DOUBLE FOUR-BAR CRANK-SLIDER MECHANISM DYNAMIC BALANCING BY META-HEURISTIC ALGORITHMS

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ABSTRACT

In this paper, a new method for dynamic balancing of double four-bar crank slider mechanism by meta-heuristic-based optimization algorithms is proposed. For this purpose, a proper objective function which is necessary for balancing of this mechanism and corresponding constraints has been obtained by dynamic modeling of the mechanism. Then PSO, ABC, BGA and HGAPSO algorithms have been applied for minimizing the defined cost function in optimization step. The optimization results have been studied completely by extracting the cost function, fitness, convergence speed and runtime values of applied algorithms. It has been shown that PSO and ABC are more efficient than BGA and HGAPSO in terms of convergence speed and result quality. Also, a laboratory scale experimental doublefour-bar crank-slider mechanism was provided for validating the proposed balancing method practically.

KEYWORDS

Mechanism; balancing; BGA; PSO algorithm; ABC algorithm; HGAPSO algorithm

1. INTRODUCTION

Dynamic balancing is one of the important concerns in high speed mechanisms such as crank slider mechanism, a special attention should paid to the inertia-induced force (shaking force) and moment (shaking moment) transmitted to the frame in order to reduce vibration amplitude. The methods of balancing linkages are well developed and documented in [1]. These techniques mostly are based on mass redistribution, addition of counterweights to the moving links, and attachment of rotating disks or duplication of the linkages [2]. In these methods, the shaking forces and shaking moments should be minimized. One of these methods is “Maximum recursive dynamic algorithm” that published by Chaudhary and Saha [3]. Another method which is documented by QI and Pennestrlis [4] is called “refined algorithm”. It presents a numerically efficient technique for the optimum balancing of linkages. In this approach, instead of solving directly the dynamic equations, a technique is introduced to solve the linked dynamic equations in a “shoe string” fashion. The comprehensive mass distribution method, for an optimum balancing of the shaking force and shaking moment is used by Yu [5] to optimal balancing of the spatial RSSR mechanism.

In recent years, optimization techniques have received widespread interest in the engineering sciences. These techniques were initiated, primarily, by the advent of high speed digital computers which give a practical, economical and accurate means of obtaining solutions to

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meaningful problems in the optimization of static and dynamic systems. Dynamic balancing inherently constitutes an optimization problem. For instance, CWB (counterweight balancing) involves a trade-off between minimizing the different dynamic re-actions. Therefore, determining the counterweights' mass parameters is an optimization problem. Also, Alici and Shirinzadeh [6] considered "Sensitivity analysis". In this technique they formulated the dynamic balancing as an optimization problem such that while the shaking force balancing is accomplished through analytically obtained balancing constraints, an objective function based on the sensitivity analysis of shaking moment with respect to the position, velocity and acceleration of the links is used to minimize the shaking moment. Evolutionary algorithms such as GA and PSO are useful in optimization problems, because they are easy to implement for the complex real-world problems. In some cases that objective function could not expressed as an explicit function of design variables, using these evolutionary algorithms is more suitable for optimization than the traditional deterministic optimization methods. Wen-Yi Lin proposed a GA-DE hybrid algorithm for application to path synthesis of a four-bar linkage [7]. Acharyya and Mandal[8]applied BGA with multipoint crossover, the PSO with the CFA (constriction factor approach) and the DE to the path synthesis of a four-bar linkage. Jaamiolahmadi and Farmani [9] proposed another related work. They described the application of GA to force and moment-balance of a four bar linkage.
The aim of present work is applying new artificial intelligent based optimization methods for balancing double four-bar crank slider mechanism which is a special case of four-bar mechanism, but it has its own specification in dynamic balancing. Ettefagh and Abbasidoust [10] applied BGA for balancing of a crank slider mechanism, however in present work a comprehensive study of different algorithms proposed for balancing of a crank slider mechanism was carried out. The major objective of this paper is to compare the computational effectiveness and efficiency of BGA (Binary Genetic Algorithm), PSO (Particle Swarm Optimization), ABC (Artificial Bee Colony) and HGAPSO (Hybrid GA and PSO) algorithms. The performance of the optimization techniques in terms of computational time and convergence rate is compared in the results section. After kinematics formulating of the mechanism and extracting the object function with its' constraints, results of the proposed method on a simulated mechanism will be reported. Finally, for experimentally validation of the method, a laboratory scale experimental crank slider mechanism will be considered and the proposed optimization method will be applied for its balancing.

2. MODELLING

The selected mechanism in this paper is shown in Figure 1, which is a benchmark double four-bar mechanism and this mechanism is applied in different machines [10]. Therefore the proposed balancing method in this paper may be easily applied to other mechanisms in different machines for balancing. As shown in Figure 1, the mechanism contains two cranks-sliders and four rotating disks. Each rode is attached to disk 1 and disk 4. All disks are connected to a shaft which is rotating with an electromotor. When the mechanism is working, shaking force and moments cause frame to vibrate. Our goal is to minimize shaking forces and moments according to the regarded constraints. The mechanism is modeled as shown in Figure 2 by computing shaking forces of the mechanism on all four planes.

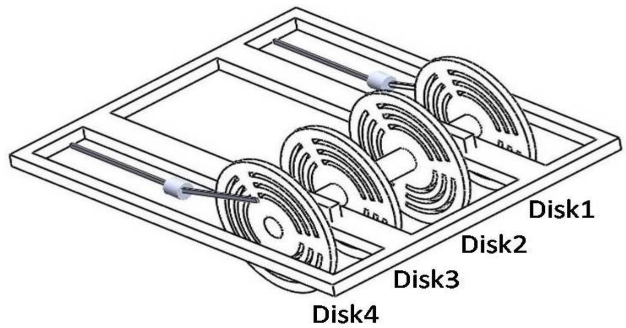


Figure 1.Schematic diagram of the considered double four-bar crank-slider mechanism [10]

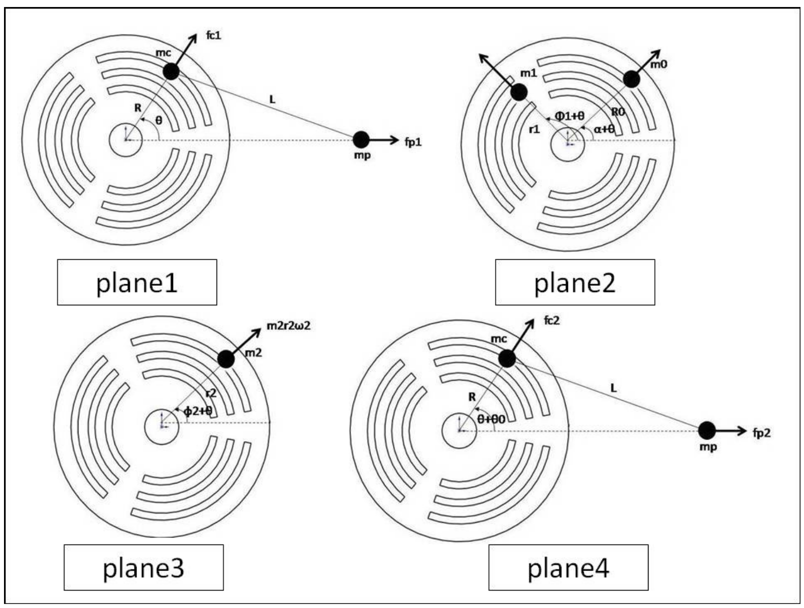


Figure 2.Shaking forces of the mechanism on all four plans [10]

In this paper, the method used for balancing is the addition of two counterweights on disks 2 and 3. In addition, system has an unbalance mass on disk 2. Shaking forces in crank slider as the dynamical forces of mechanism are formulated as:

$$f_c = m_c R\omega^2 \tag{1}$$

$$f_p = m_p R\omega^2 (\cos\theta + \frac{R}{L}\cos 2\theta) \tag{2}$$

Where m_c is the eccentric mass and m_p is the equal mass of the slider, R is corresponding radius and ω is mechanism rotating speed. Also, θ indicates the angular position of the disk and L is the connecting rod's length. Equilibrium on x and y axes due to the acting forces are described by:

$$\sum F_x = 0 \rightarrow$$
$$m_p R\omega^2 (\cos\theta + \frac{R}{L}\cos 2\theta) + m_c R\omega^2 \cos\theta + m_0 R_0 \omega^2 \cos(\theta+\alpha) + m_1 r_1 \omega^2 \cos(\theta+\varphi_1) + m_2 r_2 \omega^2 \cos(\theta+\varphi_2) +$$
$$m_p R\omega^2 (\cos(\theta+\theta_0) + \frac{R}{L}\cos 2(\theta+\theta_0)) + m_c R\omega^2 \cos(\theta+\theta_0) = 0 \quad (3)$$
$$\sum F_y = 0 \rightarrow$$
$$m_c R\omega^2 \sin\theta + m_0 R_0 \omega^2 \sin(\theta+\alpha) + m_1 r_1 \omega^2 \sin(\theta+\varphi_1) + m_2 r_2 \omega^2 \sin(\theta+\varphi_2) +$$
$$m_c R\omega^2 \sin(\theta+\theta_0) = 0 \quad (4)$$

Also Momentum equilibrium equations are written as:

$$\sum M_y = 0 \rightarrow$$
$$\left[m_0 R_0 \omega^2 \cos(\theta+\alpha) + m_1 r_1 \omega^2 \cos(\theta+\varphi_1)\right] a_1 + \left[m_2 r_2 \omega^2 \cos(\theta+\varphi_2)\right](a_1 + a_2) +$$
$$\left[m_p R\omega^2 (\cos(\theta+\theta_0) + \frac{R}{L}\cos 2(\theta+\theta_0))\right](2a_1 + a_2) + \left[m_c R\omega^2 \cos(\theta+\theta_0)\right](2a_1 + a_2) = 0 \quad (5)$$
$$\sum M_x = 0 \rightarrow$$
$$\left[m_0 R_0 \omega^2 \sin(\theta+\alpha) + m_1 r_1 \omega^2 \sin(\theta+\varphi_1)\right] a_1 + \left[m_2 r_2 \omega^2 \sin(\theta+\varphi_2)\right](a_1 + a_2) +$$
$$\left[m_c R\omega^2 \sin(\theta+\theta_0)\right](2a_1 + a_2) = 0 \quad (6)$$

m_0 is the constrain mass on disk 2, R_0 and α are corresponding radius and angular position of the mass, respectively.

In construction of optimization problems, as described before, some parameters of system is applies as the variables of cost function to minimize it. In our method, m_1, m_2, φ_1, φ_2, r_1 and r_2 are counterweights parameters that are unknown. We take r_1 and r_2 as known parameters. So we define the cost function as below. The cost function is consisting of forces equations and the constraints are considered by moment equations. For this purpose, we define some parameters as P_1, P_2, P_3 and P_4 as below:

$$P_1(\theta) = \sum F_x \quad , \quad P_2(\theta) = \sum F_y \quad (7)$$
$$P_3(\theta) = \sum M_x \quad , \quad P_4(\theta) = \sum M_y \quad (8)$$

These parameters are the sum of forces and moments in x, y direction. Consequently, the cost function is:

$$\text{Cost function: } f(m_1,m_2,\varphi_1,\varphi_2) = \int \{|P_1(\theta)| + |P_2(\theta)|\} dA \quad (9)$$

The cost function is a function of the parameters m1, m2, φ1 and φ2, which should be found. In other words, the cost function is the area that $\{|P_1(\theta)| + |P_2(\theta)|\}$ makes in polar system. Our goal is to minimize this area. Additionally, by defining C1 and C2 as follows:

$$C1(m_1,m_2,\varphi_1,\varphi_2) = \int |P_3(\theta)| dA \quad (10)$$
$$C2(m_1,m_2,\varphi_1,\varphi_2) = \int |P_4(\theta)| dA \quad (11)$$

Constraints are considered such that C1 and C2 to be less than predefined values which determined by searching among the maximum value of them during running the Meta-Heuristic Algorithms.

3. APPLYING META-HEURISTIC ALGORITHMS

PSO, ABC and HGAPSO algorithms, which is introduced in summary in following section, are applied for minimizing the mentioned cost function with defined constraints as it was described in previous section.

3.1. Particle Swarm Optimization algorithm

The PSO method introduced for the first time in 1995 by Kennedy and Eberhart [11]. This method based on social behavior of organisms such as fish schooling and bird flocking. Because of its simple concept and quick convergence, PSO can be applied to various applications in different fields. The approach uses the concept of population and a measure of performance like the fitness value used with other evolutionary algorithms. Similar to other evolutionary algorithms, the system is initialized with a population of random solutions, called particles.
Each particle maintains its own current position, its present velocity and its personal best position explored so far. The swarm is also aware of the global best position achieved by all its members. The iterative appliance of update rules leads to stochastic manipulation of velocities and flying courses. During the process of optimization the particles explore the D-dimensional space, whereas their trajectories can probably depend both on their personal experiences, on those of their neighbors and the whole swarm, respectively. In every iteration, each particle is updated by following the best solution of current particle achieved so far ($Pbest$) and the best of the population ($gbest$). When a particle takes part of the population as its topological neighbours, the best value is a local best. The particles tend to move to good areas in the search space by the information spreading to the swarm. The particle is moved to a new position calculated by the velocity updated at each time step t. This new position is calculated as the sum of the previous position and the new velocity by equation (12).

$$v_i^{t+1} = wv_i^t + c_i rand(0,1)\left(Pbest_i - x_i^t\right) + c_i rand(0,1)\left(gbest_t - x_i^t\right) \tag{12}$$

The velocity updated as following equation:

$$x_i^{t+1} = x_i^t + v_i^{t+1} \tag{13}$$

The parameter w is called the inertia weight and controls the magnitude of the old velocity v_i^t in the calculation of the new velocity which isv_i^{t+1} , whereas the acceleration factors $C_1$and C_2determine the significance of $Pbest$ and $gbest$ respectively. In the present work we selected C_1=0.25 and C_2 =0.15. Furthermore,$x_i^t$is the current particle position and $x_i^{t+1}$is the new position of the particle. $rand(0,1)$ is the random number uniformly distributed. In general, the inertia weight w is set according to the following equation:

$$w = w_{max} - \left(\frac{w_{max} - w_{min}}{Ir_{max}}\right) \times Iter \tag{14}$$

Where w_{max} is initial weight, w_{min} is final weight, Ir_{max} is the maximum number of iteration (generation) and $Iter$is current iteration number.

Main steps of the procedure are:

1. Position and initial velocity of particles are generated randomly.
2. The objective function value i calculated for each particle.

3. $Pbest$ For each particle is considered equal to its initial position (In the first iteration). Also $gbest$ determined.
4. Modify position and velocity of each particle using the equations (12) and (13).
5. Calculate the overall objective function for each particle.
6. If the value of new overall objective function is better than the value of each particle in *P-best*, then it would be replaced in *P-best* and if in whole new population gets found which is better fitting in objective function would be replaced by *g-best*.
7. Repeat steps 4 to 7 to reach the maximum number specified .The final answer is obtained from the $gbest$in the last iteration.

Figure 3 shows the flowchart of the developed PSO algorithm [11].

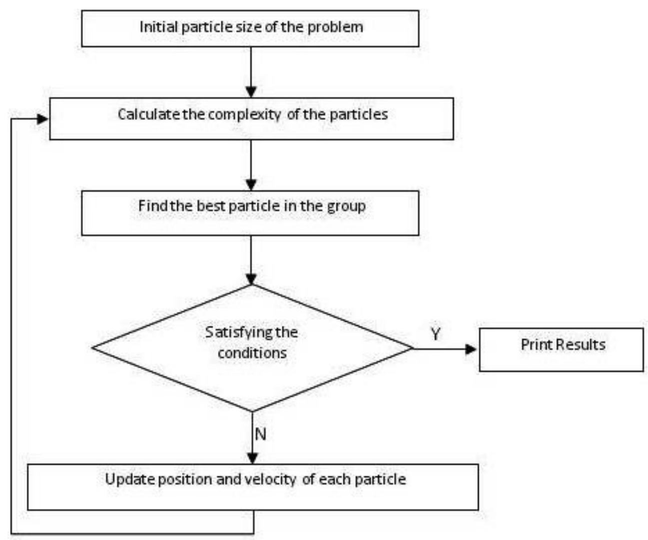


Figure 3. Flowchart of the PSO algorithm

3.2. Artificial Bee Colony algorithm

The artificial bee colony (ABC) algorithm is a new population-based stochastic heuristic approach which was introduced for the first time by Karaboga in 2005 [12]. This algorithm is very simple and flexible, which does not require external parameters like crossover rates, especially suitable for engineering application. The colony of artificial bees consists of three groups of bees to search foods generally, which includes employed bees, onlookers and scouts. The first half of colony consists of the employed artificial bees and the second half includes the onlookers. The employed bees search the food around the food source in their memory. They perform waggle dance upon returning to the hive to pass their food information to the other of the colony (the onlookers). The onlookers are waiting around the dance floor to choose any of the employed bees to follow based on the nectar amount information shared by the employed bees. The employed bee whose food source has been exhausted by the bees becomes a scout who must find new food source. For every food source, there is only one employed bee. In other words, the number of employed bees is equal to the number of food sources around the hive. The onlooker bee chooses probabilistically a food source depending on the amount of nectar shown by each employed bee, see equation (15).

$$P_i = \frac{fit_i}{\sum_{n=1}^{SN} fit_i} \tag{15}$$

Where fit_i is the fitness value of the solution i and *SN* is the number of food sources which are equal to the number of employed bees.

Each bee searches for new neighbor food source near of their hive. After that, employed bee compares the food source against the old one using equation 16. Then, it saves in their memory the best food source [13-14].

$$V_{ij}^{new} = x_{ij}^{old} + \varphi_{ij}\left(x_{ij}^{old} - x_{kj}^{old}\right) \tag{16}$$

Where $k \in \{1,2,3,\dots,NP\}$ and $j \in \{1,2,3,\dots,n\}$ are chosen randomly. φ_{ij} is a random number between [-1, 1]. In ABC, Providing that a position cannot be improved further through a predetermined number of cycles, then that food source is assumed to be abandoned. The value of predetermined number of cycles is an important control parameter of the ABC algorithm, which is called "limit" for abandonment. Assume that the abandoned source is x_i and *j= {1, 2… N}* then the scout discovers a new food source to be replaced withx_i. This operation can be defined using equation 17.

$$x_i^j = x_j^{min} + rand(0,1)\left(x_j^{max} - x_j^{min}\right) \tag{17}$$

ABC implementation stages of the algorithm:

1. Initialization
2. Place employed bees on the food sources
3. Place onlookers on the food sources
4. Send scout to carry out the global search

Flowchart of the ABC algorithm is shown in figure4 [12].

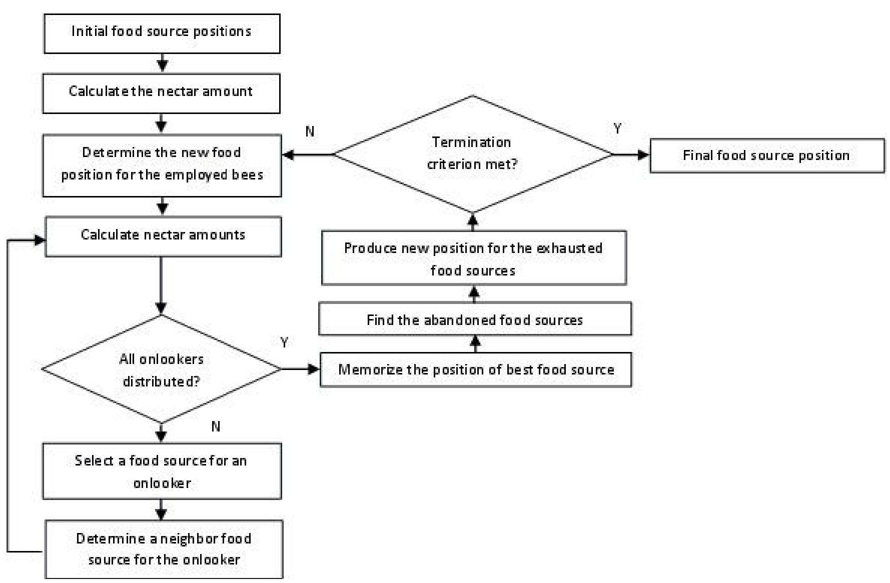


Figure 4. Flowchart of the ABC algorithm

3.3. Hybrid of Genetic Algorithm and Particle Swarm Optimization (HGAPSO)

Concept of GA:

Genetic algorithm was introduced by John Holland in 1967. Later, in1989, by Goldberg's attempts got accepted. And today, due to its capability, it has prosperous place among other methods. Routine optimization in genetic algorithm bases on random- directed procedure. In this way depending on Darwin's theory of evolution and fundamental ideas the method has been firmed. First of all, for some constants which are called population, a swarm of main parameters, eventually get produced. After performing scalar simulator program, a number that is attributed as standard deviation or set fitness data, impute as a member of that population. Fitness process is done for all created members then by summoning genetic algorithm operators such as succession (crossover), mutation and next generation selection (selection) are formed. This routine continues till satisfying convergence [15].

Concepts of PSO:

Initially, velocity and position of each particle randomly select and direct all particles gradually to the best answer. PSO has high speed in local and total search. Applying PSO takes to dominate rapid and untimely convergence of GA that is achieved with elitism operations. Also, PSO can fit particles of each generation whereas GA is seeking for an answer generation to generation. Depending on these points, GA and PSO are good supplements of each other [16].

The HGAPSO algorithm is following as bellow:

1. A population randomly should be selected, initially, which is parameters of GA and particles of PSO.
2. The fitness of concluding is calculating.
3. Half of population with high fitness would be selected and then PSO function would be performed. But a factor breeding ratio was presented with φsymbol [17]. The factor determines the percentage of population on which the PSO operation is done.
4. Enhanced elites would be transmitted to the next generation directly and mutation and remixing functions would be done on the rest population.

Figure 5 shows all the above steps and flowchart of the HGAPSO algorithm is shown in Figure6 [16].

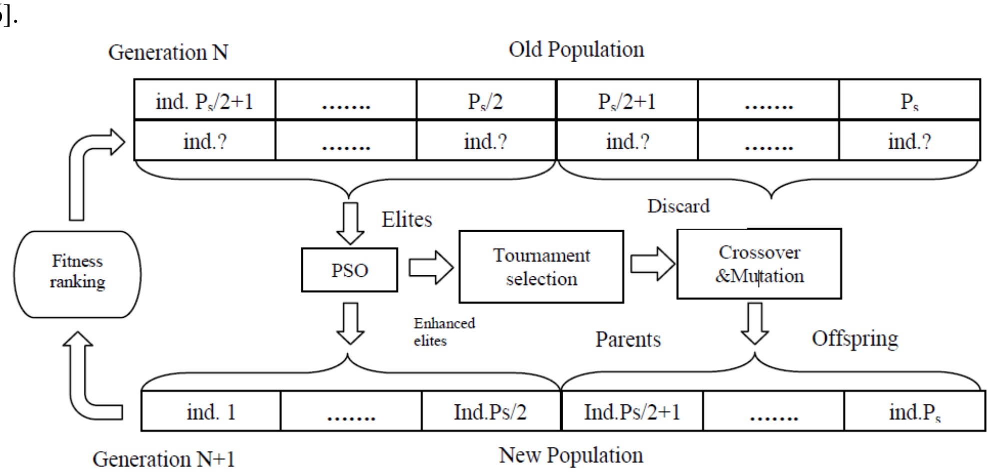


Figure5. Steps of HGAPSO algorithm [16]

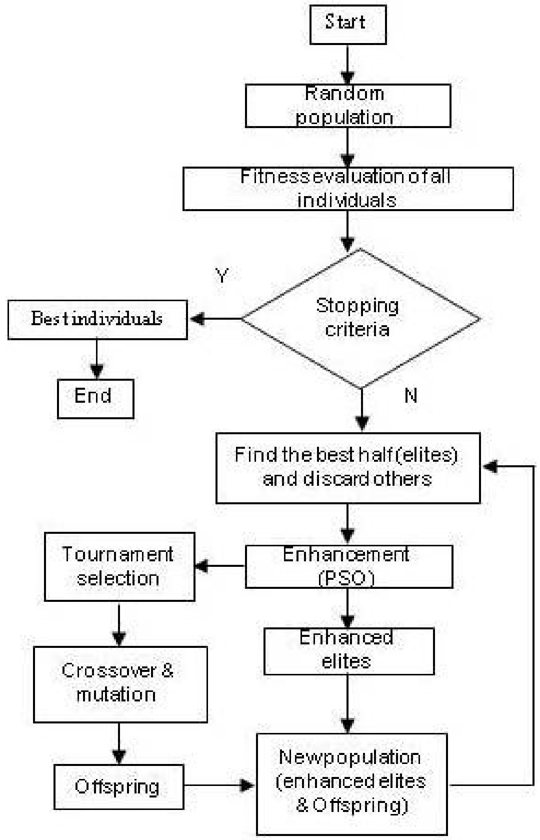


Figure 6. Flowchart of the HGAPSO algorithm

4. RESULTS AND DISCUSSION

In this section the results of mentioned algorithms implementation in our optimization problem for minimizing cost function will be presented and discussed. Table 1 expresses the results of dynamic balancing optimization with PSO, ABC, BGA and HGAPSO algorithms for 200 and 300 iterations. Also programming is done with MATLAB12, with 2.8 GHZ computer system processor and 1024MB memory. By these tables, best and worst average results are shown in bold. Results comparison indicates that PSO algorithm is more efficient than other algorithms, as the average cost of objective function for 20 iterations is 29853.35062, and for 300 iterations is 29853.30955 that is less than three other algorithms.

Table 1. Results of dynamic balancing optimization with PSO, ABC, BGA and HGAPSO algorithms for 200 and 300 iterations

Statistical Results Obtained by the BGA algorithm for 200 Generation

Experiment	M1	M2	Fi1	Fi2	Cost	CPU Time
#1	425.2199	770.088	2.260227	4.907395	29917.7403	27.816430
#2	200	312.61	3.144664	4.710854	30037.9671	29.935968
#3	425.2199	648.6804	2.395349	4.944247	29982.0926	28.821098
#4	305.5718	374.1935	3.722004	5.220633	29854.0986	28.366290
#5	312.61	648.6804	2.352356	4.876685	29914.4407	32.985386
#6	368.915	789.4428	1.228384	4.391474	29928.107	32.076005
#7	1183.5777	1099.1202	2.9419802	5.7979735	30043.6419	28.184769
#8	555.4252	310.8504	3.924688	6.04365	29876.8727	28.312547
#9	425.2199	873.9003	1.959273	4.802982	29867.9256	31.578058
#10	536.0704	407.6246	5.312762	3.138522	29895.7188	30.211240
Average					**29931.86**	**29.82878**
Best					**29854.1**	**27.81643**
Worst					**30043.64**	**32.98539**

Statistical Results Obtained by the ABC algorithm for 200 Iterations

Experiment	M1	M2	Fi1	Fi2	Cost	CPU Time
#1	957.917	878.0169	9.631981	4.870459	29853.8571	24.515309
#2	458.3323	857.7992	8.598309	5.188452	29854.7879	24.497529
#3	1131.1942	1101.4885	9.2855979	1.8518603	29856.3607	25.638495
#4	217.0502	221.4425	10.7222	13.26839	29854.8753	25.814662
#5	260.4993	623.3153	8.486066	11.19885	29855.1337	26.448376
#6	677.15	321.5682	10.37823	6.049843	29854.5122	28.761479
#7	1237.6854	960.86413	10.019323	5.8620878	29856.5621	27.566192
#8	746.1877	749.8799	6.339937	9.548391	29854.274	27.581421
#9	639.2974	315.6203	7.741611	12.66076	29855.4856	27.869337
#10	683.5569	888.9545	2.799224	3.648658	29854.6395	27.622605
Average					**29855.04881**	**26.6315405**
Best					**29853.8571**	**24.497529**
Worst					**29856.5621**	**28.761479**

Statistical Results Obtained by the BGA algorithm for 300 Generation

Experiment	M1	M2	Fi1	Fi2	Cost	CPU Time
#1	585.3372	416.4223	3.777281	5.94538	29860.512	69.617549
#2	537.8299	845.7478	0.393083	3.881694	29979.2346	75.797888
#3	363.6364	536.0704	3.040251	5.208349	29900.57	70.299023
#4	620.5279	0.7861659	4.121229	256.305	29988.9287	61.185702
#5	397.0674	648.6804	2.745439	5.128504	29896.1839	67.436636
#6	321.4076	529.0323	5.920812	3.90012	29866.535	73.210396
#7	228.1525	690.9091	1.940847	4.710854	29866.4603	85.515155
#8	200	564.2229	1.670603	4.465177	29976.0744	67.414340
#9	268.6217	310.8504	3.924688	5.067085	29864.7926	65.666551
#10	485.044	423.4604	3.531605	5.650567	29900.5253	77.981415
Average					**29909.98**	**71.41247**
Best					**29860.51**	**61.1857**
Worst					**29988.93**	**85.51516**

Statistical Results Obtained by the ABC algorithm for 300 Iterations

Experiment	M1	M2	Fi1	Fi2	Cost	CPU Time
#1	889.97288	1026.2293	6.8552951	13.822746	29856.0266	40.422035
#2	374.24233	1405.1666	7.839461	10.87474	29859.7044	42.796960
#3	260.895	501.8795	7.752119	10.27209	29854.4018	40.764053
#4	1624.3941	1153.022	10.633852	7.5664349	29855.7171	43.498866
#5	843.7006	359.6281	11.00391	8.106481	29854.1593	45.076684
#6	772.2693	653.4779	5.531582	9.657654	29854.0499	48.079070
#7	2632.9495	1494.202	4.5137612	7.6742805	29854.0659	48.203408
#8	1440.1067	1182.0524	10.868796	9.1406666	29854.8792	47.887119
#9	782.1371	569.479	9.691396	6.195521	29855.4519	49.274214
#10	655.3956	612.1464	9.454865	5.618574	29853.7587	45.614997
Average					**29855.22148**	**45.1617406**
Best					**29853.7587**	**40.422035**
Worst					**29859.7044**	**49.274214**

Statistical Results Obtained by the PSO algorithm for 200 Iterations

Experiment	M1	M2	Fi1	Fi2	Cost	CPU Time
#1	945.7894	457.6034	4.413292	7.388778	29853.3719	13.877018
#2	464.4661	715.8224	9.17736	5.266925	29853.3846	13.174372
#3	83.58313	483.6949	5.854242	10.68152	29853.3894	12.264391
#4	142.892	479.2902	6.42547	11.13792	29853.4599	12.552338
#5	190.3871	344.1711	7.216235	11.11191	29853.3813	12.357725
#6	112.7041	583.2056	6.888962	10.70696	29853.305	13.300798
#7	156.9876	467.6164	5.76949	10.52967	29853.2973	13.855493
#8	1201.8414	738.00028	4.2686516	10.352361	29853.2971	14.755708
#9	527.3684	161.494	10.53725	6.146666	29853.3101	13.943058
#10	766.8097	318.9964	11.13244	8.445869	29853.3096	12.585938
Average					**29853.35062**	**13.2666839**
Best					**29853.2971**	**12.264391**
Worst					**29853.4599**	**14.755708**

Statistical Results Obtained by the HGAPSO algorithm for 200 Generation

Experiment	M1	M2	Fi1	Fi2	Cost	CPU Time
#1	1319.7893	1775.2657	6.7011554	6.7630704	30080.102	32.479893
#2	352.3594	690.4537	9.285448	9.868578	29960.9037	34.840757
#3	476.5722	573.7634	9.527518	9.562658	30036.1098	34.614229
#4	828.16894	1221.9607	8.309838	9.2001952	29943.6233	34.057494
#5	1841.2912	1609.2847	6.4433827	9.4164658	29994.6861	33.216922
#6	1508.8175	772.7226	7.3714832	7.1583033	30080.1051	33.737740
#7	1036.9438	1116.5328	7.1023018	9.321701	30033.1305	35.140728
#8	1494.2831	632.94301	9.5999394	9.6251599	30069.7696	34.970999
#9	763.2089	318.8483	7.74299	7.563557	30040.2645	34.003678
#10	1129.1558	619.2222	9.6453097	6.6337606	30060.2337	35.567686
Average					**30029.89283**	**34.2630126**
Best					**29943.6233**	**32.479893**
Worst					**30080.1051**	**35.567686**

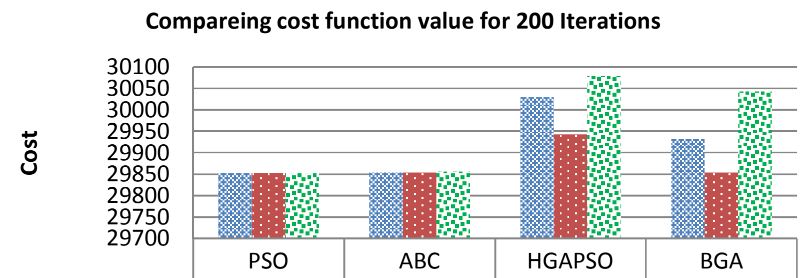
Statistical Results Obtained by the PSO algorithm for 300 Iterations.

Experiment	M1	M2	Fi1	Fi2	Cost	CPU Time
#1	393.2882	107.7893	7.67673	14.09963	29853.3602	21.686771
#2	244.4886	443.838	9.758278	8.21717	29853.297	21.145141
#3	388.6466	160.5542	11.11079	7.028177	29853.2968	20.927836
#4	384.6346	115.9811	10.82956	7.769524	29853.3014	20.836519
#5	262.538	702.0516	5.413787	7.99123	29853.3227	21.101022
#6	360.6737	355.9938	8.498214	6.902059	29853.3127	20.567431
#7	428.9131	143.0469	7.97523	6.787767	29853.2976	22.235461
#8	349.7185	152.8699	10.91113	10.70469	29853.2995	21.991660
#9	1370.8073	960.25814	10.353903	6.9624157	29853.2968	22.241028
#10	493.1262	83.99186	83.99186	5.966398	29853.3108	21.751784
Average					**29853.30955**	**21.4484653**
Best					**29853.2968**	**20.567431**
Worst					**29853.3602**	**22.241028**

Statistical Results Obtained by the HGAPSO algorithm for 300 Generation.

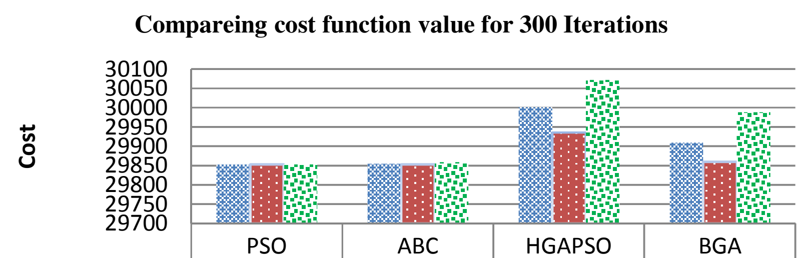
Experiment	M1	M2	Fi1	Fi2	Cost	CPU Time
#1	772.9007	595.1176	6.86203	7.937233	30073.0299	51.955371
#2	882.80336	1896.9992	7.2606345	9.959396	29955.7353	55.753747
#3	375.9766	405.99	7.360915	9.92088	30037.4567	55.435066
#4	355.42156	1227.6115	9.7068992	9.2411975	29982.7794	55.902381
#5	1572.9019	874.43037	7.0439925	8.9360977	30068.9326	55.842394
#6	398.9521	827.0116	7.097475	8.669514	30007.8626	54.642494
#7	1411.5414	574.13944	8.6237598	6.9623394	29936.2702	56.950295
#8	1856.2111	871.64681	7.7394652	9.7647663	30046.7941	56.097725
#9	1827.0208	321.74463	8.1571052	9.2847123	29968.9997	56.730746
#10	770.12423	1724.5737	9.4666394	8.4071409	29951.5584	55.731429
Average					**30002.94189**	**55.5041648**
Best					**29936.2702**	**51.955371**
Worst					**30073.0299**	**56.950295**

Also, above mentioned results in the table are illustrated in Figures7 and 8 in bar chart which show the comparison of objective function cost. By observing these figures, it may be concluded that the cost order is as following: PSO<ABC<BGA<HGAPSO.



	PSO	ABC	HGAPSO	BGA
Average Cost	29853.35062	29855.04881	30029.89283	29931.86
Best Cost	29853.2971	29853.8571	29943.6233	29854.1
Worst Cost	29853.4599	29856.5621	30080.1051	30043.64

Figure7. Comparing cost function value for 200 Iterations



	PSO	ABC	HGAPSO	BGA
Average Cost	29853.30955	29855.22148	30002.94189	29909.98
Best Cost	29853.2968	29853.7587	29936.2702	29860.51
Worst Cost	29853.3602	29859.7044	30073.0299	29988.93

Figure8 . Comparing cost function value for 300 Iterations

In addition, the runtime comparison shows that PSO algorithm finds the optimal solution in shorter time than the others. Also the average runtime for this algorithm for 200 iterations is 13.2666839 seconds and for 300 iterations is 21.4484653 seconds. According to numerical results PSO algorithm is 3.84 times faster than BGA and 2.56 times faster than HGAPSO and 2.21 times faster than ABC. Figures 9 and 10 indicate the runtime of these algorithms for one performance with 200 and 300 iterations, respectively. By observing these figures, it maybe found that the runtime order is as following: PSO<ABC<HGAPSO<BGA. It should be mentioned that the runtime for Hybrid algorithm of BGA and PSO algorithm is 1.5 times faster than BGA algorithm in reaching optimal solution.

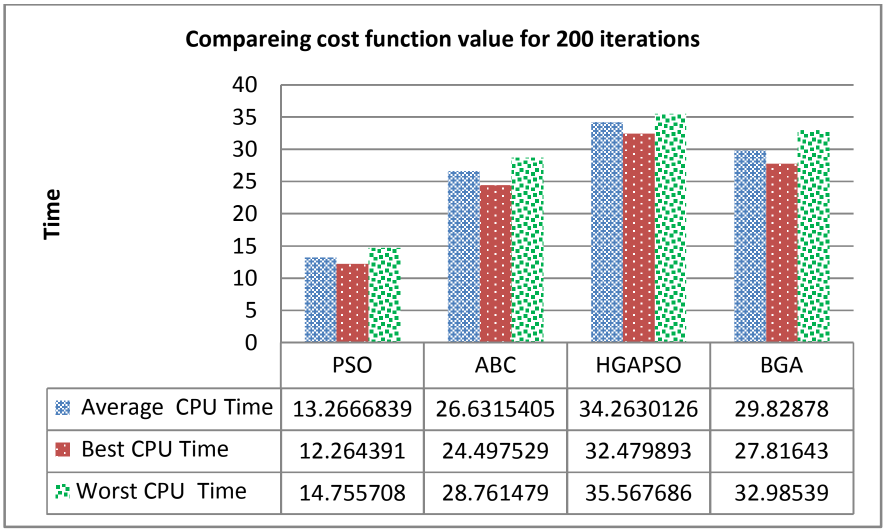


Figure 9. Comparing runtime for 200 iterations

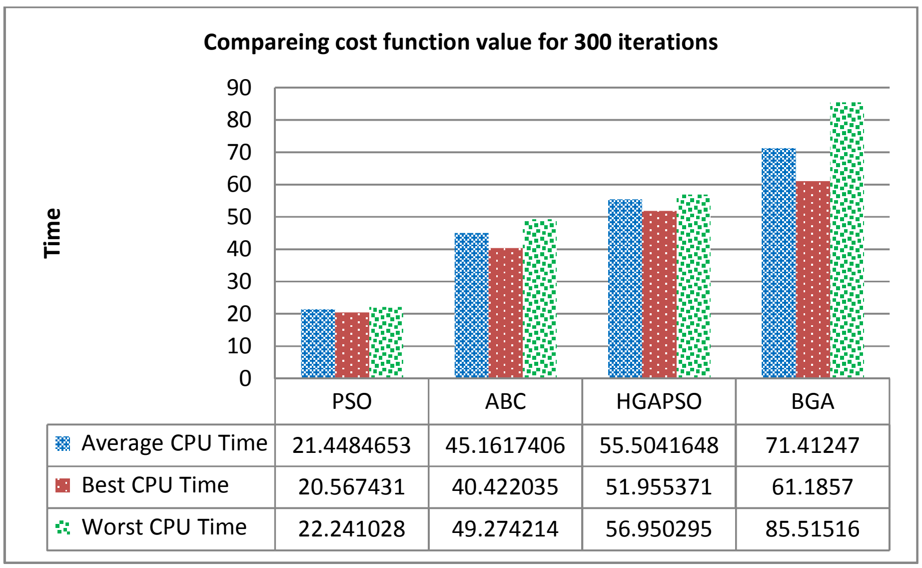


Figure 10. Comparing runtime for 300 iterations

Figure 11 indicates the time order of these algorithms for one performance with 100 and 200 repetitions. In this chart, the implementation of time progress of these algorithms is in term of seconds.

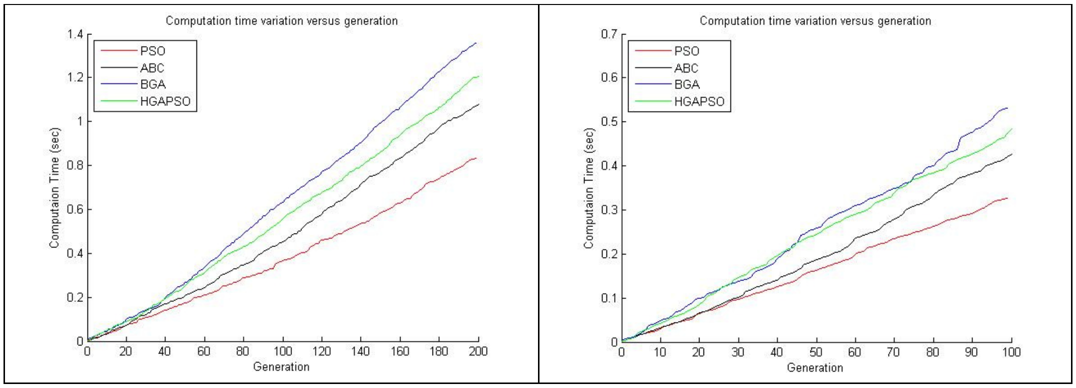


Figure 11. Computation time variation versus generation for 100 iterations
(Left) and 200 iterations (right)

Figure 12 shows fitness functions of four algorithms in 100 runs. In this figure the range of fluctuation of fitness value for BGA and HGAPSO algorithms is between 29853 and 29855, while this range for BGA and HGAPSO is approximately between 29853 and 30200. Also high difference between the best and worst result of the BGA and HGAPSO algorithms indicates the weakness and dependence of these two algorithms and their sensitivity to the initial population, while PSO and ABC solution range is around the mean values, so it indicates the stability of them. Also, the PSO and ABC algorithms are close to average result that this matter indicates the stability of these two algorithms.

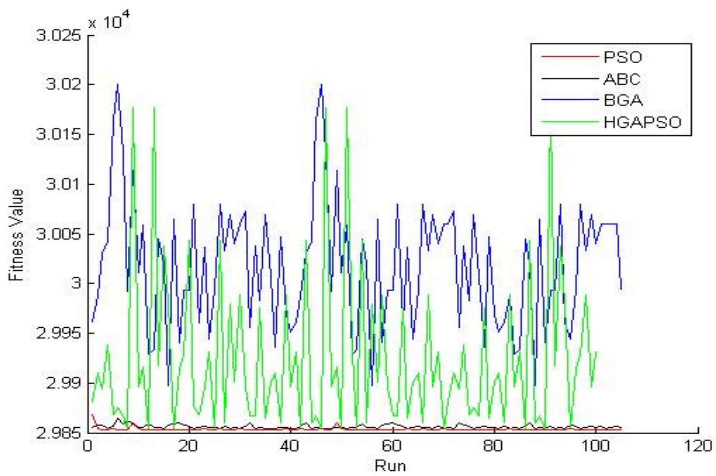


Figure12. Fitness functions fluctuation for 100 runs for four algorithms

Figure 13 and 14 display the four algorithms convergence in a sample run of them (for 200 and 300 iterations). According to the minimization target, an important point which should be considered is that the charts are descending. In addition the scale of 10^4 is using for measuring of objective function. As comparing of these two figures, it may be observed that the PSO and ABC algorithms get convergence approximately after 30 generations also they achieve the optimized solution in high speed rather than HGAPSO and GA.

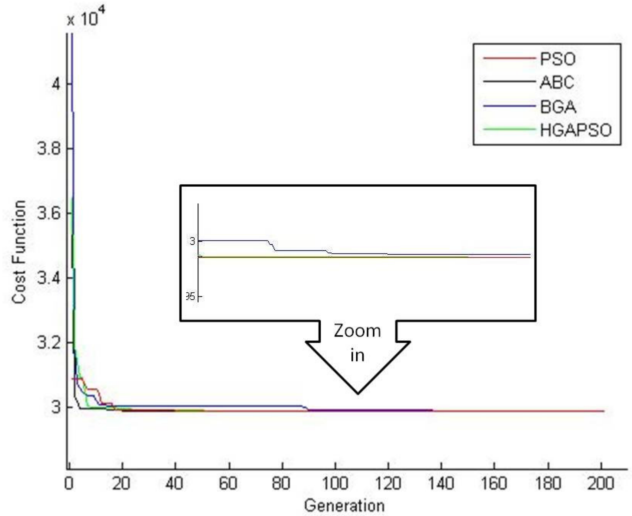


Figure13.Convergence plot for 200 iterations

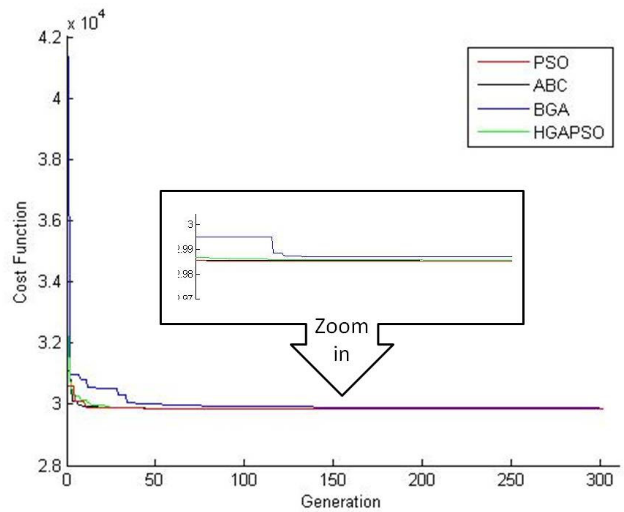


Figure14.Convergence plot for 300 iterations

Finally, Figure15 indicates cost function diagram in balanced and unbalanced states by mentioned algorithms in polar plot. This type of plot is a standard plot which applied for illustrating the ability of the proposed method in balancing of the mechanism in one revolution of the mechanism driver (0-360^{o}). As it was described in previous sections, the main purpose of optimization is minimizing of the cost function in equation 9 which maybe interpreted as minimizing the limited area in the mentioned plot. Therefore better balancing method is a method which has minimum and uniform area in the polar plot. By observing this figure, it maybe concluded that PSO has better performance than other algorithm, because it contains minimum area in comparing with other algorithms.

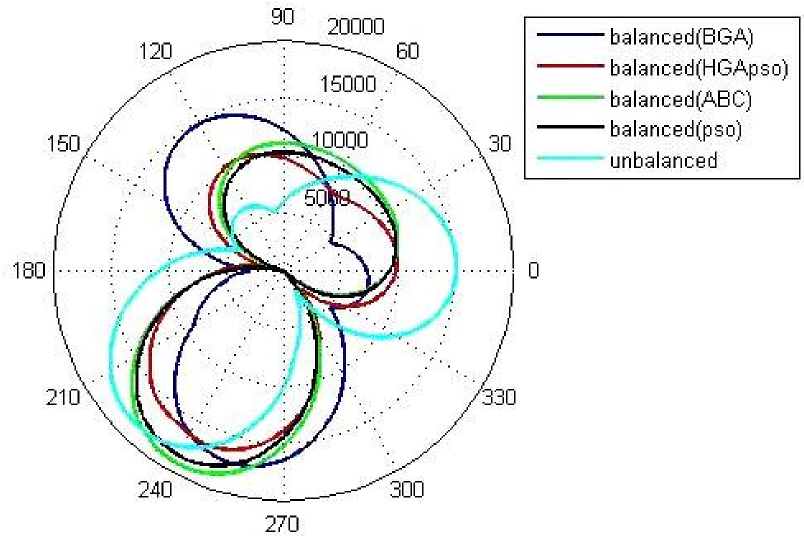


Figure 15. Polar plot of cost function for unbalanced and balanced states by applying different algorithms

5. EXPERIMENTALLY VALIDATION OF THE PROPOSED METHOD

For showing the practicability of the proposed balancing method based on mentioned optimization algorithms, a laboratory scale experimental double four-bar crank-slider mechanism was provided as shown in Figure16 [10].By using two accelerometers (type 4507 B&K Co.) and data acquisition system (PULSE B&K Co.), the acceleration of the right and left bearing of the mechanism can be extracted. Also a tachometer (Type 0024 MM B&K Co.) is applied for identifying the one revolution of the crank for estimating the angular acceleration. As a sample, the acceleration signals of the unbalanced and balanced mechanism, applying BGA, are illustrated in Figures 17 and 18. By comparing the mentioned linear and angular acceleration signal of the unbalanced and balanced mechanism, the possibility and accuracy of the proposed method in balancing of real mechanisms can be observed. In addition the corresponding angular acceleration signals are illustrated in Figure 19. As it is obvious from these figures, the proposed method is able to balance the mechanism because the overall amplitude of the linear and angular acceleration was decreased after balancing. Other similar results may be obtained by applying other algorithms, which cannot be illustrated in this paper because of the page limitation. By considering the experimental result, it can be observed that the same conclusion maybe derived as in previous section while comparing these algorithms.

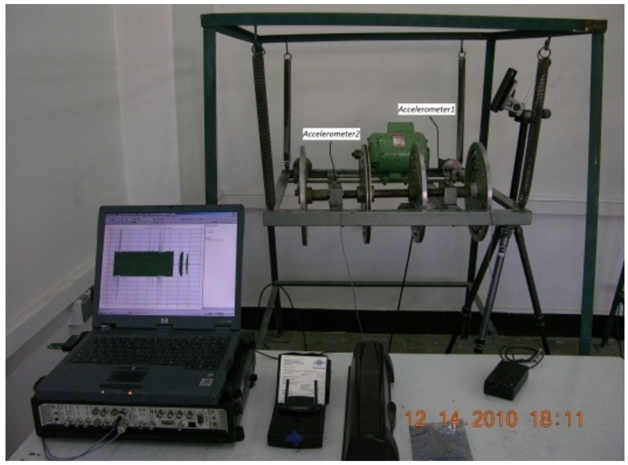


Figure16.A laboratory scale experimental double four-bar crank-slider mechanism setup

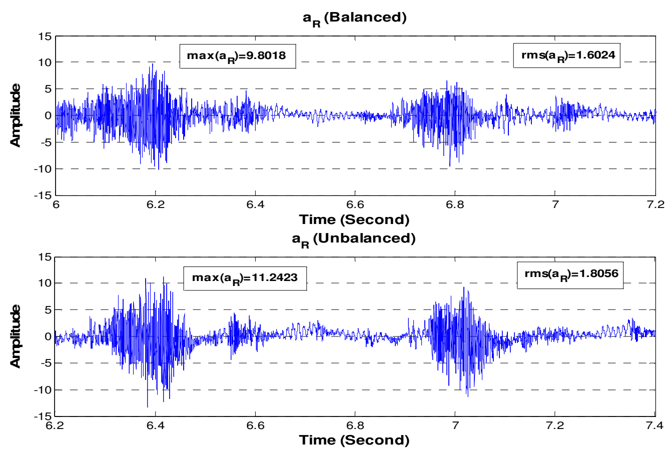


Figure17. Acceleration signal of the right part of the mechanism for before and after balancing

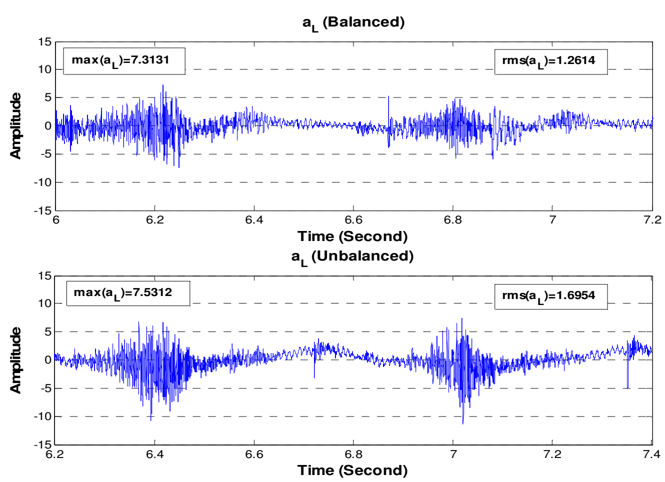


Figure18.Acceleration signal of the left part of the mechanism for before and after balancing

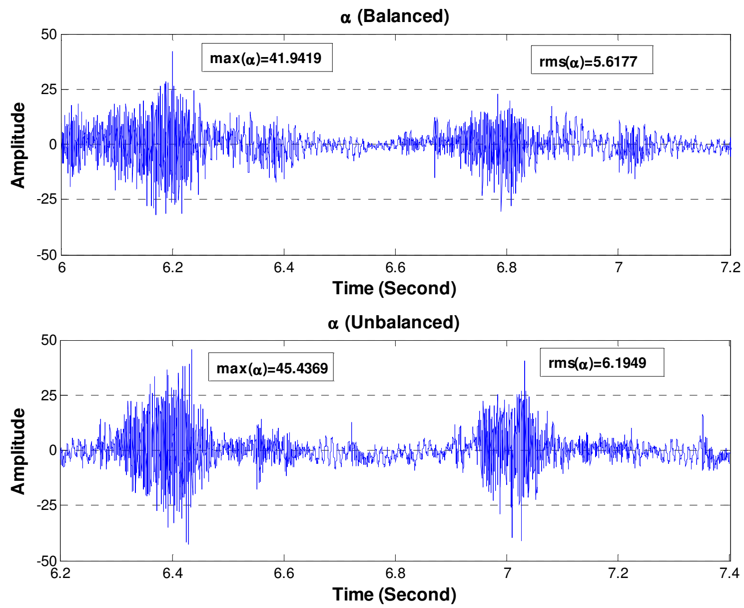


Figure 19. Angular acceleration signal of the mechanism for before and after balancing

6. CONCLUSION

In this paper, four Meta-Heuristic algorithms, that are PSO, ABC, BGA and HGAPSO, were applied for balancing of double four-bar crank slider mechanism. This mechanism is a basic and benchmark mechanism which is applied in different machine and engines. Therefore proposed balancing method may be applied for different type of machines for reducing the vibration and noise because of unbalancing. Kinematic modelling of the mechanism and suitable objective function which should be minimized and the constraints are derived. In order to comparing the optimization algorithm, different results based on cost function, fitness, convergence speed and runtime values were extracted and studied. The results show that the PSO algorithm converges quickly to the optimum solution, while the optimality of PSO solutions has a higher quality than other algorithms. Also, reviewing the responses of the four algorithms in several performances with various primary populations determined that, PSO and ABC are more stable than BGA and HGAPSO. Therefore PSO and ABC have a good potential in finding optimal solution and its convergence characteristics are more favourable. In addition, the practicability of the method was proved by applying the proposed method on a laboratory scale experimental complex crank slider mechanism.

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