated as the optimal solution [21,22].

Pheromone-based bees algorithm in parallel HEV optimization: In order to apply PBA to the simultaneous optimization of parallel HEVs, the fitness in step 2 is the inverse of objective function G (x) in Equation (1). However, the optimization task is required to maintain the on road performances such as acceleration and grad-ability of parallel HEVs. Unfortunately, the PBA cannot work directly with constrained optimization problem. To solve this problem, it is necessary to add penalty functions into objective function G(x) [23].

$$\text{Min } G(\mathbf{x}) \; x = (x_1, x_2 \text{---} x_{10}) \tag{2}$$

Subject to $h_i(x) \leq 0 \; i = 1, 2, \ldots, 7$

$$
\begin{cases}
C_1(x) = \max(0, F_1(x) - \alpha_1) \\
C_2(x) = \max(0, F_2(x) - \alpha_1) \\
C_3(x) = \max(0, F_3(x) - \alpha_1) \\
C_4(x) = \max(0, \alpha_4 - F_4(x)) \\
C_5(x) = \max(0, \alpha_5 - F_5(x)) \\
C_6(x) = \max(0, \alpha_6 - F_6(x)) \\
C_7(x) = \max(0, \alpha_7 - F_7(x))
\end{cases}
\tag{3}
$$

$$fitness(S_j)_{(x)} = \frac{1}{G(S_j)_{(x)} + \sum_{i=1}^{7} k_i \times C_i(S_j)_{(x)}} \tag{4}$$

Where, $x_1, x_2 \ldots x_{10}$ are parameters of component sizes and control strategy listed in (Table 1)

$C_i(S_j)_{(x)}$, α_i and $F_i(x)$ are penalty function, desired value and evaluated value related to i^{th} constrain $h_i(x)$ in (Table 2)

The penalty function is used to penalize infeasible solutions by reducing their fitness values. $C_i(S_j)_{(x)} = 0$, if the constrain $h_i(x)$ is satisfied.

k_i is penalty factor chosen by trial and error as given in (Table 2)

Parameters	Description
fc_trq_scale	scaling factor for torque range of ICE
mc_trq_scale	torque scaling factor of EM
ess_module_num	number of battery modules in a pack
cs_hi_soc	highest desired battery state of charge
cs_lo_soc	lowest desired battery state of charge
cs_electric_launch_spd_lo	Vehicle speed below which vehicle runs as pure electric vehicle (ZEV mode) at low battery SOC
cs_electric_launch_spd_hi	Vehicle speed below which vehicle runs as pure electric vehicle (ZEV mode) at high battery SOC
cs_off_trq_frac	cs_off_trq_frac·T_{max} = minimum torque threshold; when commanded at a lower torque, the engine will shut off if SOC > cs_lo_soc
cs_min_trq_frac	cs_min_trq_frac · T_{max}= minimum torque threshold; when commanded at a lower torque, the engine will operate at the threshold torque and the motor acts as a generator if the SOC < cs_lo_soc
cs_charge_trq	cs_charge_trq·((cs_lo_soc + cs_hi_soc)/2-SOC) = an accessory like torque loading on the engine to recharge the battery pack whenever the engine is on.

Table 1: Parameters of component size and EACS

Parameterst	Description	k_i
Acceleration time	*Time for 0–96.6 km/hr ≤ 12s*	1.2
	Time for 64.4–96.6 km/hr ≤ 5.3s	1.5
	Time for 0–136.8 km/hr ≤ 23.4s	1.2
Gradeability	6.5 % grade ability at 88.5 km/hr, 272kg additional weight for 20 min	2.0
Maximum speed	≥ 137 km/hr	1.2
Maximum acceleration	≥ 5 m/s²	1.2
Distance in 5 sec	≥ 42.7m	1.2

Table 2: PNGV performance constraints

1. Initialise a Population of ***n*** Scout Bees

2. Evaluate the Fitness of the Population

Neighborhood Search

3. Select ***e*** Sites for Neighborhood Search

4. Determine the Size of Neighborhood (Patch Size ***n_gh***)

5. Recruit Bees for Selected Sites

6. Select the Fittest Bee from Each Site

7. Assign the ***(n−e)*** Bees to Random Search
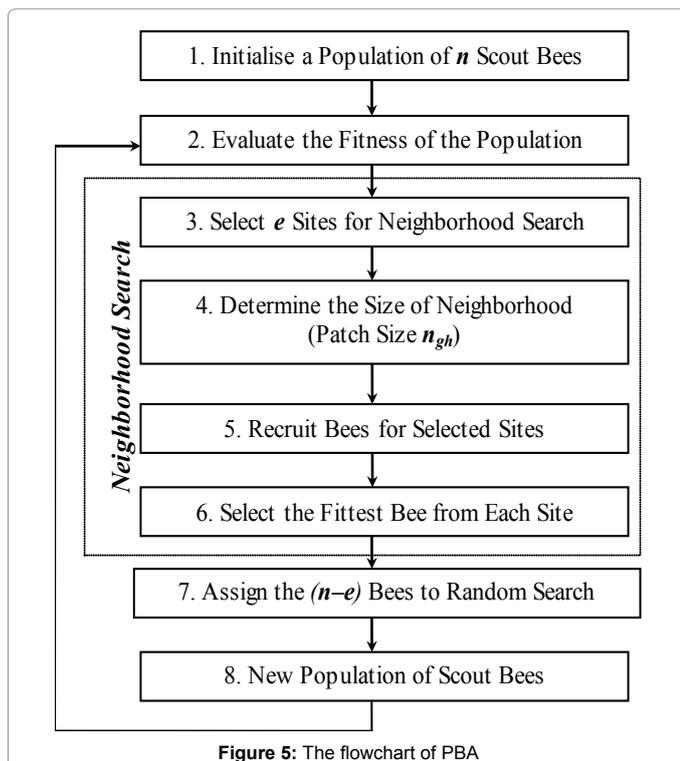
8. New Population of Scout Bees

Figure 5: The flowchart of PBA

fitness (S_j)$_{(x)}$ is the fitness value of site S_j

The optimization process using PBA for parallel HEVs can be stated as follows:

Step 1: Initialize the population of scout bees, each scout is a set of specific values of all variables of component sizes and control strategy in (Table 1)

Step 2: Evaluate the FC, HC, CO, NO$_x$ and penalty functions $C_i(x)$ for each scout bee by combining between PBA and ADVISOR software

Step 3: Calculate the fitness value of all scout bees according to Equation (3) and (4)

Step 4: Choose **e** bees with highest fitness

Step 5: Recruit bees for selected "**e**" sites according to the pheromone levels at those sites (local search) to conduct searches in the neighborhood of the selected e sites and choose a bee with the highest fitness for each site. The number of bees given by nb (S_j, t) recruited for a site S_j of **e** sites at time t is calculated from Equation (5)

Step 6: Assign the remaining (**n-e**) bees to search randomly around the search space for new potential solutions

Step 7: At the end of the local and global search, the best bees from all the sites are sorted according to their fitness

Step 8: Update new population

Step 9: Update pheromone level on each site by using Equation (7)

Step 10: Stop the program if the convergence criteria is satisfied, otherwise go to step 4.

$$n_b(S_j,t) = \frac{ph(S_j,t-1)^\alpha \; x \; f_s(S_j)^\beta}{\sum_{i=1}^{e}\left[ph(S_i,t-1)^\alpha \; x \; f_s(S_i)^\beta\right]} \; x \; m \; x \; e \tag{5}$$

$$fs(S_j) = \frac{fitness(S_j) - fitness(S_{e+1})}{\sum_{i=1}^{e}\left[fitness(S_i) - fitness(S_{e+1})\right]} \tag{6}$$

$$ph(S_j,t) = ph(S_j,t-1) \; x \; \rho + f_s(S_j) \; x \; n_b(S_j,t) \tag{7}$$

Where, $fs\,(S_j)$ is the fitness score of site S_j. S_{e+1} are the best performing site among the non-selected sites. Note that the fitness score $fs\,(S_j)$ is normalized to smooth noise and suppress systematic variations. The optimization process is programmed and linked with ADVISOR by using *.m file in Matlab [7]. The linkage configuration between ADVISOR and PBA is described in (Figure 6). The parameters of PBA used in this optimization are chosen as in (Table 4)

Where, up. Bound $_{(i)}$ and lo. Bound $_{(i)}$ are the upper bound and lower bound of variable ith listed in (Table 6)

ADVISOR software gives different component modules such as fuel converter, energy storage, motor, etc. to build a vehicle system. In

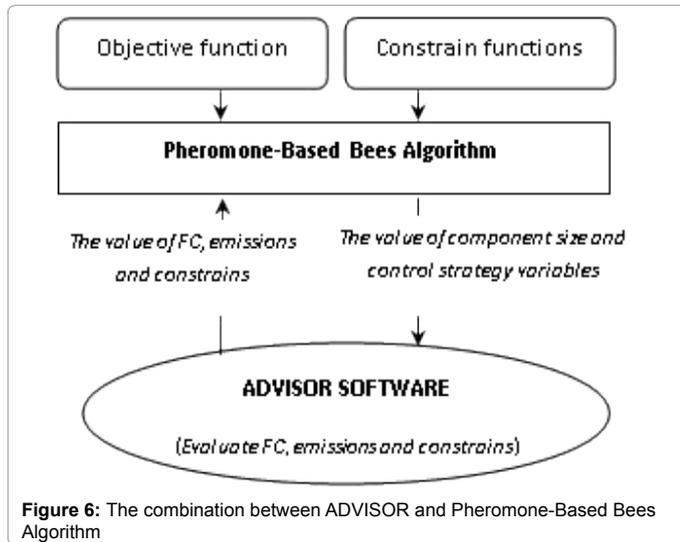| Parameters	Description
n	number of scout bees
e	number of sites selected out of n visited sites
m	number of bees recruited for selected e sites
n_{gh}	size of patches, which includes site and its neighborhood

Table 3: The parameters of PBA

Figure 6: The combination between ADVISOR and Pheromone-Based Bees Algorithm

n	e	m	$n_{gh(i)}$
23	7	5	(up. bound$_{(i)}$-lo. Bound $_{(i)}$)/40

Table 4: The parameters of PBA

order to continuously adjust component sizes in the search space, the fixed parameters are used for the simulation of the parallel HEV shown in (Table 5). To vary component size, the baseline ICE of Geo Metro 1.0L SI engine is used. The engine torque scale factor, *fc_trq_scale*, is also used to vary the ICE size. In addition, for the baseline electric motor, a Westinghouse AC induction motor is employed. The same as ICE, the motor torque scale factor, *mc_trq_scale*, is used to vary the EM size. Similarly, the Hawker Genesis Valve-Regulated Lead-Acid (VRLA) battery is used for battery sizing. To vary the battery size, the number of battery modules, *ess_module_num*, is changed [8].

The range of component size and control strategy variables is given in (Table 6).

Simulation results and analysis: In order to eliminate the influence of energy from the battery on fuel consumption, the simulation has been run several times starting with different initial SOC values until the final SOC is close to the initial SOC. After running the optimization program with PBA parameters in (Table 4) following three driving cycles, FTP, ECE-EUDC and UDDS. The optimal parameters, FC, emissions and dynamic performances, are shown in (Tables 7-9).

The results in the above tables prove the power of the PBA. With the optimal parameters of component sizes and control strategy listed in (Table 7), the FC, HC, CO and NOx are improved and dynamic performances are satisfied the PNGV constrains. The FC, emissions and vehicle performances obtained by using PBA with the driving cycles FTP, ECE-EUDC and UDDS are nearly same as ones employed by BBA. However, the rate of convergence of PBA is faster than that optimized

by BBA [13,14]. The optimization process in this research will be stopped after 30 iterations or when the value of objective function does not reduce after 15 iterations. The set of component size and control strategy variables of the last best bee at the last iteration is considered as the best solution for optimization of the parallel HEVs. Compared to the BBA, the new version, PBA, showed an improvement of about 25 % in convergence speed. This indicates the good performance of the PBA approach in saving time to achieve the optimal parameters.

Conclusions

The paper presents a simultaneous optimization of parallel HEV component sizes and control strategy to minimize the weighted sum of FC and emissions without sacrificing road performance by using a new approach, Pheromone-Based Bees Algorithm. Similar to the BBA, the PBA employs a type of neighborhood search (local search) combined with a random search (global search) in the solution space, so the results of component size and control strategy parameters of parallel HEVs are ensured to be global solutions. However, as the PBA employs pheromones to attract bees to explore promising regions of the search space, it can find the best solution approximately 25% faster than the basic Bees Algorithm. The results show that, the PBA approach is powerful in searching the best parameters of parallel HEVs in the solution space resulting in improvement of FC and reduction of HC, CO and NOx, while PNGV constrains are maintained.

Parameters	Description
ICE	Geo Metro 1.0L SI engine with the maximum power output of 41 kW and peak efficiency of 0.34
EM	Westinghouse AC induction motor with a maximum power output of 75 kW and peak efficiency of 0.92
Battery pack	Lead-Acid (VRLA), 12V26Ah
Body mass	592 kg
Rolling resistance coefficient	0.009
Body aerodynamic drag coefficient	0.335
Vehicle front area	2 m²
Wheel radius	0.282 m
Gearbox *Gear ratio*:	2.84, 3.77, 5.01, 5.57 and 13.45
Efficiency:	95 %
Catalyst converter	close-coupled conventional converter for an SI engine
Cargo mass	136 kg.

Table 5: The fixed parameters of parallel HEVs

Parameters	Lower bound	Upper bound
fc_trq_scale	0.5	1.5
mc_trq_scale	0.1	1.2
ess_module_num	7	30
cs_electric_launch_spd_lo (m/s)	0	10
cs_electric_launch_spd_hi (m/s)	11	35
cs_min_trq_frac	0.1	0.8
cs_off_trq_frac	0	0.2
cs_lo_soc	0.15	0.57
cs_hi_soc	0.58	0.95
cs_charge_trq (N.m)	5	40

Table 6: The range of variables
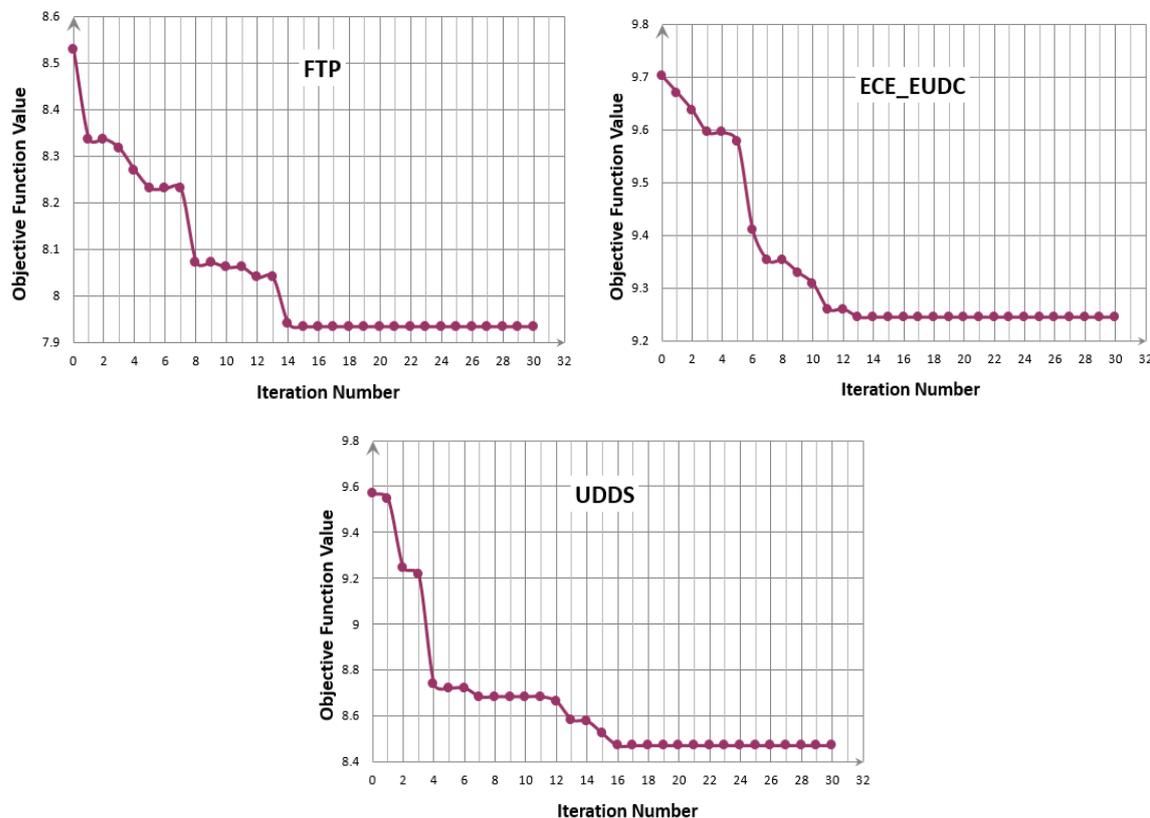
Figure 7: Optimization process for three driving cycles

Parameters	FTP	ECE-EUDC	UDDS
fc_trq_scale	1.090	1.010	1.061
mc_trq_scale	0.165	0.181	0.162
ess_module_num	12.895	14.253	13.028
cs_electric_launch_spd_lo (m/s)	0.375	4.294	0.232
cs_electric_launch_spd_hi (m/s)	29.609	13.828	30.506
cs_min_trq_frac	0.109	0.346	0.122
cs_off_trq_frac	0.146	0.021	0.150
cs_lo_soc	0.537	0.459	0.542
cs_hi_soc	0.719	0.800	0.726
cs_charge_trq (N.m)	6.526	23.569	8.971

Table 7: The value of optimal parameters

Parameters	FTP	ECE-EUDC	UDDS
FC (liter/100km)	5.3	5.9	5.4
HC (g/km)	0.291	0.39	0.37
CO (g/km)	1.234	1.76	1.60
NO_x (g/km)	0.244	0.27	0.29

Table 8: FC and emissions

Parameters	FTP	ECE-EUDC	UDDS
Grade	7.4	7.0	7.2
(0-97)km/h (s)	10.4	10.5	10.5
(64-97)km/h (s)	5.3	5.3	5.3
(0-137)km/h (s)	21.9	22.2	22.0
Max. speed (m/s)	176.6	174.9	175.7
Max. acc (m/s^2)	5.0	5.0	5.0
Dist. In 5 sec. (m)	50.8	50.8	50.6

Table 9: The dynamic performances

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