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Hybrid artificial bee colony-grey wolf algorithm for multi-objective engine optimization of converted plug-in hybrid electric vehicle

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Abstract. The paper proposes a hybrid approach of artificial bee colony (ABC) and grey wolf optimizer (GWO) algorithm for multi-objective and multidimensional engine optimization of a converted plug-in hybrid electric vehicle. The proposed strategy is used to optimize all emissions along with brake specific fuel consumption (FC) for converted parallel operated diesel plug-in hybrid electric vehicle (PHEV). All emissions particulate matter (PM), nitrogen oxide (NOx), carbon monoxide (CO) and hydrocarbon (HC) are considered as optimization parameters with weighted factors. 70 hp engine data of NOx, PM, HC, CO and FC obtained from Oak Ridge National Laboratory is used for the study. The algorithm is initialized with feasible solutions followed by the employee bee phase of artificial bee colony algorithm to provide exploitation. Onlooker and scout bee phase is replaced by GWO algorithm to provide exploration. MATLAB program is used for simulation. Hybrid ABC-GWO algorithm developed is tested extensively for various values of speeds and torque. The optimization performance and its environmental impact are discussed in detail. The optimization results obtained are verified by real data engine maps. It is also compared with modified ABC and GWO algorithm for checking the effectiveness of proposed algorithm. Hybrid ABC-GWO offers combine benefits of ABC and GWO by reducing computational load and complexity with less computation time providing a balance of exploitation and exploration and passes repeatability towards use for real-time optimization.

Keywords: ABC; emissions; GWO; MATLAB; optimization; PHEV

1. Introduction

The economic growth of a country extensively depends on transportation via road, rail, sea and air. Foremost among them is road transport. In India almost, all vehicles rely on fossil fuel-based transportation i.e., most on Petrol (Spark plug ignition IC engines) and Diesel (Compression ignition IC engine). These pollutes atmosphere by the emission of greenhouse gasses & causes global warming. 27 Indian cities are in the top 100 cities with the worst air pollution in the world

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as per world health organization (WHO). In 2012 ambient (outdoor air pollution) in both cities and rural areas was estimated to cause 3 million premature deaths worldwide (Fact sheet. 2016). India stands third in the CO2 emission (The Carbon Brief 2019). Hence crucial steps are required to be taken to reduce emissions of present vehicles running on the road. Considering the available options hybridization of the conventional vehicle (CV) to electric can be one of the promising and necessary steps need to be taken. This will reduce the environmental impacts of automobile use without losing comforts, performance, storage room and extended driving range. However, there is less attention in terms of research on conversion of CV into PHEV and its energy management strategies as few papers are observed in literature related to the conversion of CV into HEV/PHEV, conversion of HEV to PHEV and converted HEV/PHEV (Ghorbani *et al*. 2010, Zulkifli, *et al*. 2012, Gupte 2014, AI-Atabil and Tala1 2002, Jenkins and Ferdowsi 2008, McIntyre *et al*. 2012, Zulkifli *et al*. 2012, Fuengwarodsakul 2009, Rizzo *et al*. 2011, Jenkinsand Ferdowsi 2014, Tara *et al*. 2010, Ghorbani *et al*. 2013, Zeman and Lewis 2013, Wirasingha *et al*. 2008, Kaleg *et al*. 2015, Zhang *et al*. 2015, Gujarathi *et al*. 2015, Tavares *et al*. 2018, Gujarathi *et al*. 2017a, b, Gujarathi *et al*. 2018, 2019). Some of them are related to energy management strategies, however complete vehicle simulation has done for power split in order to obtain fuel economy (Ghorbani *et al*. 2010, Zulkifli *et al*. 2012 and Guptea 2014) and emissions (Al-Atabi and Yusaf 2002, Gujarathi *et al*. 2018, 2019). Fuzzy logic controller is proposed by Ghorbani *et al*. (2010) to decide power sharing during Toyota Prius HEV to PHEV conversion. Testing has carried out for various driving cycles with different modes and improvement in fuel economy is observed mostly during the low state of charge (SOC) of the battery. Zulkifli *et al.* (2012) has shown saving of 25 % of fuel consumption by development of split axle parallel HEV with in-wheel-motor using rule-based energy management strategy. Experimental analysis and feasibility study has been carried out by Gupte (2014) for 1400 cc diesel engine car converted into the HEV by using BLDC hub motors. Significant improvement in fuel consumption has been observed with a simple on-off strategy. Al-Atabi and Yusaf (2002) has done experimental investigation in a single cylinder diesel engine for its use as a hybrid power unit (HPU) for a series hybrid electric vehicle. The results identified the minimum emission range of engine operation and shows the great potential in use of diesel engines as HPU for series HEV. Gujarathi *et al.* (2017) has shown substantial reduction in specific fuel consumption and emission using fuzzy logic based energy management strategy for converted parallel plug-in hybrid electric vehicle. Complete vehicle is simulated by Gujarathi *et al.* (2018). The emissions are observed to comply with BSIII norms for converted PHEV compared to conventional diesel vehicle for sample Indian urban driving cycle using fuzzy logic. Recently study on fuel economy and emissions for converted plug-in parallel hybrid electric vehicle versus conventional diesel vehicle on standard driving cycles has been carried out by Gujarathi *et al.* (2019). The results confirm the converted PHEV has less fuel consumption and emissions (NOx and PM) than a conventional vehicle.

It is observed that there is a lot of research took place on the use of energy management strategies of PHEV mostly on power split to improve fuel economy by a variety of system parameters and few on reduction in emissions. However, after power split, if the engine needs to be operated then in-depth optimization of all emissions of the engine are not considered. Also, as per comprehensive analysis of energy management strategies carried out by Zhang *et al. (*2015), the existing approaches reduce computation load at the expense of optimization performance. Hence there is a need for optimization of both fuel economy and emissions of the engine, reducing computational complexity without compromise of optimization performance. However, fuel economy and emissions minimization are conflicting objectives and hence multiobjective multidimensional problem becomes very complex.

Recently swarm intelligence has proven its importance for the solution of those problems that cannot be easily dealt with classical mathematical techniques. The performance of artificial bee colony (ABC) algorithm is seen to be superior over other evolutionary algorithms (Karaboga and Basturk 2007, 2008). In 2009, Karaboga and Akay used ABC algorithm for multi-dimensional numeric engineering problems (high data with surface and counter plots) and results showed that ABC algorithm performs better than the differential evolution (DE), particle swarm optimization (PSO) and evolutionary algorithm (EA). However, the requirement of more time and poor exploration makes it unable for real-time. In contrast, Grey wolf optimizer proposed by Mirjalili *et al.* (2014) is comparatively simple, fast and gives comparable results. However, need further improvement in consistency of results for repeatable input of similar values (Gujarathi *et al.* 2018). Hence investigations are done by combining both to get required benefit towards real-time implementation. In continuation of work carried by Gujarathi *et al.* (2018) towards real-time implementable strategy, in this paper hybrid artificial bee colony-grey wolf algorithm is proposed for real world multi-objective engine optimization of converted plug-in hybrid electric vehicle. The papers contribute to first, reduction of emissions and fuel consumption together by using hybrid multi-objective ABC-GWO approach for converted PHEV to avail combine benefits of ABC and GWO. Second, investigate in a reduction in computational complexity and computational time without compromise of optimization performance. The proposed algorithm is simple, has less computational load and time, provide optimized results with strong capability towards practical real-time implementation. The rest of the paper is organized as follow:

Section 2 provide details about proposed hybrid ABC-GWO algorithm applied for engine optimization of converted PHEV. Results are analyzed and discussed in section 3 followed by a conclusion. Details of engine maps generated are provided in the appendix for reference.

2. Hybrid ABC-GWO optimization algorithm for converted PHEV

2.1 Background

For a converted PHEV, as per requirement of speed and torque of the engine, torque value is generated greater than required torque for optimized values of fuel consumption and emissions using ABC-GWO algorithm. Extra torque is used to charge the battery of PHEV. The overview of the algorithm can be seen from Fig. 1.

The main goal of optimization is to determine the best operating point of the engine with minimized PM, NOx, CO, HC and FC. Since reduction of all emissions and brake specific fuel consumption together are not possible due to conflicting objective, a best-compromised solution is a required solution. In this work, the following objective function is considered:

$$\text{Min} \quad f(X) = w_1 * \frac{\text{FCi}}{\text{FC req}} + w_2 * \frac{\text{COi}}{\text{CO req}} + w_3 * \frac{\text{HCi}}{\text{HC req}} + w_4 * \frac{\text{NOxi}}{\text{NOx req}} + w_5 * \frac{\text{PMi}}{\text{PM req}} \qquad i = \{1, 2, 3 \ldots SN\} \tag{1}$$

where PM_i, NOx_i, HC_i CO_i, and FC_i are *PM, NOx, CO, HC, and FC* at index *i*, *PMreq*, *NOxreq HCreq*, *COreq* and *FCreq* are required value of *PM, NOx, HC, CO and FC* respectively. The weightage factors given to each variable are w_1 = 0.25, w_2=0.15, w_3=0.15, w_4=0.3 and w_5=0.15.

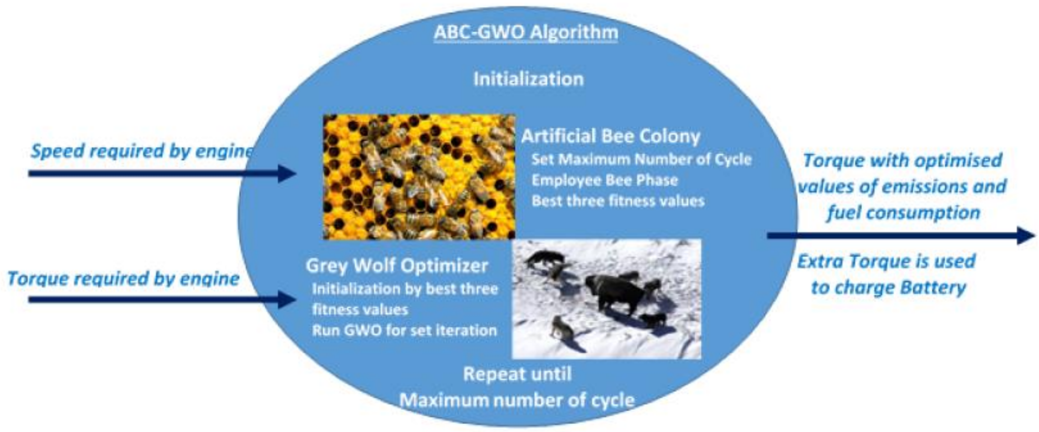


Fig. 1 Hybrid ABC-GWO approach (images: Sustainablog. 2014 and Mirjalili *et al.* 2014)

The required emission values considered for heavy diesel engine as per BSII norms applicable (ARAI 2011). PMreq = 0.15 g/kWh, NOxreq = 7 g/kWh, COreq = 4 g/kWh HCreq = 1.1 g/kWh and FCreq = 400 g/kWh. The optimized value of torque should be greater than or equal to required torque and less than or equal to maximum torque.

$$T \geq Treq \leq Tmax \qquad (Tmax= 135\ Nm) \tag{2}$$

The optimized solution should be such that the specific fuel consumption and emissions should be within limits.

$$\text{i.e.} \quad FC \leq FCreq,\ HC \leq HCreq,\ CO \leq COreq,\ NOx \leq NOxreq \text{ and } PM \leq PMreq \tag{3}$$

2.2 Hybrid ABC-GWO optimization algorithm

The first step of ABC Algorithm is the initialization of solution matrix which is done by generating random values within upper and lower limits. The solution matrix generated is with feasible and infeasible solutions. Because in ABC algorithm initialization with feasible solutions is a very time-consuming process and, in some cases, it is impossible to produce a feasible solution randomly (Karaboga and Basturk 2007). In this algorithm, the first step in ABC algorithm is followed but the initialization of solution matrix is done with feasible solutions.

Emission and brake specific fuel consumption data are located in the form of a matrix generated from data obtained from Oak Ridge National Laboratory (Advance Vehicle Simulation Software). All these variables are a function of speed and torque. The torque range is divided from minimum value to maximum value into 27 parts in steps of 5 N-m i.e., from 0 to 135 Nm. Hence here swarm number SN=28 is considered as possible solutions for six optimization variables T, FC, CO, HC, NOx and PM i.e., D=6. The speed range of engine is 700 to 5000 rpm and is divided into 30 parts. For all mention value of speed and torque, the values of all emissions and brake specific fuel consumption are stored in the form of a matrix of dimension 31 x 28 as shown in Fig. 2. Any other value required can be calculated by an interpolation method. Hence the first step is to read offline data stored, then check for any required speed and torque. If there is a requirement,

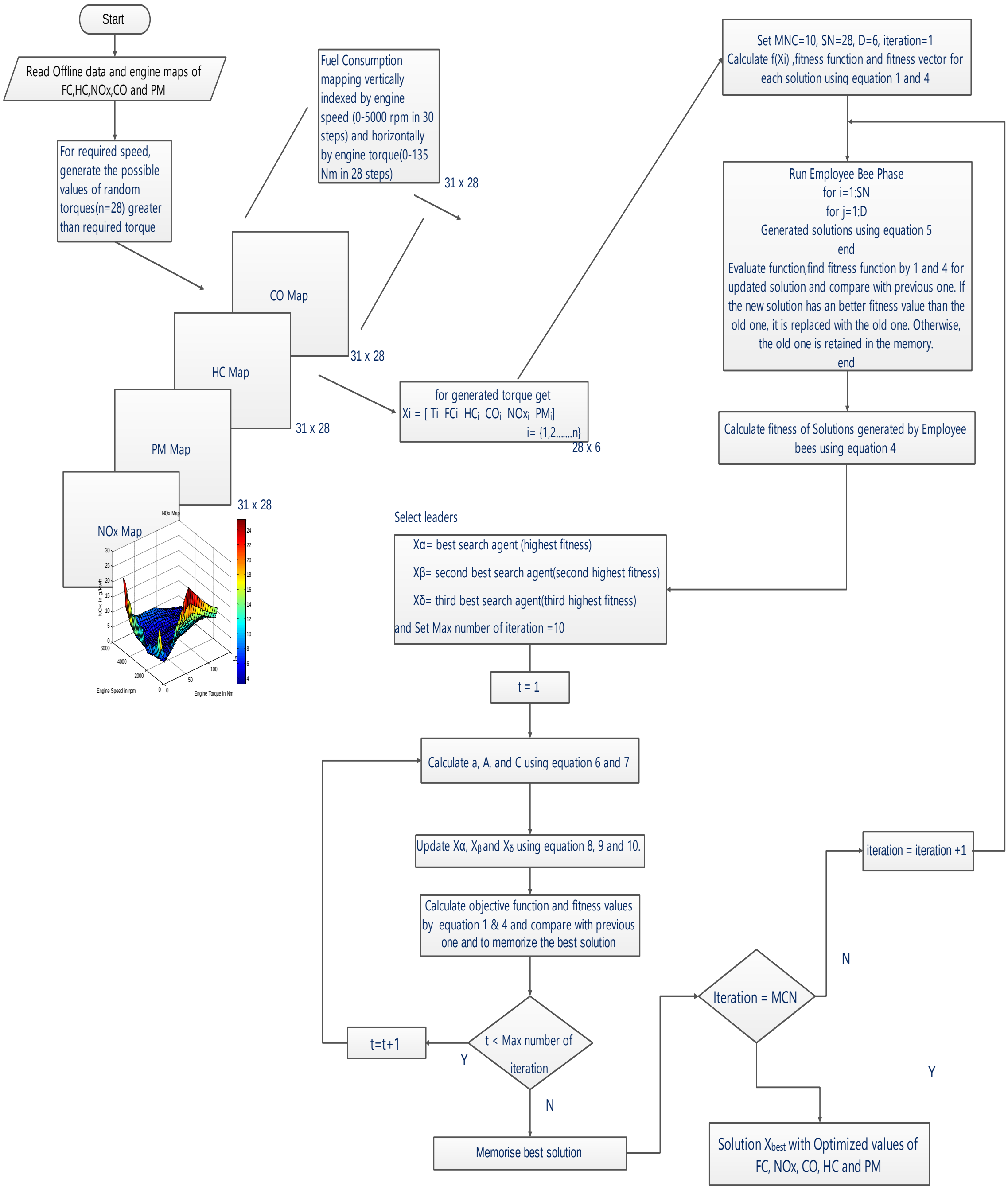


Fig. 2 Hybrid ABC-GWO optimization algorithm

then for that value of speed and value of torque greater than required torque (T >Treq), random values of torque are generated (SN=28) and for that value of torque PM, NOx CO, HC and FC values are extracted as seen in Fig. 2 to get initial 28 solutions vector i.e., 28 x 6. A number of cycles (MNC) are set to 2. The value of the objective function ($f(X_i)$) is calculated to get the fitness vector by using the Eqs. (1) and (4).

$$\begin{aligned} fit_i &= \frac{1}{1+f(x_i)} && \text{if } f(x_i) \geq 0 \\ &= 1 + abs(f(x_I)) && \text{if } f(x_i) < 0 \\ & && i = 1,2 \ldots SN \end{aligned} \tag{4}$$

In order to produce a new solution, the following expression (5) is used in the employee bee phase:

$$V_{ij=}\ X_{ij} + \phi_{ij}(X_{kj} - X_{ij}) \tag{5}$$

where $k \in \{1, 2... SN\}$ *and* $j \in \{1, 2... D\}$ are randomly chosen indexes and are same for all j. Although k is determined randomly, it has to be different from i. $\varphi_{i,j}$ is a random number between [-1, 1].

If a parameter value produced by this operation exceeds its predetermined limit, the parameter can be set to its limit value. After each candidate source position $V_{i,j}$ is produced and then evaluated by Eqs. (1) and (4), its performance is compared with that of its old one. If the new solution has better fitness value than the old one, new solution is stored at old place. Otherwise, the old one is retained in the memory. Now fitness values of updated solutions are calculated by Eq. (4). After this phase best three fitness values are selected to start GWO phase and considered this as search agent X_{α}, X_{β} and X_{δ}.

The values of A and C are *calculated with random* values of r_1 and r_2 between 0 to 1 using Eqs. (6) and (7). Whereas 'a' is linearly decreased from 2 to 0 over the iterations.

$$A = 2\,a\,r_1 - a \tag{6}$$

$$C = 2\,r_2 \tag{7}$$

Using values of a, A and C, for each search agent the search position are updated by Eqs. (8) to (10).

$$D\alpha = C_1\,X\alpha - X\ ,\ D_{\beta} = C_2\,X_{\beta} - X,\ D_{\delta} = C_3\,X_{\delta} - X \tag{8}$$

$$X_1 = X\alpha - A_1\,D\alpha,\ X_2 = X_{\beta} - A_2\,D_{\beta},\ X_3 = X_{\delta} - A_3\,D_{\delta} \tag{9}$$

$$X\,(t+1) = (X_1 + X_2 + X_3)/3 \tag{10}$$

The value of the objective function and fitness value is calculated. Now values of A and C is calculated by using Eqs. (6) and (7) to update search agents using Eqs. (8), (9) and (10). The fitness value is computed and compared with previous one and procedure is repeated up to a maximum number of iteration (t=10) to get the best solution. The entire procedure of employee bee phase and GWO is repeated for set maximum number of cycles (MNI=2) to get a best final solution as shown in Fig. 2.

3. Results and discussion

A hybrid ABC-GWO algorithm coding is developed in MATLAB and tested extensively for various values of speed and torque. The maximum number cycles considered are 2 and number of iterations in GWO phase are 10. The results are given in Tables 1 and 2. Results are compared with work done by Gujarathi, Shah and Lokhande (2018) for grey wolf optimizer (GWO) algorithm run for 2 cycles and for modified artificial bee colony algorithm (MABC) run for 10 iterations along with available engine maps. A repeatability test, fitness value comparison and number of iterations for maximum fitness along with environmental impact are shown in Figs. 3-10.

Table 1 Results for PM, NOx, CO, HC and FC optimization

Engine Speed required in rpm	**Engine Torque required/ Optimized in Nm**	**Method**	**FC** (required 400 g/kWh)	**CO** (required 4 g/kWh)	**HC** (required 1.1 g/kWh)	**NOx** (required 7 g/kWh)	**PM** (required 0.15 g/kWh)	**Fitness Value**
4999	31.93	Normal	432.62	9.4975	1.6659	9.0873	0.4461	0.2797
	134.89	MABC	219.96	1.3483	0.4107	4.8404	0.5276	0.4143
		Engine Mapping	219.97	1.3483	0.4106	4.8405	0.6039	0.3955
	54.16	GWO	347.75	1.7169	0.5021	8.6379	0.4568	0.3754
		Engine Mapping	347.75	1.7169	0.5021	8.6378	0.4568	0.3754
	132.99	ABC-GWO	223.05	1.3672	0.4164	4.9085	0.5069	0.4181
		Engine Mapping	223.18	1.3680	0.4167	4.9113	0.6127	0.3921
4802	78.73	Normal	314.81	1.5114	0.5434	7.8161	0.4881	0.3796
	133.75	MABC	224.96	1.2570	0.3722	5.0000	0.4881	0.4253
		Engine Mapping	224.96	1.2569	0.3721	5.0000	0.4978	0.4226
	128.41	GWO	234.33	1.3093	0.3877	5.2083	0.5186	0.4127
		Engine Mapping	234.33	1.3093	0.3877	5.2082	0.5185	0.4127
	107.82	ABC-GWO	279.48	1.5622	0.4640	6.2165	0.6197	0.3704
		Engine Mapping	279.13	1.5596	0.4618	6.2041	0.6176	0.3710
4550	108.18	Normal	282.99	1.4801	0.4482	5.9254	0.6448	0.3687
	132.66	MABC	230.74	1.2068	0.3654	4.8312	0.5257	0.4173
		Engine Mapping	230.73	1.2068	0.3654	4.8310	0.5257	0.4173
	108.34	GWO	282.55	1.4778	0.4475	5.9161	0.6437	0.3690
		Engine Mapping	282.56	1.4779	0.4475	5.9162	0.6438	0.3690
	126.02	ABC-GWO	242.87	1.2703	0.3846	5.0852	0.5533	0.4049
		Engine Mapping	242.87	1.2702	0.3846	5.0851	0.5534	0.4049
4333	114.58	Normal	272.59	1.3575	0.4225	5.3108	0.6469	0.3763
	133.67	MABC	233.70	1.1638	0.3622	4.5530	0.5546	0.4131
		Engine Mapping	233.70	1.1638	0.3622	4.5531	0.5546	0.4131

Table 1 Continued

Engine Speed required in rpm	**Engine Torque required/ Optimized in Nm**	**Method**	**FC** (required 400 g/kWh)	**CO** (required 4 g/kWh)	**HC** (required 1.1 g/kWh)	**NOx** (required 7 g/kWh)	**PM** (required 0.15 g/kWh)	**Fitness Value**
4333	128.81	GWO	242.52	1.2077	0.3759	4.7248	0.5756	0.4041
		Engine Mapping	242.52	1.2077	0.3759	4.7249	0.5755	0.4041
	130.82	ABC-GWO	238.52	1.1230	0.3488	4.5035	0.5079	0.4265
		Engine Mapping	238.61	1.1235	0.3489	4.5052	0.5081	0.4264
4182	117.73	Normal	270.77	1.2749	0.3960	5.1125	0.5766	0.3958
	133.80	MABC	238.21	1.1216	0.3484	4.4977	0.5073	0.4268
		Engine Mapping	238.21	1.1216	0.3484	4.4977	0.5073	0.4268
	118.35	GWO	269.36	1.2682	0.3939	5.0858	0.5736	0.3971
		Engine Mapping	269.35	1.2682	0.3939	5.0856	0.5736	0.3971
	123.87	ABC-GWO	257.70	1.2134	0.3769	4.8657	0.5488	0.4077
		Engine Mapping	257.31	1.2115	0.3763	4.8583	0.5479	0.4081
3850	123.71	Normal	292.64	2.3338	0.3844	5.6819	0.6228	0.3676
	134.89	MABC	270.68	2.1746	0.3551	5.2840	0.5775	0.3852
		Engine Mapping	270.69	2.1745	0.3551	5.2842	0.5774	0.3852
	124.06	GWO	292.45	2.3376	0.3840	5.6859	0.6229	0.3675
		Engine Mapping	292.45	2.3376	0.3840	5.6859	0.6229	0.3675
	131.51	ABC-GWO	277.72	2.2311	0.3643	5.4213	0.5925	0.3791
		Engine Mapping	277.72	2.2310	0.3643	5.4214	0.5924	0.3791
3700	126.02	Normal	292.17	2.1719	0.3684	5.6845	0.5322	0.3893
	133.92	MABC	280.37	2.0003	0.3533	5.5353	0.4956	0.4031
		Engine Mapping	280.37	2.0002	0.3533	5.5352	0.4955	0.4031
	127.44	GWO	290.86	2.1327	0.3666	5.6872	0.5245	0.3917
		Engine Mapping	290.86	2.1326	0.3666	5.6872	0.5245	0.3917
	134.70	ABC-GWO	278.74	1.9879	0.3512	5.5037	0.4925	0.4045
		Engine Mapping	279.15	1.9909	0.3517	5.5117	0.4933	0.4042
3500	128.67	Normal	292.26	1.9208	0.3372	5.7941	0.4255	0.4185
	134.89	MABC	287.00	1.7637	0.3252	5.7859	0.3996	0.4288
		Engine Mapping	287.00	1.7636	0.3252	5.7860	0.3996	0.4288
	129.15	GWO	292.13	1.9053	0.3364	5.8035	0.4231	0.4193
		Engine Mapping	292.13	1.9052	0.3364	5.8036	0.4231	0.4193
	128.81	ABC-GWO	292.22	1.9162	0.3370	5.7968	0.4248	0.4188
		Engine Mapping	292.22	1.9162	0.3369	5.7969	0.4248	0.4188
3150	132.18	Normal	291.32	1.6524	0.2710	6.3274	0.3109	0.4518
	134.95	MABC	290.70	1.5736	0.2665	6.3541	0.3003	0.4562
		Engine Mapping	290.70	1.5736	0.2665	6.3543	0.3003	0.4562

Table 1 Continued

Engine Speed required in rpm	**Engine Torque required/ Optimized in Nm**	**Method**	**FC** (required 400 g/kWh)	**CO** (required 4 g/kWh)	**HC** (required 1.1 g/kWh)	**NOx** (required 7 g/kWh)	**PM** (required 0.15 g/kWh)	**Fitness Value**
3150	134.47	GWO	290.81	1.5873	0.2673	6.3495	0.3022	0.4554
		Engine Mapping	290.81	1.5873	0.2673	6.3496	0.3021	0.4554
	134.49	ABC-GWO	290.80	1.5866	0.2672	6.3497	0.3021	0.4555
		Engine Mapping	290.80	1.5866	0.2672	6.3499	0.3020	0.4555
2456	134.57	Normal	299.29	1.3227	0.2498	7.6195	0.1471	0.4948
	134.98	MABC	299.20	1.3143	0.2492	7.6344	0.1462	0.4952
		Engine Mapping	299.20	1.3143	0.2491	7.6345	0.1462	0.4952
	134.64	GWO	299.27	1.3213	0.2497	7.6220	0.1469	0.4949
		Engine Mapping	299.28	1.3213	0.2497	7.6221	0.1469	0.4949
	134.98	ABC-GWO	299.20	1.3142	0.2491	7.6345	0.1462	0.4952
		Engine Mapping	299.20	1.3142	0.2491	7.6346	0.1462	0.4952
2160	126.43	Normal	308.37	1.2701	0.2789	8.4600	0.1290	0.4872
	134.85	MABC	307.21	1.1333	0.2743	8.8787	0.1123	0.4901
		Engine Mapping	307.21	1.1332	0.2743	8.8792	0.1123	0.4901
	133.41	GWO	307.40	1.1560	0.2752	8.8098	0.1150	0.4896
		Engine Mapping	307.41	1.1560	0.2752	8.8100	0.1150	0.4896
	126.43	ABC-GWO	307.87	1.1790	0.2759	8.5995	0.1179	0.4911
		Engine Mapping	308.37	1.2700	0.2789	8.4604	0.1290	0.4872
2000	116.73	Normal	314.86	1.3005	0.2561	8.5217	0.1348	0.4840
	133.79	MABC	312.76	1.0416	0.2436	9.4562	0.1046	0.4870
		Engine Mapping	312.77	1.0416	0.2435	9.4565	0.1046	0.4870
	120.57	GWO	307.40	1.1560	0.2752	8.8098	0.1150	0.4896
		Engine Mapping	313.70	1.2457	0.2497	8.7350	0.1292	0.4845
	132.20	ABC-GWO	312.76	1.0240	0.2432	8.8764	0.1024	0.4966
		Engine Mapping	312.77	1.0663	0.2440	9.3726	0.1077	0.4867
1888	106.84	Normal	323.41	1.3218	0.2544	8.4607	0.1353	0.4832
	115.97	MABC	320.80	1.1419	0.2311	8.9967	0.1150	0.4876
		Engine Mapping	320.87	1.1580	0.2337	9.0051	0.1174	0.4862
	111.63	GWO	322.01	1.2178	0.2403	8.7337	0.1232	0.4864
		Engine Mapping	322.01	1.2177	0.2403	8.7341	0.1231	0.4864
	107.25	ABC-GWO	323.18	1.1323	0.2269	8.4607	0.1090	0.4976
		Engine Mapping	323.29	1.3111	0.2528	8.4833	0.1339	0.4836
1700	84.47	Normal	344.41	1.8458	0.3288	7.8159	0.2344	0.4447
	125.27	MABC	332.81	1.1405	0.2045	9.3046	0.1106	0.4844
		Engine Mapping	332.92	1.1219	0.2043	9.3977	0.1111	0.4833

Table 1 Continued

Engine Speed required in rpm	**Engine Torque required/ Optimized in Nm**	**Method**	**FC** (required 400 g/kWh)	**CO** (required 4 g/kWh)	**HC** (required 1.1 g/kWh)	**NOx** (required 7 g/kWh)	**PM** (required 0.15 g/kWh)	**Fitness Value**
1700	84.68	GWO	344.28	1.8356	0.3271	7.8283	0.2333	0.4451
		Engine Mapping	357.15	3.2547	0.5925	6.9231	0.3105	0.4027
	118.53	ABC-GWO	333.05	1.0252	0.1946	9.1506	0.1013	0.4925
		Engine Mapping	333.51	1.1427	0.2092	9.2617	0.1194	0.4816
1500	51.00	Normal	392.97	4.1249	0.7691	6.6170	0.3232	0.3829
	133.48	MABC	354.05	1.3612	0.1857	9.6070	0.1254	0.4695
		Engine Mapping	353.49	1.2162	0.1857	9.9159	0.1318	0.4658
	68.75	GWO	373.25	2.4900	0.4403	8.1240	0.2861	0.4104
		Engine Mapping	373.26	2.4899	0.4403	8.1244	0.2861	0.4104
	103.39	ABC-GWO	354.80	1.1033	0.2102	10.1934	0.1596	0.4539
		Engine Mapping	354.81	1.1033	0.2102	10.1939	0.1596	0.4539
1350	45.90	Normal	420.59	4.6916	1.0189	6.6750	0.3224	0.3663
	134.20	MABC	372.08	0.9745	0.1826	11.3120	0.1301	0.4503
		Engine Mapping	372.30	1.4546	0.1826	10.2135	0.1887	0.4388
	101.07	GWO	373.97	1.0641	0.2163	11.1960	0.1427	0.4447
		Engine Mapping	373.98	1.0641	0.2163	11.1968	0.1427	0.4447
	85.95	ABC-GWO	378.63	1.2462	0.1854	10.4011	0.1288	0.4567
		Engine Mapping	378.86	1.4171	0.2641	10.5585	0.1935	0.4298
1234	41.96	Normal	445.74	5.3683	1.2652	6.5215	0.3577	0.3452
	119.27	MABC	381.99	1.0909	0.1843	11.7730	0.1431	0.4379
		Engine Mapping	378.75	1.2519	0.1898	11.2212	0.1685	0.4348
	49.12	GWO	429.73	4.0972	0.9050	7.8798	0.3191	0.3659
		Engine Mapping	429.74	4.0971	0.9049	7.8802	0.3191	0.3659
	63.11	ABC-GWO	408.77	2.0120	0.1838	9.5821	0.1430	0.4469
		Engine Mapping	409.69	2.5502	0.5178	10.0253	0.2398	0.3959
1111	37.77	Normal	480.9200	6.1965	1.4983	6.1590	0.0209	0.4906
	128.15	MABC	364.54	1.4630	0.1757	10.0840	0.1978	0.4387
		Engine Mapping	364.70	1.5206	0.1757	10.6899	0.2048	0.4291
	54.11	GWO	442.68	3.5586	0.7329	10.0930	0.3666	0.3490
		Engine Mapping	442.70	3.5587	0.7329	10.0940	0.3667	0.3489
	130.09	ABC-GWO	364.85	1.5649	0.1746	10.5813	0.2117	0.4278
		Engine Mapping	364.85	1.5650	0.1746	10.5814	0.2117	0.4278
845	28.73	Normal	596.75	9.2749	2.4330	6.3403	0.7663	0.2409
	132.03	MABC	355.56	1.7281	0.1850	11.6660	0.2773	0.3984
		Engine Mapping	361.61	1.7574	0.1882	12.1295	0.2821	0.3919

Table 1 Continued

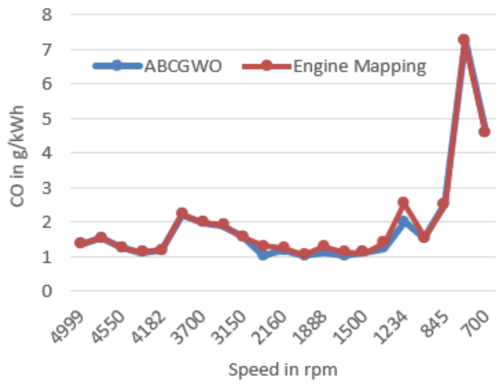
Engine Speed required in rpm	**Engine Torque required/ Optimized in Nm**	**Method**	**FC** (required 400 g/kWh)	**CO** (required 4 g/kWh)	**HC** (required 1.1 g/kWh)	**NOx** (required 7 g/kWh)	**PM** (required 0.15 g/kWh)	**Fitness Value**
845	95.84	GWO	489.49	2.3083	0.2592	16.6250	0.3792	0.3221
		Engine Mapping	489.51	2.3085	0.2592	16.6267	0.3792	0.3221
	64.90	ABC-GWO	496.29	2.5170	0.4843	17.8956	0.4091	0.3034
		Engine Mapping	496.31	2.5172	0.4844	17.8976	0.4092	0.3033
800	27.20	Normal	626.85	10.2320	2.7355	6.7161	0.8108	0.2273
	128.30	MABC	374.51	1.8047	0.2036	10.4090	0.3113	0.3989
		Engine Mapping	374.50	1.8047	0.2036	13.1997	0.3113	0.3739
	84.15	GWO	510.19	2.0560	0.3174	19.5020	0.4060	0.3008
		Engine Mapping	510.22	2.0562	0.3174	19.5037	0.4060	0.3008
	38.32	ABC-GWO	567.92	7.2598	1.6649	9.9227	0.7887	0.2465
		Engine Mapping	567.94	7.2602	1.6650	9.9240	0.7888	0.2465
700	3.40	Normal	1794.20	50.9860	20.0700	17.9420	0.8109	0.0781
	124.13	MABC	392.56	1.8559	0.2335	11.8520	0.3704	0.3698
		Engine Mapping	392.57	1.8560	0.2335	15.3070	0.3704	0.3434
	29.10	GWO	658.74	10.4840	2.7420	8.9444	0.8399	0.2166
		Engine Mapping	658.74	10.4843	2.7421	8.9442	0.8399	0.2166
	53.64	ABC-GWO	571.81	4.6165	0.9032	18.7493	0.8103	0.2353
		Engine Mapping	571.81	4.6165	0.9032	18.7493	0.8103	0.2353

It can be seen that almost all constrained are within limit except NOx and PM (deviation of NOx is more at lower values of speeds whereas PM at higher values). It is critical and not feasible to keep all the emissions within limit at all speeds of the engine. The optimization results show that if we are operating the engine at higher torque value irrespective of speed requirement, the fuel consumption and emissions can be lower. It is also observed that at lower values of speed, the specific fuel consumption of engine is higher e.g., at speed of 1100 rpm, the specific fuel consumption is 364.85.22 g/kWh, whereas as speed value increases it reduces e.g., at speed of 3700 rpm, the specific fuel consumption is 278.74 g/kWh. If the required speed of the engine is lower, specific fuel consumption can be improved by operating engine at a higher torque.

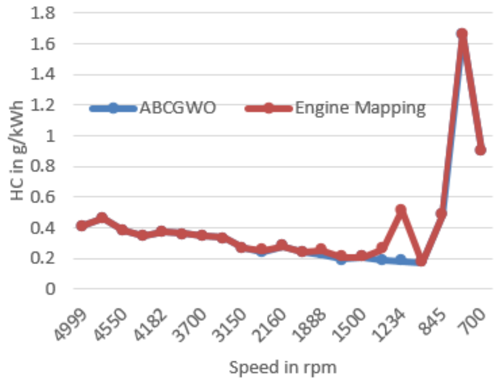
It is observed that hybrid ABC-GWO algorithm shows better fitness value for a wider range of speed i.e., from 1350 rpm to 3700 rpm followed by MABC and then GWO with few exceptions.

Moreover, the MABC is better at lower and very higher values of speed. It can also be seen that the results obtained by optimization algorithm are matching with actual engine maps. The plotting of same is shown in Fig. 3. It can be seen that almost all values of optimization parameters obtained by ABC-GWO are nearly same as compared to actual engine mapping with some exceptions as shown in Fig. 3 below.

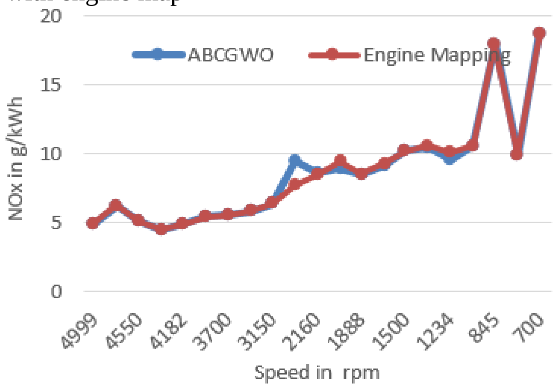
The environmental impact of hybrid ABC-GWO and comparison with MABC and GWO is shown in Figs. 4-7. The entire range of speed is divided into two parts: Range of speed from idle



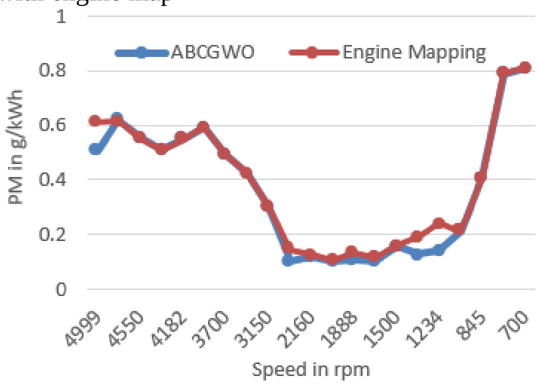
(a) Comparison of CO obtained by ABC-GWO with engine map



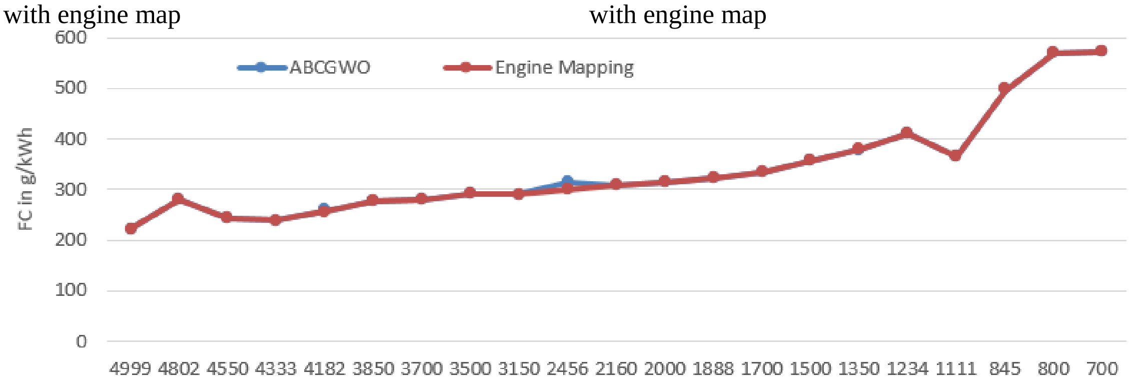
(b) Comparison of HC obtained by ABC-GWO with engine map



(c) Comparison of NOx obtained by ABC-GWO with engine map



(d) Comparison of PM obtained by ABC-GWO with engine map



(e) Comparison of FC obtained by ABC-GWO with engine map

Fig. 3 Comparison of values of optimization parameters obtained by ABC-GWO with Engine Map

speed 700 rpm to 2000 rpm and 2001 to 5000 rpm for better interpretation of results.

It is observed from Figs. 4 and 5 that there is a substantial reduction in CO and HC above 4182 rpm and at lower values below 1700 rpm of engine speed compared to normal. Moreover, there is a slight reduction in all other values. Also, MABC gives lowest values mostly followed by ABC-GWO and then GWO.

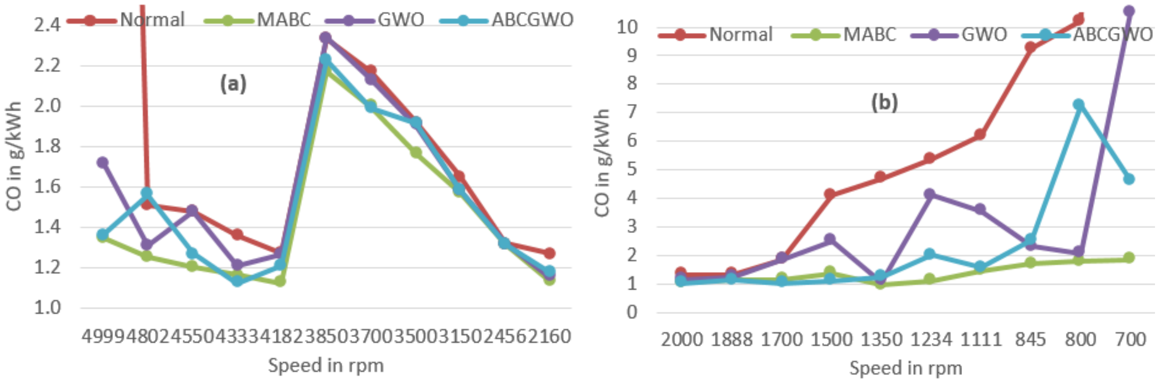


Fig. 4 Comparison of optimized CO obtained by ABC-GWO with MABC, GWO and normal

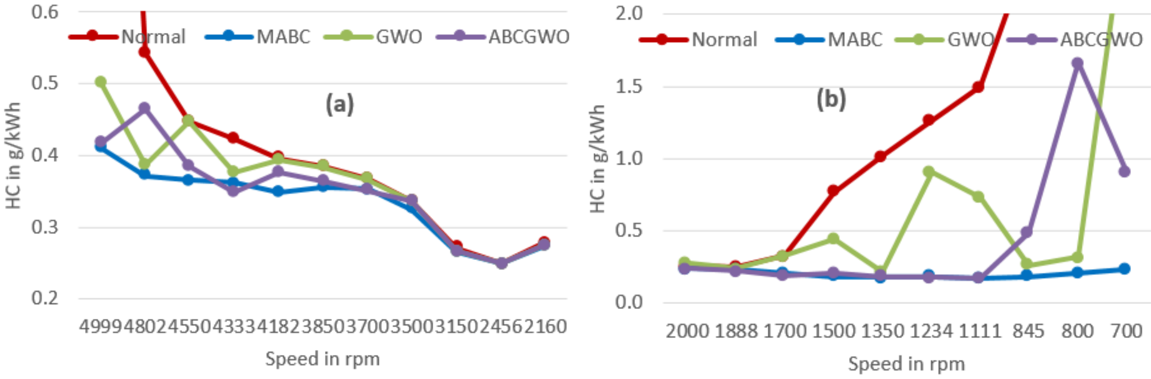


Fig. 5 Comparison of optimized HC obtained by ABC-GWO with MABC, GWO and normal

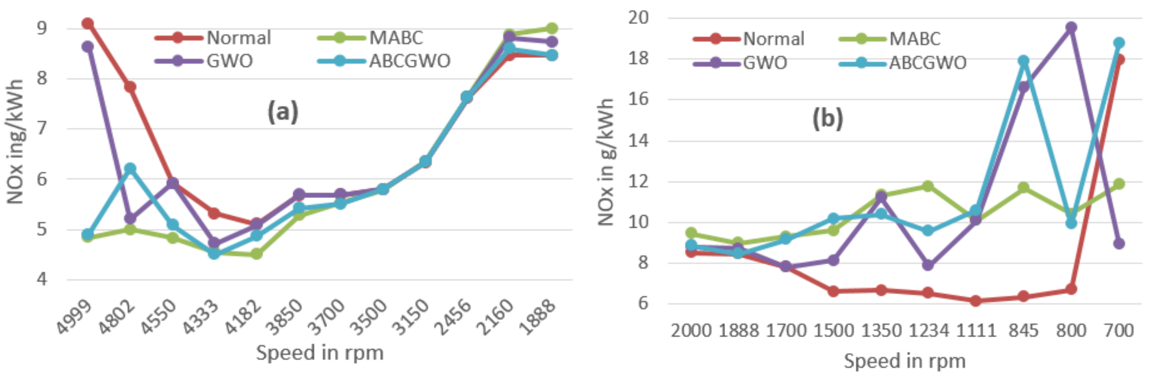


Fig. 6 Comparison of optimized NOx obtained by ABC-GWO with MABC, GWO and normal

It can be seen from Fig. 6 that NOx can be optimized at higher values of speed (i.e., above 4182 rpm from Fig. 6(a) and it is increased for a speed less than 1700 rpm at the compromise of reduction in other optimization parameters. Also, MABC gives lowest values for higher speed followed by ABC-GWO and GWO gives lowest values at lower speed with exceptions mostly followed by ABC-GWO.

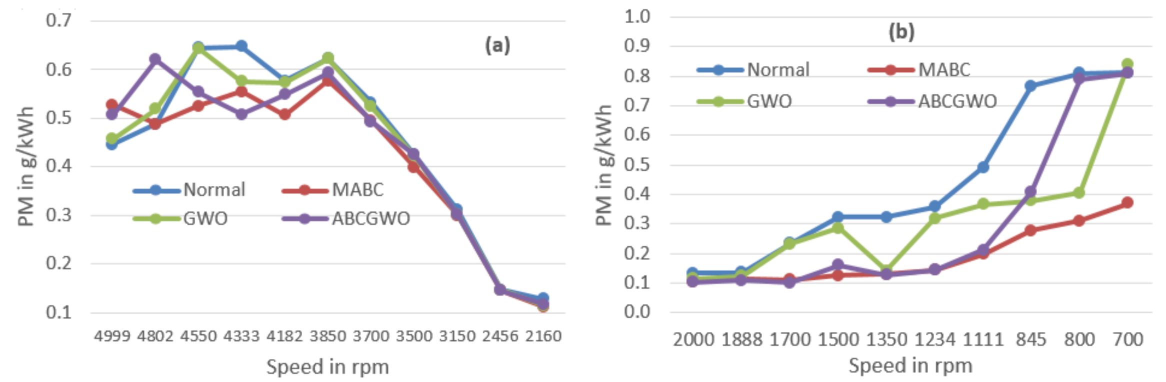


Fig. 7 Comparison of optimized PM obtained by ABC-GWO with MABC, GWO and normal

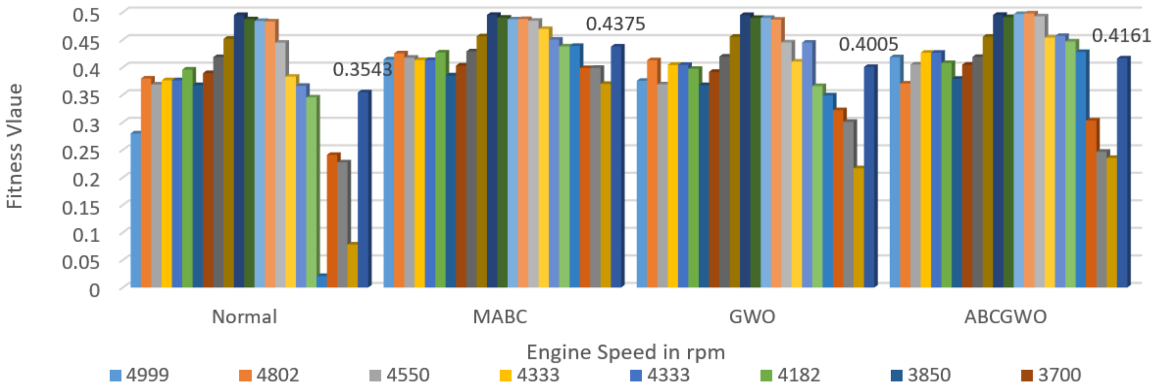


Fig. 8 Fitness value for optimized algorithms

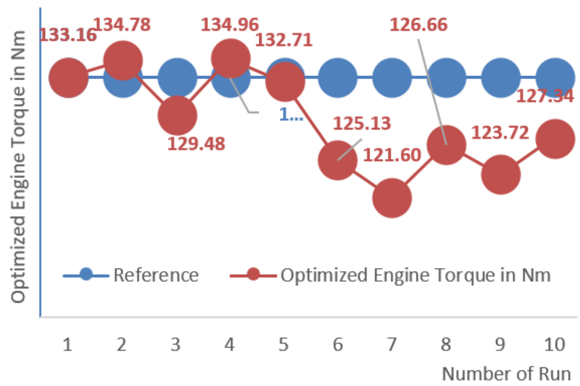


Fig. 9 Repeatability test for optimized torque

It can be seen from Fig. 7 that PM can be optimized at almost all of values of speed with few exceptions as shown in Fig. 7(a). ABC-GWO gives lowest values for lower speed and MABC gives lowest values at higher speed with exceptions.

The fitness function comparison of ABC-GWO with MABC and GWO algorithm at different engine speeds are shown in Fig. 8.

It is observed that average fitness value of hybrid ABC-GWO is better than GWO, however, less than MABC. It is observed that ABC-GWO performs better in the mid and high range of speeds whereas MABC performs better in the lower range of speeds.

For the engine speed requirement of 4000 rpm, hybrid ABC-GWO algorithm has been run for

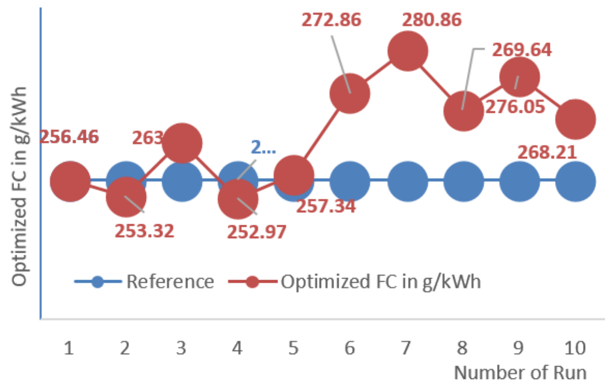


Fig. 10 Repeatability test for optimized specific fuel consumption

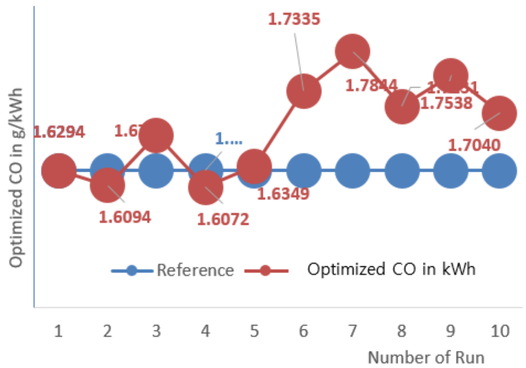


Fig. 11 Repeatability test for optimized CO

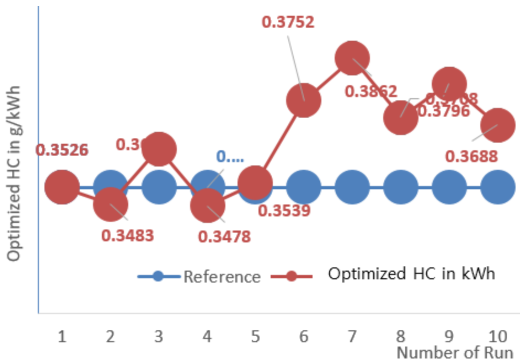


Fig. 12 Repeatability test for optimized HC

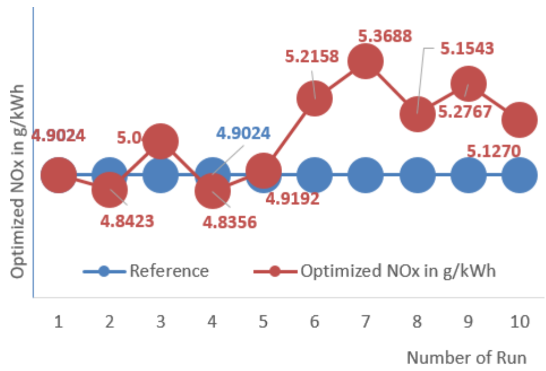


Fig. 13 Repeatability test for optimized NOx

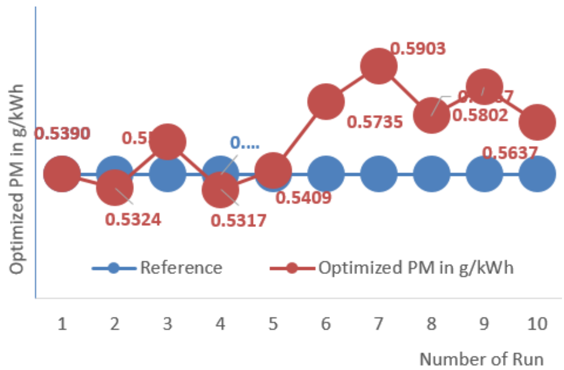


Fig. 14 Repeatability test for optimized PM

10 times to check the consistency of results obtained. It is observed that ABC-GWO algorithm gives deviated results. Figs. 9-13 show the deviations in optimized value with reference to values obtained during the first run.

There are slight deviations in results if same input is applied repeatedly. The deviation in the result for optimized torque is +1.8 Nm and -11.56 Nm w.r.t. first reference value obtains i.e., 133.16 Nm. The deviation in the result for fuel consumption is more i.e., +24.4 g/kWh and -3.49 g/kWh i.e., w.r.t. first reference value obtains i.e., 256.46 g/kWh. However, deviations in CO and HC are observed to be less i.e., +0.1041 g/kWh and -0.0222 g/kWh for CO and +0.0226 and -0.048 g/kWh for HC as seen in Figs. 11 and 12. The NOx and PM variations are observed to be +0.4664, -0.0668 and +0.0513, -0.0073 respectively. It can be seen that ABC-GWO likely to give results on slightly higher values compared to a first reference value.

4. Conclusions

Hybrid ABC-GWO algorithm has proposed and simulated for minimization of specific fuel consumption and emissions for the engine of converted PHEV. Results show that a trade-off is required between emissions and specific fuel consumption to get properly optimized value. The confirmation of results obtained with mapping of the engine and other optimization algorithms like MABC and GWO validates the effectiveness of proposed strategy. The observations are: first, MABC is better in fitness function at lower values of speed with the requirement of more time, GWO is fastest with lowest average fitness value and hybrid ABC-GWO offers comparable fitness function with less time compared to MABC and better fitness function and comparable time with referenced GWO. Second, there is balance in exploitation and exploration. Exploitation is better in a number of cycles whereas exploration is observed over the number of iterations. Third, the deviation in results are observed on the higher side for repeatability of same input and fourth, computation time is around 3 sec to run the complete algorithm for 2 cycles/10 iterations with acceptable results for core i5 processor with 4 GB RAM compared to 4 sec of MABC and 2 sec of GWO. Hence hybrid ABC-GWO can be examined for practicability.

For future work, we are going to use this algorithm for performance analysis of converted PHEV with different driving cycles.

References

Advance Vehicle Simulator Software (2003), FC_CI60_emis.m, National Renewable Energy Laboratory, Colorado, U.S.A.

Al-Atabi, M.T. and Yusaf, T.F. (2002), “Experimental investigation of a single cylinder diesel engine as a hybrid power unit for a series hybrid electric vehicle”, *Proceedings of the Student Conference on Research and Development*, Shah Alam, Malaysia, July.

ARAI (2011), Indian Emission Regulation.

Fact sheet (September 2016), Ambient (outdoor) air quality and health, World Health Organization. http://www.who.int/mediacentre/factsheets/fs313/en.

Fuengwarodsakul, N.H. (2009), “Retrofitting a used car with hybrid electric”, *Proceedings of the IEEE Propulsion System Conference*, Pattaya, Chonburi, Thailand, May.

Ghorbani, R., Bibeau, E. and Filizadeh, S. (2010), “On conversion of hybrid electric vehicles to plug-in”, *IEEE T. Vehicul. Technol.*, **59**(4), 2016-2020. https://doi.org/10.1109/TVT.2010.2041563.

Ghorbani, R., Bibeau, E. and Filizadeh, S. (2013), “Influence of motor power and efficiency on fuel consumption of retrofit-conversion split-parallel hybrid electric vehicle”, *Proceedings of the 2013 IEEE Vehicle Power and Propulsion Conference (VPPC)*, Beijing, China, October.

Gujarathi, P.., Shah, V.A. and Lokhande, M.M. (2018), “Grey wolf algorithm for multidimensional engine optimization of converted plug-in hybrid electric vehicle”, *Transport. Res. Part D Transport Environ.*, **63**, 632-648. https://doi.org/10.1016/j.trd.2018.06.003.

Gujarathi, P.K., Shah, V.A. and Lokhande, M.M. (2015), “Design, modelling and simulation for conversion of conventional Tata Indica Car into plug in hybrid electric vehicle”, *Proceedings of the 20th International Electrical Vehicle Symposium and Exhibition (EVS28)*, Seoul, Korea, May.

Gujarathi, P.K., Shah, V.A. and Lokhande, M.M. (2017), “Fuzzy logic based energy management strategy for converted parallel plug-in hybrid electric vehicle”, *Proceedings of the IEEE 8th Control and System Graduate Research Colloquium (ICSGRC)*, Shah Alam, Malaysia, October.

Gujarathi, P.K., Shah, V.A. and Lokhande, M.M. (2017), “Performance analysis of converted parallel plug-in hybrid electric vehicle”, *Proceedings of the IEEE 8th Control and System Graduate Research Colloquium (ICSGRC)*, Shah Alam, Malaysia, October.

Gujarathi, P.K., Shah, V.A. and Lokhande, M.M. (2018), “Emission reduction and improvement in fuel economy by fuzzy algorithm for converted plug-in hybrid electric vehicle”, *J. Adv. Res. Dyn. Control Syst.*, **10**(6), 1071-1076.

Gujarathi, P.K., Shah, V.A. and Lokhande, M.M. (2019), “Study of fuel economy and emissions for converted plug-in parallel hybrid electric vehicle versus conventional diesel vehicle on standard driving cycles”, *Current Sci. Fortnightly J. Res.*

Gupte, S. (2014), “Experimental analysis and feasibility study of 1400 CC diesel engine car converted into hybrid electric vehicle by using BLDC hub motors”, *Energy Procedia*, **54**, 177-184. https://doi.org/10.1016/j.egypro.2014.07.261.

International Energy Agency (2012), *CO2 Emissions from Fuel Combustion*, International Energy Agency, IEA Statistics 2012.

Jenkins, S. and Ferdowsi, M. (2008), "HEV to PHEV conversion compatibility", *Proceedings of the IEEE Vehicle Power and Propulsion Conference (VPPC)*, Harbin, China, September.

Jenkins, S. and Ferdowsi, M. (2014), "Urban bus fleet conversion to hybrid fuel cell optimal powertrains", *Proceedings of the 16th Meeting of the EURO Working Group on Transportation*, Porto, Portugal, September.

Kaleg, S., Hapid, A. and Kurnia, A.R. (2015), "Electric vehicle conversion based on distance, speed and cost requirements", *Energy Procedia*, **68**, 446-454. https://doi.org/10.1016/j.egypro.2015.03.276.

Karaboga, D. and Akay, B. (2009), "A comparative study of artificial bee colony algorithm", *Appl. Math. Comput.*, **214**(1), 108-132. https://doi.org/10.1016/j.amc.2009.03.090.

Karaboga, D. and Basturk, B. (2007), "Artificial bee colony (ABC) optimization algorithm for solving constrained optimization problems", *Proceedings of the International Fuzzy Systems Association World Congress*, Cancun, Mexico, June.

Karaboga, D. and Basturk, B. (2008), "On the performance of artificial bee colony (ABC) algorithm", *Appl. Soft Comput.*, **8**(1), 687-697. https://doi.org/10.1016/j.asoc.2007.05.007.

McIntyre, M.L., Young, M. and Kessigner, M. (2012), "On conversion of hybrid electric vehicles to plug-in", *Proceedings of the IEEE International Electric Vehicle Conference*, Greenville, South Carolina, U.S.A., March.

Mirjalili, S., Mirjalili, S.M. and Andrew, L. (2014), "Grey wolf optimizer", *Adv. Eng. Softw.*, **69**, 46-61. http://doi.org/10.1016/j.advengsoft.2013.12.007.

Rizzo, G., Sorrentino, M., Speltino, C., Arsie, I., Fiengo, G. and Vasca, F. (2011), "Converting conventional cars in mild hybrid solar vehicles", *IFAC Proc.*, **44**(1), 9715-9720. https://doi.org/10.3182/20110828-6-IT-1002.03319.

Sustainablog (2014), http://sustainablog.org/wp-content/uploads/2014/06/honey-bees-graphic.jpg.

Tara, E., Shahidinejad, S., Filizadeh, S. and Bibeau, S. (2010), "Battery storage sizing in a retrofitted plug-in hybrid electric vehicle", *IEEE T. Vehicul. Technol.*, **59**(6), 2786-2794. https://doi.org/10.1109/TVT.2010.2046659.

Tavares, A.A., Fornasa, I., Cutipa-Luque, J.C., Saldias, C.E.P., Carbonera, L.F.B. and Carvalho, B.E.B. (2019), "Power losses analysis and efficiency evaluation of an electric vehicle conversion", *Proceedings of the IEEE International Conference on Electrical Systems for Aircraft, Railway, Ship Propulsion and Road Vehicles & International Transportation Electrification Conference (ESARS-ITEC)*, Nottingham, U.K., January.

Wirasingha, S.G., Schofield, N. and Emadi, A. (2008), "Feasibility analysis of converting a Chicago Transit Authority (CTA) transit bus to a plug-in hybrid electric vehicle", *Proceedings of the IEEE Vehicle Power and Propulsion Conference (VPPC)*, Harbin, China, September.

Zeman, F. and Lewis, R. (2013), "Retrofitted plug-in hybrid vehicles: Results of NYIT drive share program", *Transport. Res. Part D*, **17**(7), 514-518. https://doi.org/10.1016/j.trd.2012.06.001.

Zhang, P., Yan, F. and Du, C. (2015), "A comprehensive analysis of energy management strategies for hybrid electric vehicles based on bibliometrics", *Renew. Sust. Energy Rev.*, **48**, 88-104. http://dx.doi.org/10.1016/j.rser.2015.03.093.

Zulkifli, S.A., Saad, N., Syaifuddin, M. and Aziz, A.R.A. (2012), "Split-parallel in wheel-motor retrofit hybrid electric vehicles", *Proceedings of the IEEE International Power Engineering and Optimization Conference*, Melaka, Malaysia, June.

Zulkifli, S.A., Saad, N., Syaifuddin, M., Maharun, M., Saad, N. and Aziz, A.R.A. (2012), "Development of split axle parallel hybrid electric vehicles with in wheel-motor", *Proceedings of the 4th International Conference on Intelligent and Advanced Systems (ICIAS2012)*, Kuala Lumpur, Malaysia, June.

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