IMPROVING THE PERFORMANCE OF A PARALLEL HYBRID ELECTRIC VEHICLE BY HEURISTIC CONTROL METHOD

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ABSTRACT

Hybrid Electric Vehicles (HEV) are expected as one of key solutions for mobility in the future, with reduced pollutions and better fuel economy alternative. In this paper, an analysis on Parallel HEV to reduce fuel usage and improve emission control performance, in addition to optimising the size of its key components has been presented. Various number of optimisation strategies have been proposed in literature. With respect of real time implementation, most of the papers in the literature have proposed on the use of heuristics. Despite the research advances made, the key challenge with heuristic strategies remain in achieving reasonable fuel savings without over depleting the battery state of charge at the end of the trip. To handle this Challenge, this paper offers an effective heuristic control strategy based on Artificial Bee Colony(ABC) algorithm and also in addition a modified approach, in analysing and dynamically optimizing key vehicle key component size, which influence the vehicle performance and to find a right combination of these significant parameters, which would maximize vehicle performance through reduced fuel consumption and emission. The potential of the proposed heuristic control strategy was explored over various drive cycles, which reflect different driving scenarios. Results from this analysis show, that as much as 22% fuel savings could be achieved over the UDDS driving cycle, which is the maximum, when compared with other driving cycles considered. Also in comparison to a basic ABC algorithm, the Modified Artificial Bee Colony(MABC) algorithm was found to be outperforming, in that it achieved impressive real time fuel savings and reduced emissions, without much penalty to the final battery state of charge along with reduced key vehicle components size for different driving cycles.

Keywords: *Automotive system, Dynamic Optimisation, Parallel Hybrid Electric Vehicle, Artificial Bee Colony Algorithm*

1 Introduction

Conventional fossil fuel based Automobiles are considered as one of the key sources for atmospheric pollution and related effects on the environment. Hence one of the primary requirements for the automobile manufacturers, has to come up with alternative modern vehicle design technologies, that could support reduced pollution and improved useful energy efficiency. Hybrid electric vehicle performance in terms of reduced emissions and improved fuel efficiency seems to be promising as an alternative technology. These type of vehicles generally have energy storage system and energy conversion possibilities, with which, it propels. The hybridization factor of a hybrid electric vehicles can be defined by the ratio of power provided by the electric motor to total power available by both ICE and the motor. In order to achieve the maximum possible fuel efficiency and reduced emissions, more accuracy is needed in terms of modelling and control of the said vehicle. Three types of vehicle modelling exist in literature known as the kinematic or backward approach, the quasi static or forward approach, and the dynamic approach. The kinematic approach is a backward methodology where speed of the vehicle and the road grade are the input variables. In this method, the engine speed will be determined using simple kinematics based relationships starting from the wheel revolution speed and the total transmission ratio of the driveline. The assumption on the kinematic approach is that the vehicle meets the target performance, so that the vehicle speed is known already and hence it has the advantage of simplicity and low computational cost [1]. In this method, there exist no guarantees that the given vehicle will actually be able to meet the desired speed trace, since the power request is directly computed from the speed and not checked against the actual power train capabilities. Another flaw of this modelling technique is its negligence of thermal transient behaviour of engines which are noticeable after an engine cold start. The quasi static approach of HEV modelling makes use of a driver model typically a PID which compares that target vehicle speed (drive cycle speed), with the actual speed profile, of the vehicle and then generates a power demand profile which is needed to follow the target vehicle speed profile. This power demand profile is generated by solving the differential motion equation of the vehicle [2]. The suitability and accuracy of the quasi-static modelling approach necessitates a more detailed engine simulation model in order to properly capture engine transient behaviour in a detailed way.

Also the power management strategies of a HEV could be broadly classified in to two approaches namely optimization based methods that control the power split using exact knowledge of the vehicle power demand, and rule based real time implementable methods, which control the power split without exact knowledge of the future vehicle power demand. Optimization based control strategies decide the control signals either by minimizing the sum of the objective function over time (global optimization) or by instantaneously minimizing the objective function (local optimization). The two common types of rule based optimisation methods are Dynamic Programming(DP) and Pontryagins Minimum Principle(PMP) for HEV optimal energy management. DP originally developed by Richard Bellman, solves discrete multi-stage decision problems by selecting a decision based on the optimization criterion from a finite number of decision variables at each time step. DP can work better if the initial conditions of vehicle performance are already known. And also DP needs a kind of post processing steps like based on neural networks based processing or an equivalent method in order to finalise the results. This makes it even more complicated to arrive at the optimal solution. Equivalently PMP as proposed by Namwook [3] can be seen better than DP in terms of computing time, but there is a high chance of solution being trapped to local optima rather than reaching a global optimal solution.

There are also other approaches in the literature like Equivalent Consumption Minimization Strategy(ECMS) [4] which is based on the Euler-Lagrange equation of variational calculus, which characterizes the equivalent fuel for electrical energy consumption. While this approach is useful in identifying the ultimate fuel saving potential of an HEV over a given driving cycle, this is not suitable for real time implementation as such, as it is time consuming and requires information about the vehicle’s future power demand before the trip, which is not practically possible. There are number of variants of this ECMS methodology available in literature, for instance the Adaptive ECMS [5] and Telemetry ECMS [6], which adjust the equivalent factor based on past driving data and future prediction. The main drawback or disadvantage of these adaptive techniques however, is the need for equipment’s like GPS (global positioning system), which often adds additional cost. Xiong has presented a paper which explains on adaptive energy management of hybrid electric vehicles using driver pattern recognition for fuel efficiency only. Again this is also based on Dynamic Programming strategy which still has the drawbacks of DP as mentioned earlier [7]. PSO based optimisation approach was also proposed by Wu, in which a single objective optimisation goal attainment method was used instead of a multi objective optimisation problem [8]. Montazeri tried to apply Genetic Algorithm to achieve optimal values for HEV components sizing and control strategy with minimum fuel consumption and emissions [9]. A major similarity of the studies mentioned above is that the approach for the optimal design is either for the component sizing or the control strategy, while other parameter is kept fixed. However, in practical scenario, in a vehicle, both the component sizing and the control strategy influence each other, in achieving the vehicle performance efficiency. Hence it becomes imperative to make simultaneous optimization of component sizes and control strategy parameters, so as to obtain a more optimal design of a Hybrid electric vehicle. Heuristic strategies when compared with other methods discussed above, are easily implementable in real time and with the potential for simplicity, customization and robustness; they have been reported to show a near optimal performance, if the rules are made clear and detailed so as to take care of circumstances that may affect the vehicle performance [10][11][12].

Recent advances in heuristic controller research have focused on the use of heuristic approaches like the one proposed by Long VT [13], which mainly focuses on application of Artificial Bee

Colony(ABC) algorithm based approach for HEV optimisation. In this approach, he used a Basic ABC(BABC) algorithm to find out the optimal solution for simultaneous optimisation of component sizes and also a control strategy for HEV. Also one more theory proposed by him in 2014 uses a pheromone based approach [14] wherein which the computation time has been reduced compared to the previous one. In both of these approaches, the optimisation method used was a basic ABC method which has the problem of exploration and exploitation during the optimal solution search. The exploration refers to the ability to investigate the various unknown regions in the given solution space to discover the global optimum, while, the exploitation refers to the ability to apply the knowledge of the previous good solutions to find better solutions.

In this paper, usage of a Modified ABC algorithm(MABC) based on global best solution guided approach is proposed to obtain better optimal solution through avoiding aforementioned issues. The significance of this work lies in analysing and dynamically optimizing different vehicle key component size, fuel consumption and emission parameters, which influence the vehicle performance and to find a right combination of these significant parameters, which would maximize vehicle performance through reduced fuel consumption and emission. The Key parameters considered are vehicle component size, fuel consumption, emissions and energy consumption of different vehicle components. The optimisation, for given driving cycle is performed using both the BABC/MABC approach, while vehicle has to still satisfy PNGV constraints.

Also Driving cycle plays key role in fixing vehicle key parameters. In this paper, the weighting factor of vehicle performance parameters in objective function is varied and optimisation simulation is carried out for different driving cycles like FTP, UDDS and ECE-EUDC using BABC and MABC. Also the results of BABC and MABC are compared, and the results signifies the improvement of MABC in searching a better optimal solution of HEV parameters, with the similar boundary conditions, while still satisfying the PNGV constraints like acceleration and vehicle grade requirements.

2 HEV Powertrain Modelling

In order to improve efficiency of the HEV with better fuel economy and reduced emissions, it is imperative to develop vehicle models with accurate sub-system modelling and better predictability of fuel consumption and emissions under various driving conditions. This section will compose mainly of the physical and mathematical modelling of a parallel hybrid electric vehicle in a Matlab/Simulink environment. The vehicle subsystems detailed in this section aim to model to a high level of accuracy the vehicle components, which significantly affect fuel consumption and emission. Block diagram shown in Figure 1 below.

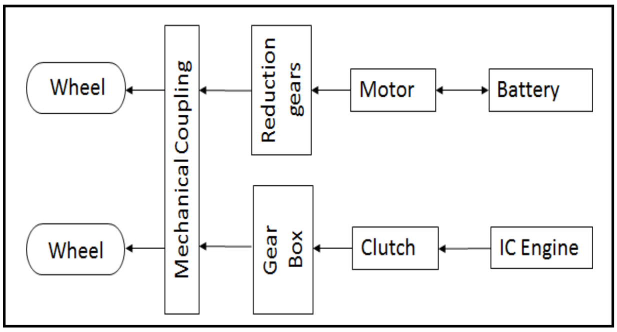

Fig. 1. Parallel HEV Block Diagram

The above said Vehicle's Dynamic modelling has been defined as below. Whenever there is a movement of vehicle in forward direction, there exists a forward shift resistance or a ground reaction force which enables the vehicle movement which is termed as the rolling resistance moment of vehicle. This can be expressed as in equation 1:

$$V_{rolling} = \mu N_c R_w \quad (1)$$

The Wheel rolling force (Wrolling) to balance the $V_{rolling}$ moment can be expressed as in equation 2:

$$W_{rolling} = \mu N_c \quad (2)$$

The coefficient of rolling resistance μ is a function of the material of tyre, its structure, temperature, inflation pressure and geometry. Whenever a vehicle travels in a particular speed in air, it faces a force resisting in opposition to its motion [15]. This opposing force is called as aerodynamic force, which will result mainly from two components: shape drag and skin friction. Thus Aerodynamic force (DFaero) could be expressed as a function of the vehicle speed, vehicle frontal area, air density and coefficient of air drag. The aerodynamic force (equation 3) could be expressed mathematically thus

$$DF_{aero} = 0.5\rho A_f C_d (V_v - V_a)^2 \quad (3)$$

When a vehicle moves up or down a slope, its weight results in a component load, which is always directed towards the downward direction. This component load could result in either supporting the forward motion or opposing the forward motion. This is termed as the Grade of the vehicle. The grade of that vehicle could thus be expressed thus as in equation 4:

$$V_{grade} = mgsin(\beta) \quad (4)$$

Combining the vehicle loads derived according to Newton's second law, for a parallel hybrid electric vehicle, the engine torque and speed equation, could be thus expressed as in equation 5 and equation 6:

$$T_{ICE} = \frac{(m\frac{dV_v}{dt} + \sum(DF_{aero} + V_{rolling} + V_{grade} + V_{extra}))R_w}{FDRG_E Eff} - \frac{T_{mot}G_M}{G_E} \quad (5)$$

Where

$$T_{motor} = \frac{P_{mot}}{G_M FDRW_{wheel}\frac{2\pi}{60}} \quad (6)$$

The general engine speed equation could be expressed as in equation 7 below:

$$W_{ICE} = W_{wheel} FDRG_E \frac{2\pi}{60} \quad (7)$$

Engine modelling

Engine modelling is one of the imperative steps in this analysis, since only with more accurate modelling of the engine, the main objective of fuel consumption reduction could be accurately predicted. The engine considered for modelling and simulation is Geo 1.0L(41KW) SI engine. Using the engine torque and speed values for the given engine, fuel converter efficiency for each engine torque-speed point could be read off as detailed in Figure 2. The engine fuel conversion efficiency in this manner implies that transmission losses have already been accounted for.

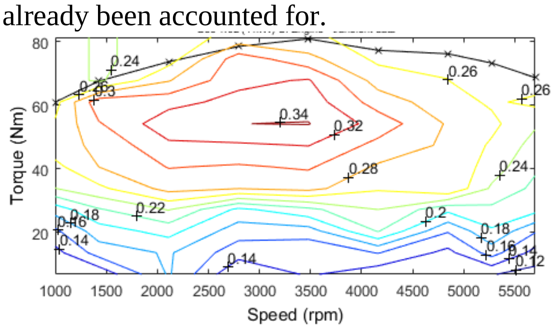

Fig. 2. Engine fuel consumption map

Gear shift strategy

The gearbox of a multi-speed transmission houses gears of different gear ratios that are used to transmit torque from the engine or tractive motor to the final drive and on to the wheels. It thereby allows a number of discrete speed reduction and torque multiplication factors. Effects on torque and speed in the gearbox include torque multiplication and speed reduction via the gear ratio, torque loss due to the acceleration of rotational inertia, and torque loss due to the friction of the turning gears. There are several methods existing in expressing the gear shift for a given driving cycle. André [16] pioneered a new strategy strategy known as the "Artermis strategy". This strategy considers simultaneously: the driving condition (engine speed and power demand) and driving styles of the drivers [17]. The gear shift strategy considered in this simulation is a 5 speed manual transmission.

Electric motor modelling

Wide range of motor designs are available in the market for this kind of applications. The key parameters to be considered while selecting the motor for HEV includes power, speed- torque characteristics and the efficiency when coupled with battery and the engine. The efficiency of the electrical machine is dynamically adjusted with respect to its speed and torque characteristics. Also the power source for the motor in the vehicle would be the battery power. In the current analysis, the motor considered is Westinghouse, 75 kW, AC Induction motor. The power drawn from the battery by the electrical machine could be electrically modelled as in equation 8

$$P_{electric} = \frac{2\pi}{60} P_{motor} \eta_{motor} \quad (8)$$

Also the torque speed characteristics of the motor is shown below in figure 3:

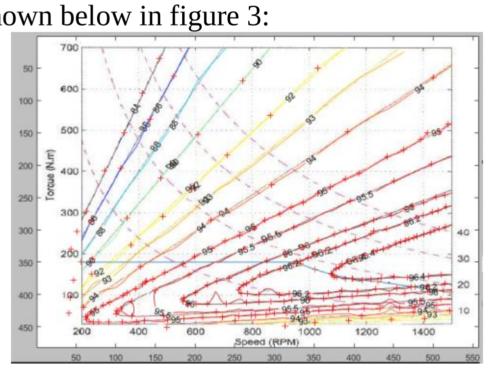

Fig. 3. Speed-Torque Curves

Electric battery modelling

In a HEV, there will be power flow in both directions for the battery, meaning, there will be charging and discharging cycles, based on the operating mode of the vehicle. The battery power would be considered as negative during charging and positive during discharging. The measure of charge left in a battery as a proportion of the maximum possible charge of the battery is termed a State of Charge(SOC) of the battery. During simulation, an integral of battery current (I) over the maximum possible battery charge is used to calculate the battery state of charge. For the current analysis, a Hawker Genesis 12V26Ah VRLA battery is considered. At every simulation time step, the battery state of charge can be calculated thus in equation 9:

$$SOC_{t+1} = SOC_t \mp \int_t^{t+1} \frac{I}{Q} dt \qquad (9)$$

Where '+' indicates charging and '– 'indicates discharging of the battery. A typical SOC curve for considered battery could be depicted as below in figure 4. There are basically two types of SOC correction possible namely Linear and Zero delta method. In this analysis, Zero delta method is used.

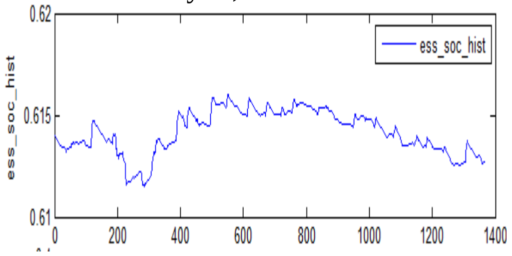

Fig. 4. SOC curve

Control Strategy

The control strategy plays a key role in determining the ideal operating point of the vehicle's engine and motor, to obtain the minimum fuel consumption and emission targets during vehicle optimisation [11]. The flexibility of this strategy lies in allowing a vehicle to adjust its controls based on its driving location or local control limits, real-time adjustment to driving cycles and Incorporating the temperature effects on fuel use, engine-out emissions, and catalyst behaviour [12]. In this analysis, the parallel Electric Assist Control Strategy(EACS) has been utilised. The EACS uses the motor for additional power, when needed by the vehicle and maintains charge in the batteries. The parallel assist strategy can use the electric motor in a variety of ways:

1.The motor can be used for all driving torque below a certain minimum vehicle speed.
2.The motor is used for torque assist if the required torque is greater than the max torque deliverable by the engine at the engine's operating speed.
3.The motor charges the batteries by regenerative braking.
4.When the engine would run inefficiently at the required engine torque at a given speed, the engine shuts off and the motor produce the required torque.
5.When the battery SOC is low, the engine will provide excess torque which will be used by the motor to charge the battery.

Driving Cycles

The FTP, ECE-EUDC and UDDS are considered as the base driving cycles for the analysis. These vehicle driving cycles are considered due to the fact that they cover the majority part of the different driving conditions that a vehicle, would face during its usage [18]. The corresponding driving cycle details as shown in the figures 5, figure 6 and figure 7 below:

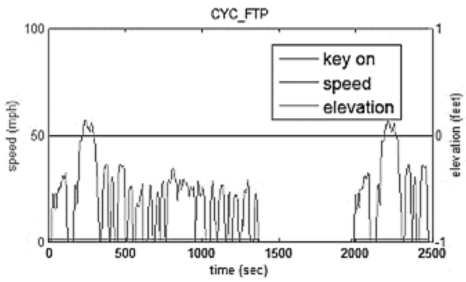

Fig. 5. FTP driving cycle

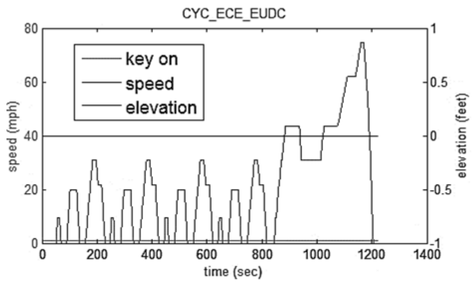

Fig. 6. ECE-EUDC driving cycle

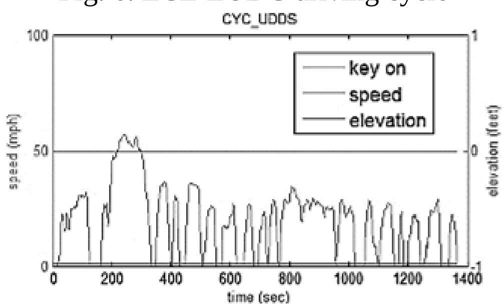

Fig. 7. UDDS driving cycle

Vehicle model baseline validation

The Parallel HEV considered in the ADVISOR tool has various subsystems in the modelled vehicle. The key components include fuel converter, torque coupling, motor controller, energy storage, transmission, wheel axle, exhaust after treatment, power train control and accessory modules. Each module has a set of variables defined, which can be varied and analysed for vehicle performance. The key parameters of the vehicle considered are as depicted in Table 1. The vehicle considered in this optimisation is a parallel hybrid electric vehicle using the ADVISOR [19] [20] as a simulation tool, with gasoline engine and battery as sources of power for vehicle driving [21]. The considered vehicle is depicted in a block diagram as shown below in figure 8:

Vehicle Parameter	**Description**
Engine type	Geo 1.0L (41kW) SI Engine
Power train	Parallel Hybrid
Motor	Westinghouse, 75 kW, AC Induction motor
Transmission	5-Speed Manual Transmission
Motor efficiency	92 %
Vehicle mass(m)	592 Kg
Fuel converter efficiency	34 %
Battery	12V, 26Ah VRLA battery
Wheel Radius R_W	0.282 m
Frontal area A_f	2.0 m2
Coefficient of drag C_d	0.335

Table 1. Vehicle Parameters

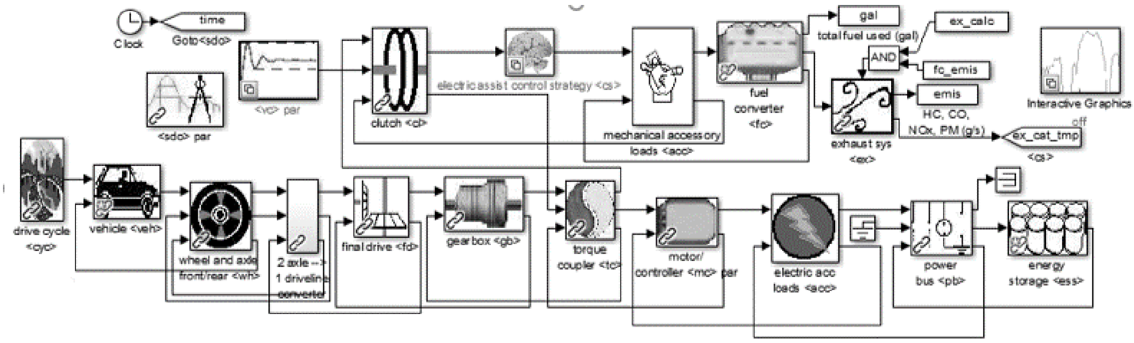

Fig. 8. Simulation vehicle block diagram

In this analysis, the key input parameters considered are fuel converter scaling factor for torque range, motor/controller torque scaling range, number of battery modules and a set of control strategy parameters as shown in table 2 below. The mentioned parameters are given as input to the heuristic algorithm and the resultant optimised outputs in terms of fuel consumption and emissions are obtained. The approach is discussed in detail below.

Objective function and constraints

The key objective function of this paper is to minimise the parameters of Fuel Consumption(FC), Carbon Monoxide(CO), Nitrous Oxide(NOX) and Hydro Carbons(HC), so as to obtain maximum vehicle performance. The objective function is as follows as in equation 10:

$$\text{Min } F(x) = b1FC+b2CO+b3NOX+b4HC \quad (10)$$

Where b1 to b4 are termed as weighting factors of different parameters considered in the objective function, subjected to following constraints as stated below in equation (11) until equation (18)

Acceleration time for 0-60mph(t1) $\leq$ 12s (11)

Acceleration time for 40-60mph(t2) $\leq$ 5.3s (12)

Acceleration time for 0-85mph(t3) $\leq$ 23.4s (13)

The gradeability at 55mph for 1200s $\geq$ 6.5% (14)

Maximum speed $\geq$ 85.1mph (15)

Maximum acceleration >16.4 ft/s^{-2} (16)

Distance in 5 s >140 ft (17)

Delta State of Charge ΔSOC $\leq$ 0.5% (18)

These are the PNGV constraint limits as defined by US Consortium. Also the considered system is pertaining to the following environment conditions as per equation 19, equation 20 and equation 21:

a. The engine can only produce power:

$$P_{engine} > 0 \quad (19)$$

b. The power output of engine is limited to the max power rating of the engine, which is stated as:

$$0<P_{engine}<P_{engine\_max\_power} \quad (20)$$

c. To behave as a charge sustaining control system, the State Of Charge (SOC) of battery should be always within the defined minimum and maximum limits: $SOC_{low} < SOC_{battery} < SOC_{high}$ (21)

3 Heuristic Approach

Approach 1: Basic Artificial Bee colony based optimisation

The optimisation algorithm used for the problem is Artificial Bee Colony (ABC) algorithm for the heuristic approach based solution search. The details of the Basic ABC are detailed below. The ABC algorithm is a swarm based meta-heuristic algorithm, introduced by Karaboga in 2005 (Karaboga, 2005) for optimizing numerical problems. It was inspired by the intelligent foraging behaviour of honey bees. To apply ABC, the considered optimization problem has to be first converted to the problem of finding the best possible solution (values of parameters), which maximises the fitness [22]. Then, the artificial bees randomly discover a population of initial solution vectors and then iteratively improve them by employing the strategies: moving towards better solutions by means of a neighbourhood search mechanism, meanwhile forgetting the abandoned poor solutions [13] [14]. This can be mathematically represented as per equation 22

$$v_{i,j} = x_{i,j} + \Phi_{i,j}(x_{i,j} - x_{k,j}) \quad (22)$$

The major steps of the ABC algorithm are outlined as follows:

Initialize all parameters;

Repeat while Termination criteria is not met

Step 1: Employed bee phase for computing new food sources.

Step 2: Onlooker bees phase for updating location the food sources based on their amount of nectar.

Step 3: Scout bee phase for searching new food sources in place of rejected food sources.

Step 4: Memorize the best food source identified so far. End of while

The Output of the algorithm would be, the best solution identified so far. Using the foraging behaviour, the vehicle component size has been optimised, in turn, reducing emissions and fuel consumption. The basic ABC has a disadvantage of exploration and exploitation problems, which causes the algorithm to get trapped to local optima and may not achieve global optimal solution. The exploration refers to the ability to investigate the various unknown regions in the given solution space to discover the global optimum, while, the exploitation refers to the ability to apply the knowledge of the previous good solutions to find better solutions, as mentioned previously.

Approach 2: Modified Artificial Bee Colony based optimisation(MABC)

In order to overcome the "exploitation" issue with BABC, a Modified ABC(MABC) algorithm has been utilised for the proposed problem optimisation, which overcomes the issues of basic ABC and provides better optimisation results. In the MABC algorithm, a new search equation described by Global best guided ABC inspired by PSO, in order to improve the exploitation, takes advantage of the information of the global best(Gbest) solution to guide the search of candidate solutions by Zhu and Kwong [23] has been utilised. This improves the solution, through reducing aforementioned problems of basic ABC and to take advantage of the global best solution information as shown in equation 23 below:

$$v_{i,j} = x_{i,j} + \Phi_{i,j}(x_{i,j} - x_{k,j}) + \Psi_{i,j}(y_j - x_{i,j}) \quad (23)$$

where $v_{i,j}$ is the new neighbouring food source, y_j is the jth element of global best solution, $\Psi_{i,j}$ is a uniform random number in the range of 0 to 1.5, $\Phi_{i,j}$ is a random number in the range$[-1, 1]$, and $j \in \{1, 2, \ldots, n\}$ is a randomly chosen index. $\Psi_{i,j}(y_j - x_{i,j})$ is the Gbest term added in addition to basic ABC. Practically the exploration and exploitation contradict with each other, and in order to achieve good optimization performance, the two abilities should be well balanced. Hence here compared to basic ABC, the search of candidate solution is guided, which helps to reach the global optimum.

4 Simulation and analysis

The key vehicle parameters are set in ADVISOR tool [19] [20] developed by NREL in MATLAB for vehicle simulation to obtain the output parameters, as required for objective function. Also additional tests like acceleration and grade tests with the required conditions were set and the tool will perform the simulation. The result window typically provides FC, HC, CO, NOX, Gradeability and Acceleration tests results. In this approach, as mentioned earlier the zero delta SOC correction technique is used. The Zero-Delta correction routine adjusts the initial SOC until the simulation run yields a zero change in SOC +/- a 0.5%

tolerance band, which is one of the mandatory PNGV constraints. The FTP, UDDS and ECE-EUDC are considered as the base driving cycles [18]. There are four different cases considered. In case 1 and case 2, the weighting factor for minimisation of fuel usage is kept as high as 50 %, while the weightage of other three parameters are distributed with remaining 50%. While in Case 3 and Case 4 the weightage of Emissions kept as 70% while Fuel usage were kept within 30% weightage. This strategy of varying the weightage has been taken in this research, so as to analyse the effectiveness of algorithm under various requirements of the vehicle. Also the driving cycle utilised has an influence on the results based on the peak speed and distance relationship, and related fuel consumption and emission.

FTP Driving cycle - ABC						
Items		Case 1	Case 2	Case 3	Case 4	Initial Value
Variables	FC_torque_scale	1.500	1.500	1.500	1.385	1.349
	MC_torque_scale	0.783	1.024	1.182	1.158	1.182
	ESS_module_number	30.000	30.000	30.000	27.000	30.000
	CS_EL_Speed_lo	8.000	4.000	0.000	4.000	3.000
	CS_EL_Speed_hi	22.000	30.959	20.000	17.000	20.000
	CS_min_trq_frac	0.800	0.317	0.218	0.317	0.218
	CS_off_trq_frac	0.069	0.050	0.104	0.050	0.137
	CS_lo_soc	0.570	0.570	0.569	0.523	0.567
	CS_hi_soc	0.650	0.632	0.695	0.632	0.695
	CS_charge_torque	31.000	31.000	31.000	12.000	31.000
Constraints	Grade (%)	9.057	8.751	8.813	8.076	7.200
	0-60 mph time(t1) (s)	7.841	8.380	8.415	8.396	8.400
	40-60 mph time(t2) (s)	3.633	4.060	4.105	4.069	4.000
	0-85 mph(t3) (s)	14.882	16.410	16.536	16.475	16.300
	Max speed (mph)	131.012	127.450	127.351	126.399	127.000
	Max acce (ft/s-2)	16.400	16.400	16.400	16.400	16.400
	Distance in 5s (ft)	185.041	184.340	184.380	183.250	183.700
Objective	FC (mpg)	34.857	33.340	32.247	33.141	32.200
	HC (gms/mile)	0.605	0.611	0.603	0.566	0.564
	CO (gms/mile)	2.522	2.280	2.430	2.133	3.244
	Nox (gms/mile)	0.472	0.477	0.462	0.452	0.471

Table 2. Optimisation results for FTP driving cycle

ECE-EUDC Driving cycle - ABC						
Items		Case 1	Case 2	Case 3	Case 4	Initial Value
Variables	FC_torque_scale	1.315	1.300	1.500	1.500	1.349
	MC_torque_scale	0.952	0.700	1.200	0.967	1.182
	ESS_module_number	29.000	29.000	30.000	30.000	30.000
	CS_EL_Speed_lo	7.000	7.600	8.000	4.000	3.000
	CS_EL_Speed_hi	12.902	14.000	25.118	19.000	20.000
	CS_min_trq_frac	0.259	0.678	0.291	0.810	0.218
	CS_off_trq_frac	0.002	0.211	0.143	0.154	0.137
	CS_lo_soc	0.261	0.523	0.276	0.567	0.567
	CS_hi_soc	0.655	0.727	0.867	0.844	0.695
	CS_charge_torque	30.000	32.000	15.000	31.000	31.000
Constraints	Grade (%)	8.526	8.097	10.222	9.512	7.200
	0-60 mph time(t1) (s)	9.231	8.141	8.4426	7.621	8.400
	40-60 mph time(t2) (s)	4.614	3.842	4.1031	3.495	4.000
	0-85 mph(t3) (s)	18.618	15.677	16.574	14.325	16.300
	Max speed (mph)	120.897	127.922	127.302	130.77	127.000
	Max acce (ft/s-2)	16.4	16.4	16.4	16.4	16.400
	Distance in 5s (ft)	178.297	183.18	183.059	187.148	183.700
Objective	FC (mpg)	30.387	33.154	28.776	30.33	28.600
	HC (gms/mile)	0.74	0.763	0.888	0.85	0.768
	CO (gms/mile)	2.857	2.895	3.002	2.839	3.157
	Nox (gms/mile)	0.474	0.481	0.56	0.503	0.495

Table 3. Optimisation results for ECE-EUDC cycle

UDDS Driving cycle - ABC						
Items		Case 1	Case 2	Case 3	Case 4	Initial Value
Variables	FC_torque_scale	1.454	1.500	1.500	1.500	1.349
	MC_torque_scale	0.755	0.937	0.900	1.066	1.182
	ESS_module_number	20.214	24.000	20.000	25.000	30.000
	CS_EL_Speed_lo	4.000	3.000	4.000	0.000	3.000
	CS_EL_Speed_hi	24.000	20.000	21.000	22.000	20.000
	CS_min_trq_frac	0.216	0.278	0.318	0.100	0.218
	CS_off_trq_frac	0.116	0.182	0.080	0.068	0.137
	CS_lo_soc	0.394	0.343	0.487	0.516	0.567
	CS_hi_soc	0.765	0.844	0.680	0.950	0.695
	CS_charge_torque	29.000	31.000	34.850	40.000	31.000
Constraints	Grade (%)	10.019	10.370	9.797	10.056	7.200
	0-60 mph time(t1) (s)	8.648	8.264	8.583	8.659	8.400
	40-60 mph time(t2) (s)	4.206	3.959	4.171	4.256	4.000
	0-85 mph(t3) (s)	17.046	16.054	16.885	17.167	16.300
	Max speed (mph)	124.087	127.749	125.030	124.983	127.000
	Max acce (ft/s-2)	16.400	16.400	16.400	16.400	16.400
	Distance in 5s (ft)	181.133	183.649	181.635	182.580	183.700
Objective	FC (mpg)	35.197	34.276	33.746	32.174	31.400
	HC (gms/mile)	0.774	0.806	0.805	0.793	0.737
	CO (gms/mile)	2.726	3.506	2.782	3.061	4.833
	Nox (gms/mile)	0.545	0.581	0.566	0.548	0.557

Table 4. Optimisation results for UDDS cycle

The corresponding initial input and optimised values obtained for the considered driving cycles for optimisation approach 1, for various cases are tabulated in Table 2, Table 3 and Table 4, for different driving cycles for basic ABC. The fuel usage, SOC and emission plots are shown for a case 1 FTP for BABC in Figure 9 below.

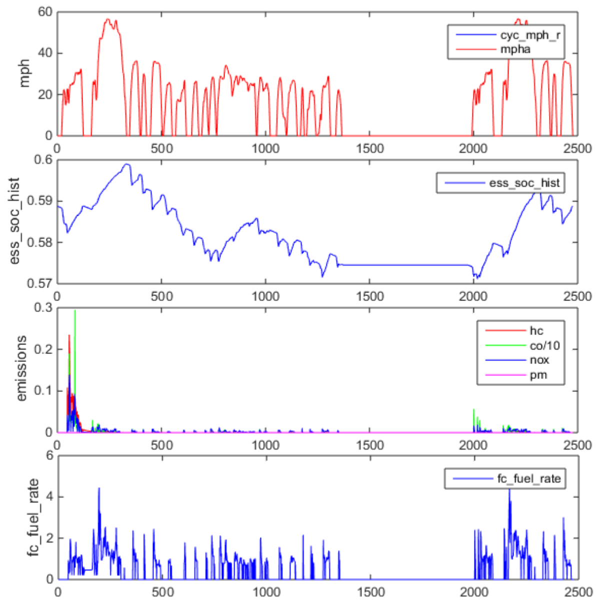

Fig. 9. BABC Fuel usage, emission and SOC plot

Also the corresponding initial input and optimised values obtained for the considered driving cycles for optimisation approach 2, for various cases are tabulated in Table 5, Table 6 and Table 7 with modified ABC. The corresponding fuel usage, SOC variation and emission plots for a driving cycle FTP case 1 is shown in Figure 10 below.

FTP Driving cycle- MABC						
	Items	Case 1	Case 2	Case 3	Case 4	Initial Value
Variables	FC_torque_scale	1.351	1.400	1.400	1.458	1.349
	MC_torque_scale	0.714	0.783	1.100	1.076	1.182
	ESS_module_number	27.741	30.000	27.000	28.000	30.000
	CS_EL_Speed_lo	4.195	7.000	3.000	1.000	3.000
	CS_EL_Speed_hi	19.595	23.000	31.000	18.000	20.000
	CS_min_trq_frac	0.442	0.800	0.317	0.311	0.218
	CS_off_trq_frac	0.051	0.069	0.050	0.139	0.137
	CS_lo_soc	0.540	0.570	0.507	0.500	0.567
	CS_hi_soc	0.753	0.650	0.617	0.680	0.695
	CS_charge_torque	13.890	31.000	25.000	31.000	31.000
Constraints	Grade (%)	8.547	8.322	8.260	8.891	7.200
	0-60 mph time(t1) (s)	8.735	7.976	8.453	8.152	8.400
	40-60 mph time(t2) (s)	4.287	3.730	4.097	3.886	4.000
	0-85 mph(t3) (s)	17.381	15.281	16.571	15.754	16.300
	Max speed (mph)	123.160	129.960	126.200	129.030	127.000
	Max acce (ft/s-2)	16.400	16.400	16.400	16.400	16.400
	Distance in 5s (ft)	181.746	184.330	182.510	184.167	183.700
Objective	FC (mpg)	35.890	35.600	33.701	33.958	32.200
	HC (gms/mile)	0.539	0.574	0.571	0.587	0.564
	CO (gms/mile)	2.236	2.639	2.504	2.519	3.244
	Nox (gms/mile)	0.418	0.460	0.459	0.457	0.471

Table 5. Optimisation results for FTP driving cycle

ECE-EUDC Driving cycle - MABC						
	Items	Case 1	Case 2	Case 3	Case 4	Initial Value
Variables	FC_torque_scale	1.190	1.200	1.300	1.210	1.349
	MC_torque_scale	0.783	0.811	0.700	0.834	1.182
	ESS_module_number	30.000	30.000	23.000	28.000	30.000
	CS_EL_Speed_lo	8.000	8.000	4.330	6.751	3.000
	CS_EL_Speed_hi	11.000	11.000	30.000	19.665	20.000
	CS_min_trq_frac	0.100	0.723	0.246	0.534	0.218
	CS_off_trq_frac	0.183	0.183	0.211	0.162	0.137
	CS_lo_soc	0.520	0.516	0.223	0.158	0.567
	CS_hi_soc	0.850	0.845	0.727	0.611	0.695
	CS_charge_torque	36.000	35.000	5.200	39.118	31.000
Constraints	Grade (%)	7.565	7.606	9.075	8.015	7.200
	0-60 mph time(t1) (s)	8.964	8.954	9.221	9.704	8.400
	40-60 mph time(t2) (s)	4.451	4.444	4.595	4.934	4.000
	0-85 mph(t3) (s)	18.105	18.071	18.675	19.935	16.300
	Max speed (mph)	120.456	120.678	119.172	119.385	127.000
	Max acce (ft/s-2)	16.4	16.4	16.4	16.4	16.400
	Distance in 5s (ft)	180.665	180.761	178.23	176.349	183.700
Objective	FC (mpg)	33.558	33.357	29.291	32.667	28.600
	HC (gms/mile)	0.724	0.729	0.736	0.736	0.768
	CO (gms/mile)	3.148	3.124	2.566	3.735	3.157
	Nox (gms/mile)	0.482	0.486	0.436	0.508	0.495

Table 6. Optimisation results for ECE-EUDC cycle

It can be observed from above results, for a given driving cycle, to achieve required PNGV performance, irrespective of the type of algorithm used, there is always a trade-off between emissions and Fuel usage, that is, the reduction of emissions is achieved, only with additional fuel consumption and vice versa, since they lie at different operating points for an SI engine. The optimal control problem set up is solved over the FTP, ECE-EUDC and UDDS drive cycles and the results are compared below to benchmark the proposed MABC algorithm over the BABC algorithm in finding the optimal solution for the defined objective function as shown in Table 8 below.

UDDS Driving cycle - MABC						
	Items	Case 1	Case 2	Case 3	Case 4	Initial Value
Variables	FC_torque_scale	1.386	1.245	1.500	1.093	1.349
	MC_torque_scale	0.619	1.089	0.820	1.200	1.182
	ESS_module_number	16.655	22.000	18.000	22.000	30.000
	CS_EL_Speed_lo	5.109	1.000	4.000	4.000	3.000
	CS_EL_Speed_hi	22.436	18.000	20.000	23.000	20.000
	CS_min_trq_frac	0.181	0.361	0.118	0.324	0.218
	CS_off_trq_frac	0.175	0.139	0.170	0.103	0.137
	CS_lo_soc	0.417	0.500	0.453	0.267	0.567
	CS_hi_soc	0.616	0.844	0.695	0.764	0.695
	CS_charge_torque	36.795	36.000	33.000	32.000	31.000
Constraints	Grade (%)	9.409	7.892	10.111	6.910	7.200
	0-60 mph time(t1) (s)	9.499	8.692	8.774	9.972	8.400
	40-60 mph time(t2) (s)	4.749	4.278	4.288	5.149	4.000
	0-85 mph(t3) (s)	19.311	17.293	17.351	21.024	16.300
	Max speed (mph)	117.698	123.230	123.577	113.148	127.000
	Max acce (ft/s-2)	16.400	16.400	16.400	16.400	16.400
	Distance in 5s (ft)	175.702	181.879	180.253	175.500	183.700
Objective	FC (mpg)	38.250	34.594	35.550	34.350	31.400
	HC (gms/mile)	0.758	0.679	0.813	0.602	0.737
	CO (gms/mile)	4.093	3.674	3.530	5.405	4.833
	Nox (gms/mile)	0.560	0.533	0.583	0.471	0.557

Table 7. Optimisation results for UDDS cycle

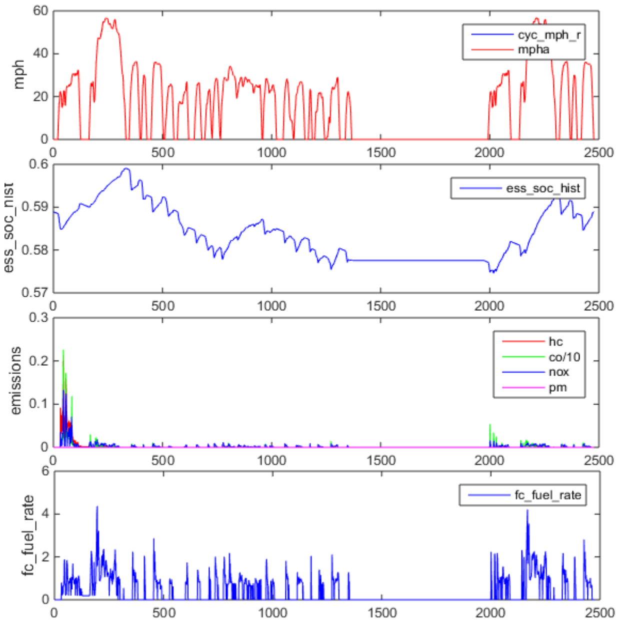

Fig.10. MABC Fuel usage, emission and SOC plot

A comparison of fuel economy and emissions before and after optimization for both approaches reveals that most of the solutions can increase the fuel economy and reduce the emission of CO, HC, NOx as shown in table above. Hence, as per the results in table 8, the MABC is identified to be superior in finding a better solution in terms of fuel consumption and emissions than BABC for various cases. Also when comparing the variables, the optimization results indicate that the engine torque scale, the electric motor torque scale and the number of the battery modules was reduced significantly in most of the cases, when compared to non-optimised values.

Parameters		Base value	Percentage change in fuel consumption and emission from base value							
			Basic ABC algorithm(%)				Modified ABC algorithm(%)			
FTP driving cycle			**Case 1**	**Case 2**	**Case 3**	**Case 4**	**Case 1**	**Case 2**	**Case 3**	**Case 4**
Objective	FC (mpg)	32.2	8.25%	3.54%	0.15%	2.92%	11.46%	10.56%	4.66%	5.46%
	HC (gms/mile)	0.564	7.27%	8.33%	6.91%	0.35%	-4.43%	1.77%	1.24%	4.08%
	CO (gms/mile)	3.244	-22.26%	-29.72%	-25.09%	-34.25%	-31.07%	-18.65%	-22.81%	-22.35%
	Nox (gms/mile)	0.471	0.21%	1.27%	-1.91%	-4.03%	-11.25%	-2.34%	-2.55%	-2.97%
ECE-EUDC cycle			**Case 1**	**Case 2**	**Case 3**	**Case 4**	**Case 1**	**Case 2**	**Case 3**	**Case 4**
Objective	FC (mpg)	28.6	6.25%	15.92%	0.62%	6.05%	17.34%	16.63%	2.42%	14.22%
	HC (gms/mile)	0.768	-3.65%	-0.65%	15.63%	10.68%	-5.73%	-5.08%	-4.17%	-4.17%
	CO (gms/mile)	3.157	-9.50%	-8.30%	-4.91%	-10.07%	-0.29%	-1.05%	-18.72%	18.31%
	Nox (gms/mile)	0.495	-4.24%	-2.83%	13.13%	1.62%	-2.63%	-1.82%	-11.92%	2.63%
UDDS driving cycle			**Case 1**	**Case 2**	**Case 3**	**Case 4**	**Case 1**	**Case 2**	**Case 3**	**Case 4**
Objective	FC (mpg)	31.4	12.09%	9.16%	7.47%	2.46%	21.82%	10.17%	13.22%	9.39%
	HC (gms/mile)	0.737	5.02%	9.36%	9.23%	7.60%	2.85%	-7.87%	10.31%	-18.32%
	CO (gms/mile)	4.833	-43.60%	-27.46%	-42.44%	-36.66%	-15.31%	-23.98%	-26.96%	11.84%
	Nox (gms/mile)	0.557	-2.15%	4.31%	1.62%	-1.62%	0.54%	-4.31%	4.67%	-15.44%

Table 8. Percentage change in Fuel consumption and emission values

Thus the drivability can be improved by optimizing the parameters of the control system with the sizing of the key vehicle components being decreased. Although in both the methods of optimisation, there are some exceptional cases, in which the improvement of fuel economy also leads to increase of certain emissions based on weighting factor and driving cycle nature, thus proving the statement that in achieving an expected vehicle performance there is always a trade-off between emissions and fuel economy.

5 Conclusion

Comparing the results of non-optimised values with respect to the performance of BABC and MABC, results shows that there is:

- Engine, motor and ESS component size could be reduced in most of the cases which results in reduced cost of overall vehicle
- Fuel economy could be increased as high as close to 22%
- Engine emissions decreased particularly CO as low as close to 44%
- Driving cycle pattern also plays an important role in deciding the fuel economy and emissions
- PNGV constraints defined was always met in every driving cycle and test case
- SOC change is within 0.5% tolerance on every solution even with reduced battery modules still meeting the required vehicle performance

The Weighting factors of objective function also has the influence on determining the parameters for the vehicle performance. Also the for this simulation, a 2.4 GHz i5 processor has been used and it took approximately 25 Hours for every test case, for the ABC & MABC algorithm to converge and reach its final optimised values. Also in comparison to a BABC algorithm, the MABC algorithm was found to be outperforming, in that it achieved impressive real time fuel savings and reduced emissions, without much penalty to the final battery state of charge along with reduced key vehicle components size for different driving cycles.

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Nomenclature – General

ADVISOR	Advanced Vehicle Simulator
CO	Carbon MonOxide
EACS	Electric Assist Control Strategy
ECE-EUDC	New European Drive Cycle
FC	Fuel Consumption
FTP	Federal Test Procedure
HC	Hydrocarbons
HEV	Hybrid Electric Vehicle
ICE	Internal Combustion Engine
NOX	Oxides of Nitrogen
NREL	National Renewable Energy Laboratory
PNGV	Partnership for a New Generation of Vehicles
PSO	Paricle Swarm Optimisation
SI	Spark Ignition
SOC	State Of Charge
UDDS	Urban Dynamometer Driving Schedule
VRLA	Valve Regulated Lead Acid

Notations

A_f	Vehicle frontal area (m2)
C_d	Aerodynamic drag coefficient
DF_{aero}	Aerodynamic drag force (N)
Eff	Drive train efficiency
E_v	Energy of Vehicle(J)
g	Gravitational constant (m/s2)
G_M	Motor gear ratio
G_E	Engine gear ratio
gms	grams
m	Effective mass of vehicle (Kg)
mpg	miles per gallon
N_c	Normal load on centre of rolling wheel (N)
P_{mot}	Motor Mechanical power(W)
P_{engine}	Engine power(W)
$P_{engine\_max\_power}$	Maximum Engine power(W)
R_w	Radius of rolling wheels (m)
T_{mot}	Motor Torque(Nm)
t_{cycle}	Driving cycle time(s)
V_a	Velocity of the air(m/s)
V_{grade}	Resistance force by grade (N)
$V_{rolling}$	Rolling resistance force (N)
V_v	Vehicle Speed(m/s)
W_{ICE}	Engine speed(RPM)
$W_{rolling}$	Wheel rolling force(N)
W_{Wheel}	Wheel Speed (RPM)
μ	Coefficient of rolling resistance
ρ	Air density (kg/m3)
β	Inclined vehicle angle
η	Efficiency

Parameter definition:

CS_hi_soc	highest desired battery state of charge
CS_lo_soc	lowest desired battery state of charge
CS_EL_Speed_lo	Vehicle speed below which vehicle runs as pure electric at low SOC
CS_EL_Speed_hi	Vehicle speed below which vehicle runs as pure electric at High SOC
CS_off_trq_frac	minimum torque threshold when commanded at a lower torque, the engine will SHUT OFF
CS_min_trq_frac	minimum torque threshold; the engine operates at low threshold torque and motor acts as generator
CS_charge_torque	an alternator like torque loading on the engine to recharge the battery pack
ESS_module_number	number of battery modules in a pack
FC_torque_scale	scaling factor for torque range of ICE
MC_torque_scale	torque scaling factor of EM