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Application of a Pheromone-Based Bees Algorithm as an Optimizer Within a Multidisciplinary Design Optimization System for Powertrain Component Sizing and Control Parameters for Hybrid E-Vehicles

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Abstract: This paper presents a Multidisciplinary Design Optimization (MDO) to optimize key component sizes and control strategy for a hybrid electric vehicle, Honda Insight 2000. A pheromone-based Bees Algorithm (PBA), where the food foraging behavior of honey bees combined with evolutionary computation, is used as an optimizer within a MDO system. The PBA uses pheromones, chemical substances secreted by bees and other insects into their environment, enabling them to communicate with other members of their own species. The values of the key component size and control strategy parameters are adjusted according to PBA to obtain the minimization of Fuel Consumption (FC) while dynamic performances have to satisfy the Partnership for a New Generation of Vehicles (PNGV) constraints. In this research, ADVISOR software has been used as the simulation tool, where driving cycles, FTP and HWFET are employed to evaluate FC and dynamic performances. Following a description of the MDO system, the paper shows the results obtained for only the control strategy parameter optimization and the simultaneous optimization of key component sizes and control strategy parameters for the Honda Insight 2000. The results demonstrate the effectiveness of PBA when it is used as the optimizer within a MDO system for determining the optimal parameters of component sizes and control strategy resulting in the reduction of FC and improvement of vehicle performances. In this research, the new version, PBA, showed an improvement of about 20-25% over the Basic Bees Algorithm (BBA) in convergence speed with the nearly same results of optimization targets.

Keywords: Hybrid Electric Vehicles, Multidisciplinary Design Optimization, Basic Bees Algorithm, Pheromone-Based Bees Algorithm, Intelligent Optimization, HEV Control Strategy, Honda Insight 2000

1. Introduction

Currently, many researchers worldwide are looking for new solutions to reduce vehicle emissions, while reducing the consumption of fossil fuels. Hybrid Electric Vehicle (HEV) systems became one of the best working solutions by utilizing the advantages of both Internal Combustion Engine (ICE) and electric energy source. A hybrid vehicle is one that employs two or more power sources to improve the overall efficiency of the system. By designing suitable component sizes and control strategy, the HEV can not only reduce toxic exhaust gas emissions but also minimize Fuel Consumption (FC) while maintaining on-road vehicle performances. When an HEV is designed, it is necessary to determine the optimal sizes of key power sources of powertrain system. In addition, the management of energy flow also plays an important role in improving HEV efficiency. These problems can be solved by a parameter optimization of control strategy [13]. A survey of the existing literature indicates that optimization of the power management logic of hybrid electric vehicles is mostly performed after the design of the powertrain architecture or the power source components are finalized.

The majority of power management control logic systems can be classified under two types: (i) a rule-based approach and (ii) an optimization-based approach. Rule-based control strategies consist of deterministic and fuzzy logic rule-based methods, while optimization-based approaches typically utilized global optimization when determining the control strategy parameters [14].

In order to optimize the key component sizes and control strategy parameters of an HEV, number of methods have been used. Assanis *et al.* (1996) tried to find optimal input variables including the sizes of ICE, Electric Motor (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 [1]. Montazeri *et al*., (2006) used a Genetic Algorithm (GA) to find optimal component sizes and control strategy [6]. Their objective was to minimize a weighted sum of FC and emissions while the PNGV performance requirements were considered as constraints [4]. Wu *et al*., (2008) used Particle Swarm Optimization to achieve optimal parameters for both the powertrain and control strategy, and vehicle performances were also defined as constraints. Their research aimed to reduce FC, emissions, and manufacturing costs of HEVs. To solve this problem, they used a single objective function with a goal-attainment method to replace the original multi-objective optimization problem [15].

In 2012, Long *et al* (2012), used a Basic Bees Algorithm to optimize parallel HEV component sizes and control strategy. The design factors included three parameters of component size and six parameters of control strategy [8], [9]. In this paper, the component sizes and control strategy parameters of a commercial HEV, Honda Insight 2000, are optimized simultaneously by using a new version of Bees Algorithm, the Pheromone-based Bees Algorithm (PBA), to obtain the minimization of weighted sum of FC and emissions when the PNGV driving performances such as acceleration and gradeability of parallel HEVs are maintained. The goal of this research is to utilize Multidisciplinary Design Optimization to automate and optimize only the control strategy parameters at first and then simultaneously find the optimum values for powertrain component sizes and control strategy parameters.

The powertrain configuration of Honda Insight 2000 is shown in Fig. 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 [2], [3]. In this research, the ICE, EM and battery are treated as key components in the design process of Honda Insight 2000.

2. Honda Insight 2000

2.1. The Powertrain Configuration

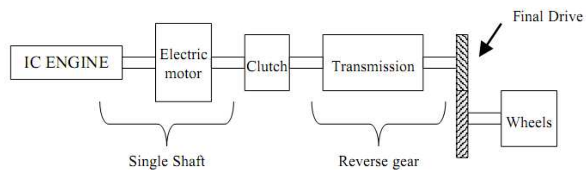

Figure 1. *The configuration of Honda Insight 2000 [2].*

2.2. The Control Strategy

Based on the working of the Honda Insight 2000, a scalable control strategy was developed in ADVISOR software (Fig. 2). The electric motor of Honda's Integrated Motor Assist (IMA) provides approximately 10Nm of assist in most cases when a large torque (approximately > 20Nm) is demanded of the vehicle (This is physically interpreted as an indication for acceleration through depressing the accelerator pedal) [7].

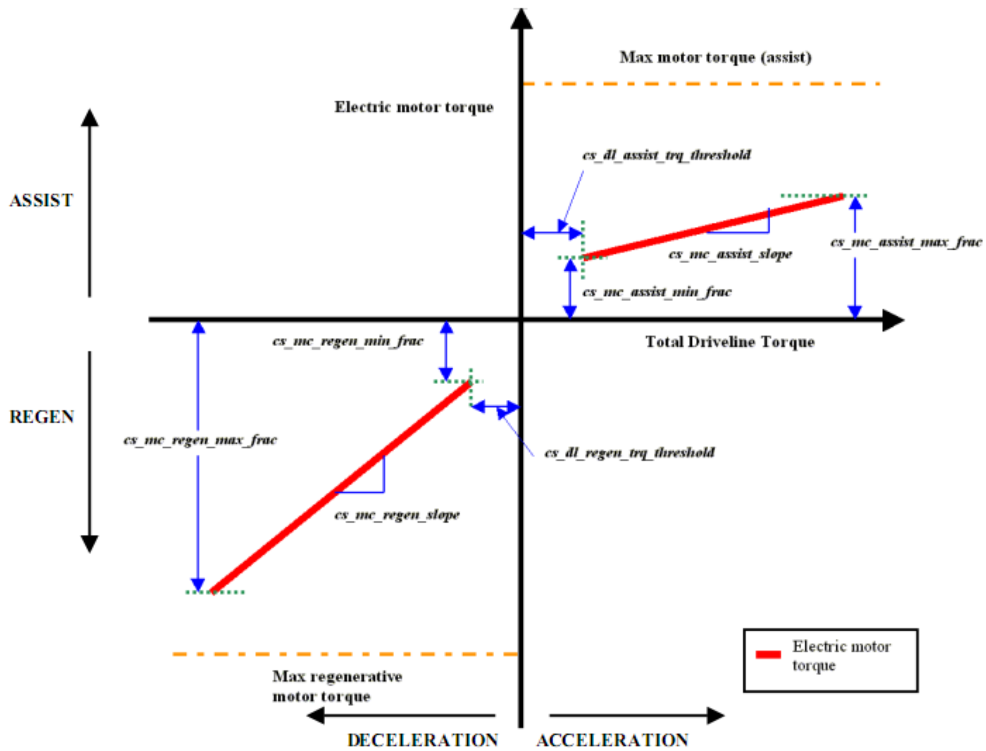

Figure 2. *The control strategy of Honda Insight 2000 [2], [7].*

The electric motor of the Integrated Motor Assist (IMA) performs regeneration when the vehicle slows down, as there is torque from the inertia of the vehicle coming into the driveline. When the brakes are depressed, there is heavy deceleration, and a lot of negative regenerative torque is seen at the driveline. The controller senses the braking, and allows the motor to return a part of that energy back to the battery. This ensures that the battery is charged and that not all of the energy is lost in the form of heat. During braking, a small portion of the braking force is provided by the electric motor, and the remaining part from the friction brakes [5].

In Fig. 2, the parameters shown are used in determining the behavior of the electric motor, based on the vehicle torque demand. The solid line in the upper right quadrant of the graph, defines the level of assist provided by the electric motor. When the driveline torque required exceeds the parameter "*cs_dl_assist_trq_threshold*," the motor provides assist, starting at a level indicated by "*cs_mc_assist_min_frac*," and increases according to the parameter "*cs_mc_assist_slope*," which indicates how much assist the motor should provide, based on the driveline torque. The maximum assist of the motor can be limited by using the parameter "*cs_mc_assist_max_frac*." The motor torque limits are represented as a fraction of the max torque capacity of the motor. Similarly, the solid line in the lower left quadrant defines the level of regeneration provided by the electric motor. When regenerative torques seen by the driveline exceed the parameter "*cs_dl_min_trq_threshold*," the motor starts regenerating with a minimum value equal to "*cs_mc_regen_min_frac*," and increases according to "*cs_mc_regen_slope*." This parameter defines the amount of regeneration the motor provides, based on what is seen at the driveline. As in the case of assist, motor regeneration torque can be limited using the parameter "*cs_mc_regen_max_frac*."

These limits are a function of the maximum regenerative capacity of the motor. Table 1 provides key component sizes and a summary of the parameters used in this scalable control strategy. For the Honda Insight 2000, the control strategy parameters are given in the 3rd column of Tab. 1.

3. Optimization Targets

As the emission map of HC, CO and NO_x in exhaust gas has not been integrated in ADVISOR software, the research objective in this research is only to minimize FC while still satisfying charge sustaining requirements and dynamic performances. The PNGV passenger car constraints described in Tab. 6 [4], [14] are used as dynamic performance requirements to show that vehicle performance is not sacrificed during optimization.

The objective function is defined as follows:

$$G(x) = FC \tag{1}$$

$$\text{Min } G(x),\ x = (x_1, x_2, \ldots, x_{14}) \tag{2}$$

subject to $h_i(x) \le 0$, $i = 1, 2, \ldots, 7$

where, $x_1, x_2, \ldots, x_{14}$ are parameters of component sizes and control strategy parameters described in Tab. 1

$h_i(x)$ are constrains listed in Tab. 6

Table. 1. *Parameters of component size and control strategy.*

Parameters	Description	Honda Insight
fc_trq_scale	Scaling factor for torque range of ICE	1.0
mc_trq_scale	Torque scaling factor of EM	1.0
ess_module_num	Number of battery modules in a pack	20
cs_dl_assist_trq_threshold	Driveline torque threshold below which the electric machine does not assist	25 Nm
cs_mc_assist_min_frac	Minimum torque normally provided by the electric motor when driveline torque exceeds threshold (as a fraction of max torque)	0.1290
cs_mc_assist_slope	Fraction (slope of the line) of the driveline torque provided by the electric motor when the driveline torque exceeds threshold	0.0909
cs_mc_assist_max_frac	Maximum motor torque requested from the motor during assist (as a fraction of max torque)	0.3200
cs_dl_regen_trq_threshold	Driveline regenerative torque threshold above which the electric machine does not regenerate at low speeds	-15 Nm
cs_mc_regen_min_frac	Minimum regenerative torque normally provided by the electric motor when driveline torque exceeds regenerative threshold (as a fraction of max regen torque)	0
cs_mc_regen_slope	Fraction (slope of the line) of the negative driveline torque regenerated by the electric motor when the driveline torque exceeds threshold	0.7
cs_mc_regen_max_frac	Maximum regenerative motor torque requested from the motor during regeneration/braking (as a fraction of max regenerative torque)	1.0
cs_decel_regen_threshold	Speed during deceleration below which the electric motor does not regenerate	10 Nm
cs_lo_soc	Lowest desired battery state of charge	0.2
cs_hi_soc	Highest desired battery state of charge	0.8

4. A Simultaneous Multidisciplinary Design Optimization System for Honda Insight 2000

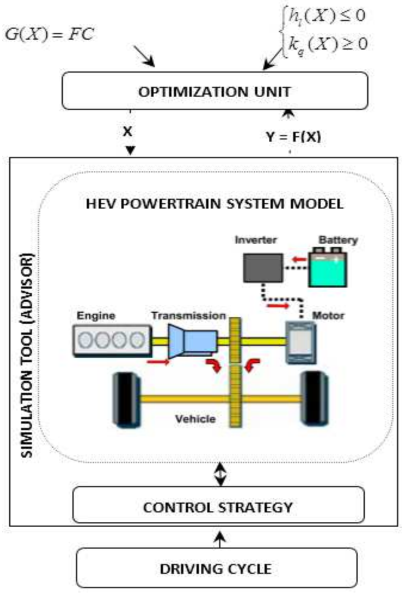

Figure 3. *A simultaneous Multidisciplinary Design Optimization system for Honda Insight 2000.*

An HEV is very complex and contains different components from various disciplines such as ICE, EM, generator, etc.. Optimal design of HEVs usually requires various engineering teams specializing in different disciplines collaborating to provide a solution. In order to increase the efficiency of the design process, this research proposes an optimization method in attempt to solve various disciplines simultaneously for Honda Insight 2000, termed Multidisciplinary Design Optimization as described in Fig. 3. An optimization software platform utilizing multidisciplinary design optimization approach is implemented containing the Honda Insight 2000 model and an optimization unit. The Honda Insight 2000 model created by National Renewable Energy Laboratory, USA in ADVISOR software is used for the simulation tool. The powertrain component properties and control strategy parameters of Honda Insight 2000 model can be changed easily following the optimization unit by using m-files. The calculations of output variables Y including FC and dynamic performances of the vehicle system are performed in ADVISOR simulation tool. The vector of design variable X in Tab. 1 is provided by the optimization unit to the coupled system of analysis disciplines (Simulation Tool), and a complete multidisciplinary analysis is performed by the Simulation Tool to obtain the system output variable Y = F(X). The system output variable Y is then subsequently used to evaluate the objective function $G(X)$ and the constraints ($h_l(X)$, $k_q(X)$). Based on the values of $G(X)$ and constraints ($h_l(X)$, $k_q(X)$), the optimization tool will change the value of X to provide for the Simulation Tool again. The process is repeated until the convergence criteria are satisfied.

The Pheromone-Based Bees Algorithm is used for the optimization unit and its detail is described as follows.

4.1. Basic Bees Algorithm

The Basic Bees Algorithm is an intelligent optimization tool imitating the food foraging behaviour 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 [10], [11], [12].

4.2. Pheromone-Based Bees Algorithm

In nature, bees are known to secrete pheromones in a liquid form which is transmitted by coming into direct contact with it or as its 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, 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 [10].

In the Pheromone-based Bees Algorithm (PBA) 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 depends 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 [10].

The Pheromone-based Bees Algorithm is shown as in Fig. 4, and its parameters are described in Tab. 2.

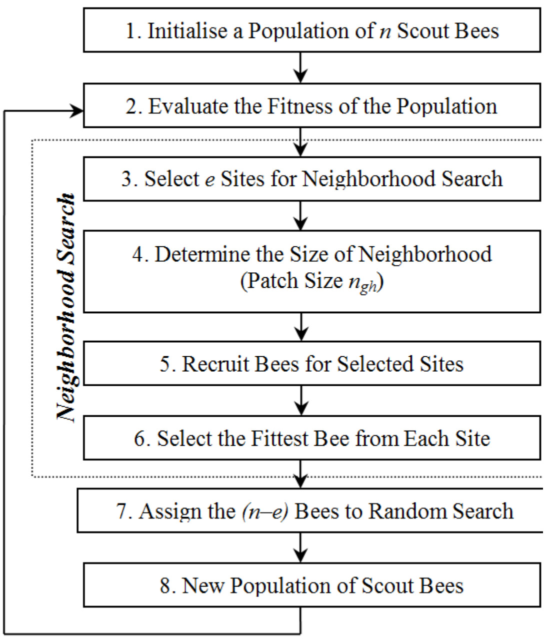

Figure 4. *The flowchart of PBA [10].*

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 [10].

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 [10], [11], [12].

Table 2. *The parameters of PBA [10].*

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

4.3. 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 the objective function G(x) in Equation (1). However, the optimization task is required to maintain the on road performances such as acceleration and gradeability of parallel HEVs. In order for the PBA to deal directly with constraints it is necessary to add penalty functions given in Equation (3) into the objective function G(**x**) [16].

$$
\begin{aligned}
C_1(S_j)_{(x)} &= \max(0, F_1(S_j)_{(x)} - a_1)/\,a_1\\
C_2(S_j)_{(x)} &= \max(0, F_2(S_j)_{(x)} - a_2)/\,a_2\\
C_3(S_j)_{(x)} &= \max(0, F_3(S_j)_{(x)} - a_3)/\,a_3\\
C_4(S_j)_{(x)} &= \max(0, a_4 - F_4(S_j)_{(x)})/\,a_4\\
C_5(S_j)_{(x)} &= \max(0, a_5 - F_5(S_j)_{(x)})/\,a_5\\
C_6(S_j)_{(x)} &= \max(0, a_6 - F_6(S_j)_{(x)})/\,a_6\\
C_7(S_j)_{(x)} &= \max(0, a_7 - F_7(S_j)_{(x)})/\,a_7
\end{aligned}
\tag{3}
$$

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

where, $C_i(S_j)_{(x)}$, α_i and $F_i(x)$ are penalty function, desired value and evaluated value related to i^{th} constraint $h_i(x)$ in Tab. 6

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

k_i is penalty factor chosen by trial and error as given in Tab. 6

$fitness(S_j)_{(x)}$ 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 Tab. 1
- Step 2: Evaluate the FC 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 $n_b(S_j, t)$ 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.

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

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

$$ph(S_j,t) = ph(S_j,t-1) \cdot \rho + f_s(S_j) \cdot n_b(S_j,t) \qquad (7)$$

where, $fs(S_j)$ is the fitness score of site S_j,. S_{e+1} is 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 [5]. The linkage configuration between ADVISOR and PBA is described in Fig. 3. The parameters of PBA used in this optimization are chosen as in Tab. 3.

Table 3. *The parameters of PBA.*

n	e	m	$n_{gh(i)}$
22	7	5	(up. $bound_{(i)}$-lo. $bound_{(i)}$)/40

where, up. $bound_{(i)}$ and lo. $bound_{(i)}$ are the upper bound and lower bound of the i^{th} variable listed in Tab. 4. It is necessary to continuously adjust component sizes in the search space in ADVISOR software. To vary component size, the baseline ICE of Honda Insight 1.0L VTEC-E 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 Preliminary Model of Honda 10 KW is employed. The same as ICE, the motor torque scale factor, *mc_trq_scale*, is used to vary the EM size. Similarly, the Spiral Wound NiMH battery is used for battery sizing. To vary the battery size, the number of battery modules, *ess_module_num*, is changed [7]. The range of input variables for component size and control strategy parameters, is given in Tab. 4.

Table 4. *The range of input variables X.*

Parameters	Lower bound	Upper bound
fc_trq_scale	0.8	2
mc_trq_scale	0.8	3
ess_module_num	15	60
cs_dl_assist_trq_threshold	5	60
cs_mc_assist_min_frac	0	0.2
cs_mc_assist_slope	0	1
cs_mc_assist_max_frac	0.21	1
cs_dl_regen_trq_threshold	-40	-5
cs_mc_regen_min_frac	0	0.2
cs_mc_regen_slope	0	1
cs_mc_regen_max_frac	0.21	1
cs_decel_regen_threshold	0	30
cs_lo_soc	0.15	0.57
cs_hi_soc	0.58	0.95

5. Experimental Results and Analysis

The experimental process of MDO to optimize for Honda Insight 2000 includes two steps.

Step 1: Optimize only control strategy. In this step, the size of ICE, EM and the number of battery modules is fixed as in the original Honda Insight 2000, it means that the structure of Honda Insight 2000 is not changed. So, the control strategy parameters are optimized as described in Section 4. After this step, if FC is improved and the dynamic performances satisfy PNGV constraints, the experimental process can be stopped, otherwise go to step 2.

Step 2: Optimize simultaneously component sizes and control strategy parameters. It means that all parameters in Tab. 4 are optimized simultaneously.

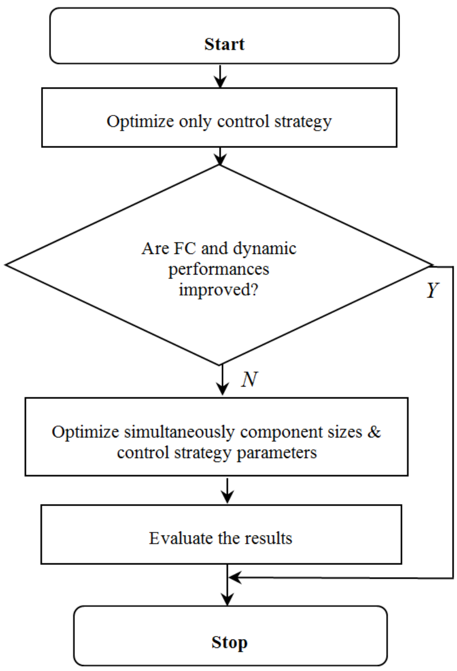

Figure 5. *The experimental process.*

In order to eliminate the influence of energy from the battery on FC, the simulation has been run several times starting with different initial SOC (battery state of charge) values until the final SOC is close to the initial SOC. The optimization program was run with PBA parameters in Tab. 3 following two driving cycles, FTP (Federal Test Procedure) and HWFET (Highway Fuel Economy Test). Optimize only the control strategy.

The control strategy parameters of Honda Insight 2000 have been optimized by Honda Company's engineers. However, as shown in Tab. 6, there are three requirements which the original Honda Insight 2000 do not fulfill. After optimizing only its control strategy parameters by using MDO method, the FC is reduced to 0.1liter/100km when running FTP driving cycle (Tab. 7) and most of requirements of PNGV constraints are improved but have not satisfied the PNGV constraints. So, it is necessary to go to step 2, simultaneous optimization of key component sizes and control strategy parameters.

Table 5. *The value of optimal parameters.*

Parameters	FTP	HWFET
cs_dl_assist_trq_threshold	5.28	17.37
cs_mc_assist_min_frac	0.11	0.17
cs_mc_assist_slope	0.32	0.24
cs_mc_assist_max_frac	0.64	0.89
cs_dl_regen_trq_threshold	-5.48	-5.00
cs_mc_regen_min_frac	0.10	0.05
cs_mc_regen_slope	0.88	0.95
cs_mc_regen_max_frac	0.96	0.94
cs_decel_regen_threshold	4.21	5.37
cs_lo_soc	0.34	0.35
cs_hi_soc	0.86	0.95

Table 6. *The PNGV performance constraints.*

Parameters	Description	k_i	Honda Insight 2000 (Original value)		Honda Insight 2000 (The value after the optimization of control strategy) - FTP		Honda Insight 2000 (The value after the optimization of control strategy) - HWFET	
			Value	Evaluation	Value	Evaluation	Value	Evaluation
Acceleration time	*Time for 0–96.6 km/h ≤ 12s*	3	11.8	Fulfilled	11.8	Fulfilled, no change	11.8	Fulfilled, no change
	Time for 64.4–96.6 km/h ≤ 5.3s	3	5.5	Not fulfilled	5.46	Not fulfilled, improvement of 0.04s	5.46	Not fulfilled, improvement of 0.04s
	Time for 0–136.8 km/h ≤ 23.4s	3	24.3	Not fulfilled	24.21	Not fulfilled, improvement of 0.09s	24.21	Not fulfilled, improvement of 0.09s
Grade ability	6.5% grade ability at 88.5 km/h, 272kg additional weight for 20 min	3	11.7	Fulfilled	11.74	Fulfilled, improvement of 0.04%	11.74	Fulfilled, improvement of 0.04%
Maximum speed	≥ 137 km/h	3	192.6	Fulfilled	194.5	Fulfilled, improvement of 1.9 km/h	194.5	Fulfilled, improvement of 1.9 km/h
Maximum acceleration	≥ 5 m/s^2	5	4.5	Not fulfilled	4.53	Not fulfilled, improvement of 0.03 m/s^2	4.53	Not fulfilled, improvement of 0.03 m/s^2
Distance in 5 sec	≥ 42.7m	3	44.4	Fulfilled	44.51	Fulfilled, improvement of 0.11 m	44.54	Fulfilled, improvement of 0.14 m

Table 7. *The fuel consumption (FC).*

Parameters	Honda Insight 2000 - FTP (The value after the optimization of control strategy)			Honda Insight 2000 – HWFET (The value after the optimization of control strategy)		
	Original Value	Value after optimization	Evaluation	Original Value	Value after optimization	Evaluation
FC (liter/100km)	3.7	3.6	Improvement of 0.1 l (2.7%)	2.8	2.8	No change

6. Optimize Simultaneously Both Key Component Sizes and Control Strategy Parameters

As presented in Tab. 8, in order to improve the FC and dynamic performances, the size of EM requires to become bigger and the number of battery module has to be increased.

Tab. 9 presents the results of the dynamic performances of the original Honda Insight 2000 and key component sizes and control strategy parameters simultaneously optimized for Honda Insight 2000. The data in this table demonstrate the effectiveness of Pheromone-based Bees Algorithm used as an optimizer within a MDO system. The results show that after optimization, the FC is reduced to 0.41liter/100km (11.1%) and 0.15liter/100km (5.1%) when running FTP and HWFET driving cycle respectively. The dynamic performances are also improved strongly, all PNGV criteria are improved and six of them satisfy PNGV constraints. Only the maximum acceleration does not fulfill its constraint, however, it is acceptable as it is only 1.8% lower than its criterion.

Table 8. *The value of optimal parameters.*

Parameters	FTP	HWFET
fc_trq_scale	0.90	0.90
mc_trq_scale	1.96	1.96
ess_module_num	50	50
cs_dl_assist_trq_threshold	9.60	8.18
cs_mc_assist_min_frac	0.06	0.09
cs_mc_assist_slope	0.54	0.64
cs_mc_assist_max_frac	0.58	0.42
cs_dl_regen_trq_threshold	-5.96	-5.74
cs_mc_regen_min_frac	0.19	0.18
cs_mc_regen_slope	0.65	0.67
cs_mc_regen_max_frac	0.99	0.96
cs_decel_regen_threshold	9.60	9.67
cs_lo_soc	0.48	0.57
cs_hi_soc	0.95	0.95

The FC and vehicle performances obtained by using PBA with the driving cycles FTP and HWFET are nearly same as ones employed by BBA. However, the rate of convergence of PBA is faster than that optimized by BBA [15] and [16]. The optimization process in this research was stopped after about 45 iterations and 65 iterations when optimizing only the control strategy parameters and simultaneous optimization respectively or when the value of objective function does not change 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 Honda Insight 2000. Compared to the BBA, the new version, PBA, showed an improvement of about 20-25% in convergence speed. This indicates the good performance of the PBA approach in saving time to achieve the optimal parameters.

7. Conclusions

The paper presents a simultaneous optimization of Honda Insight 2000' key component sizes and control strategy parameters to minimize FC without sacrificing dynamic performance by using a new approach, a 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 Honda Insight 2000 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 20-25% faster than the Basic Bees Algorithm. The results show that, the PBA approach is powerful in searching the best parameters of Honda Insight 2000' powertrain system in the solution space resulting in improvement of FC, while PNGV constrains are maintained.

Table 9. *The PNGV performance constraints.*

Parameters	Description	k_i	Honda Insight 2000 (Original value)		Honda Insight 2000 – FTP (The value after the simultaneous optimization of component sizes control strategy parameters)		Honda Insight 2000 - HWFET (The value after the simultaneous optimization of component sizes control strategy parameters)	
			Value	Evaluation	Value	Evaluation	Value	Evaluation
Accelera-tion time	*Time for 0–96.6 km/hr ≤ 12s*	3	11.8	Fulfilled	11.0	Fulfilled, improvement of 0.8s	11.0	Fulfilled, improvement of 0.8s
	Time for 64.4–96.6 km/hr ≤ 5.3s	3	5.5	Not fulfilled	5.23	Fulfilled, improvement of 0.27s	5.23	Fulfilled, improvement of 0.27s
	Time for 0–136.8 km/hr ≤ 23.4s	3	24.3	Not fulfilled	22.83	Fulfilled, improvement of 1.47s	22.83	Fulfilled, improvement of 1.47s
Grade ability	6.5% grade ability at 88.5 km/hr, 272kg additional weight for 20 min	3	11.7	Fulfilled	10.22	Fulfilled, reduction of 1.48%	10.22	Fulfilled, reduction of 1.48%
Maximum speed	≥ 137 km/hr	3	192.6	Fulfilled	196.3	Fulfilled, improvement of 3.7 km/h	196.3	Fulfilled, improvement of 3.7 km/h
Maximum accelera-tion	≥ 5 m/s^2	5	4.5	Not fulfilled	4.91	Nearly fulfilled, improvement of 0.41 m/s^2	4.91	Nearly fulfilled, improvement of 0.41 m/s^2
Distance in 5 sec	≥ 42.7m	3	44.4	Fulfilled	48.94	Fulfilled, improvement of 4.54 m	48.94	Fulfilled, improvement of 4.54 m

Table 10. *The fuel consumption (FC).*

Parameters	Honda Insight 2000 (The value after the simultaneous optimization of component sizes control strategy parameters) - FTP			Honda Insight 2000 (The value after the simultaneous optimization of component sizes control strategy parameters) - HWFET		
	Original Value	Value after optimization	Evaluation	Original Value	Value after optimization	Evaluation
FC (l/100km)	3.7	3.29	Improvement of 0.41 *l* (11.1%)	2.8	2.65	Improvement of 0.15 *l* (5.1%)

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Biography

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