Journal homepage: http://iieta.org/journals/mmep

Modelling and Analysis of the Cone Coupling Problem Using Optimization

Mubina Nancy, Elizabeth Amudhini Stephen*

Department of Mathematics, Karunya Institute of Technology and Sciences, Coimbatore 641114, India

Corresponding Author Email: elizi.felix@gmail.com

https://doi.org/10.18280/mmen.096	1520

ABSTRACT

Received: 20 April 2022 Accepted: 17 June 2022

Keywords:

cone coupling, optimization analysis, mathematical modelling, torque, axial force, flanges

A coupling is a mechanism that transmits operative power between two shafts that are revolving at different speeds. A coupling connects two shafts at their ends and can slip or fail depending on the torque limit. It is an essential component of any power transmission system and may survive for a very long time if properly designed and maintained. This study's current research, a newly developed optimization algorithms are used to minimize the volume of cone coupling. The current study presented here compares modern metaheuristic methods for optimizing the design of the cone coupling problem. The algorithms used are particle swarm optimization (PSO), crow search algorithm (CSA), enhanced honeybee mating optimization (EHBMO), Harmony search algorithm (HSA), Krill heard algorithm (KHA), Pattern search algorithm (PSA), Charged system search algorithm (CSSA), Salp swarm algorithm (SSA), Big bang big crunch optimization (B-BBBCO), Gradient based Algorithm (GBA). The performance of these algorithms is assessed both statistically and subjectively. The algorithms' performance is evaluated quantitatively and qualitatively using consistency, simplicity and quality. The experimental results on the cone clutch problem shows that PSO produces greater results than EHBMO, whereas CSA and BBCO produce approximately identical results

1. INTRODUCTION

Cone coupling are a form of friction clutch that engages and disengages the engine shaft from the transmission box shaft when the gear ratio changes. It is one of the oldest clutches in use in the vehicle industry. In comparison to positive displacement clutches, which were utilised before to the discovery of friction clutches, this clutch is simple to engage and disengage. Because of the larger contact area, a cone clutch can transfer more torque than a plate clutch of the same size. When a large amount of torque needs to be transferred at a low rotational speed, this clutch is used. The goal of the optimization problem is to reduce the volume design of the cone clutch such that it can transmit a specified minimum torque. Couplings are used to connect two pieces of rotating equipment while allowing for some degree of misalignment, end movement, or both. Cone coupling is shown in the Figure 1.



Figure 1. Cone coupling

A coupling can also be a mechanical mechanism that connects the ends of nearby pieces or objects in a broader sense. Couplings generally do not allow shafts to be disconnected during operation, however torque-limiting couplings can slip or disconnect if a torque limit is exceeded. Couplings can be chosen, installed, and maintained in such a way that maintenance time and expense are decreased.

2. LITERATURE SURVEY

Jovanović et al. [1] implements the applications of grasshopper optimization in mechanical engineering. He shows how the Grasshopper Optimization Algorithm (GOA) can be utilised to solve specific engineering optimization problems. Li et al. [2] introduced the light adaption, The sensitivity and maximum amplitude (R_{max}) of the mouse photopic electroretinogram (ERG) b-wave alter as a result of light adaptation. We investigated how manipulation of gap junctional coupling between rod and cones affects the lightadapted ERG using the ERG. Muchungi and Casey [3] is the first to suggest a cone simulator that incorporates rod input. Alizadeh et al. [4] tackles the issue of managing the lubrication regime in sliding lubricated surfaces in order to reduce wear and extend the lifespan of the friction lining material. Vyrabov [5] introduce the cone clutches and friction drives with wedgetype bodies have a circumferential force limit. Milenković [6] offers the fundamentals of a metaheuristic algorithm based on the behaviour of Harris hawks are demonstrated. Milenković and Jovanović [7] also shows how the Grasshopper Optimization Algorithm (GOA) can be utilised to solve specific engineering optimization problems. Particle Swarm

Optimization was used to do parametric optimization on the spring design problem, pressure vessel design problem, cantilever beam design problem, cone coupling design problem, and welded beam design problem is also introduced by Milenković et al. [8]. Gordy demonstrated SMAP (Soil Moisture Active and Passive) Cone Clutch Assembly (CCA) Thermal Conductance Test [9]. Nguyen et al. [10] introduced for the bias ratio and noise condition, the surface topology, cone angle, and forces acting on the cone of the clutch type limited slip differential (LSD) are important design characteristics. Chase [11] introduces d the goals of this paper are to collect information about clutch design in the United States and the United Kingdom, compare the advantages and disadvantages of various clutch types, and provide some notes on clutch theory without attempting a comprehensive treatment of the numerous factors involved. Genetic algorithm is used for optimization by Fadah et al. [12]. Volume of the fin shape is optimized by Nguyen et al. [10]. Therefore this cone coupling design problem is done by many researchers. In this study, cone coupling is optimized by different types of optimization algorithms.

3. MATHEMATICAL MODELLING

The cone coupling's design. The goal of this optimization problem is to reduce the coupling volume to allow momentum transfer. The inner radius of the connection R_1 and the outer radius of the coupling R_2 are the problem variables [13].

The minimum volume design of the cone coupling can transmit a specified torque.

By selecting the outer and inner radii of the cone R_1 and R_2 , as design variable, the objective function can be expressed as:

$$f(R_1, R_2) = \frac{1}{3}\pi h(R_1^2 + R_1 R_2 + R_2^2)$$
(1)

where, the axial thickness, h is given by

$$h = \frac{R_1 - R_2}{tan\alpha} \tag{2}$$

Eqns. (1) and (2) yield:

$$f(R_1, R_2) = k_1(R_1^3 - R_2^3)$$
(3)

where,

$$k_1 = \frac{\pi}{3tan\alpha} \tag{4}$$

 k_1 is expressed in Eqns. (3) and (4). The axial force applied (*F*) and the torque developed (*T*) are given:

$$F = \int p \, dA \sin\alpha = \int_{R_2}^{R_1} p \frac{2\pi r \, dr}{\sin\alpha} \sin\alpha$$

= $\pi p (R_1^2 - R_2^2)$ (5)

$$F = \int rfp \, dA = \int_{R_2}^{R_1} rfp \frac{2\pi r}{sin\alpha} dr$$

$$= \frac{2\pi r}{3sin\alpha} (R_1^3 - R_2^3)$$
(6)

where, p is the pressure, f the coefficient of friction, and A the area of contact. Substitution of p from Eq. (5) into (6) leads to Eqns. (7) and (8):

$$T = \frac{k_2(R_1^2 + R_1R_2 + R_2^2)}{R_1 + R_2} \tag{7}$$

where,

$$k_2 = \frac{2Ff}{3sin\alpha} \tag{8}$$

Since k_1 is a constant, the objective function can be taken as $f = (R_1^3 - R_2^3)$ in Eq. (9). The minimum torque to be transmitted is assumed to be 5k₂. In addition, the outer radius R₁ is assumed to be equal to at least twice the inner radius R₂ [14].

Thus, the optimization problems become objective function

$$f(R_1, R_2) = (R_1^3 - R_2^3)$$
(9)

Subject to

$$g_1(R_1, R_2) = \frac{R_1}{R_2} \ge 2 \tag{10}$$

$$g_2(R_1, R_2) = \frac{(R_1^2 + R_1 R_2 + R_2^2)}{(R_1 + R_2)} \ge 5$$
(11)

$$1 \le R_1, R_2 \le 10$$
 (12)

Eqns. (10) and (11) and (12) expresses the constraints.

4. OPTIMIZATION ALGORITHM

The following are some of the most common problems with traditional gradient methods and direct approaches:

- It converges to an ideal solution based on the original solution; most algorithms have a propensity to limit themselves to the sub-optimal option.
- An algorithm that solves one problem may not be efficient when applied to another.
- When dealing with problems involving nonlinear objectives, discrete variables, and a large number of restrictions, algorithms are inefficient.
- On a parallel computer, algorithms cannot be employed efficiently.

Addressing large-scale difficulties with nonlinear objectives functions is difficult using standard techniques like steepest descent, dynamic programming, and linear programming. Traditional algorithms can't address nondifferentiable problems since they rely on gradient information. In some optimization problems, there are a lot of local optima. As a result of this issue, more powerful optimization approaches are required, and our non-traditional optimization method has been discovered through research.

The following non-traditional optimization algorithms are used which is shown in the Table 1.

(1) Particle swarm optimization (PSO); (2) Crow search algorithm (CSA); (3) Enhanced honeybee mating optimization (EHBMO); (4) Harmony search algorithm (HSA); (5) Krill heard algorithm (KHA); (6) Pattern search algorithm (PSA); (7) Charged system search algorithm (CSSA); (8) Salp swarm algorithm (SSA); (9) Big bang big crunch optimization (B-BBBCO); (10) Gradient based Algorithm (GBA).

Optimization Algorithms	Methods
	(1) Particle Swarm Optimization (PSO); (2) Crow Search Algorithm (CSA)
Swarm Intelligence Algorithm	(3) Enhanced Honeybee Mating Optimization (EHBMO); (4) Krill Heard Algorithm (KHA)
	(5) Salp Swarm Algorithm (SSA)
Drusical Palatad Algorithm	(1) Harmony Search Algorithm (HSA); (2) Charged System Search Algorithm (CSSA)
Flysical Related Algorithm	(3) Big Bang Big Crunch Optimization (B-BBBCO)
Mathematical Programming	Gradient Based Algorithm (GBA)
String Searching Algorithm	Pattern Search Algorithm

5. METHODOLOGY

The non-traditional algorithm's performance will vary with each run, but the solution will always be global optimal [15]. As a result, twenty trail runs in all algorithms were performed for each problem, and the average value of the answer was calculated from all the trails. Table 2 shows the specific parameters for several techniques, whereas Table 3 shows the Functional Evaluation FEs number and Number of population NP size.

Table 2. Specific parameter settings of used algorithms

Algorithm	Parameter Settings
PSO	w _{min} =0.9, w _{max} =0.4, c ₁ =2, c ₂ =2
CSA	$c_1 = c_2 = c_3 = 2, \omega = 0.5, AP = 0.2, fl = 2, V_{max} = [2]^D$
EUDMO	No. of drones=40, No. of broods=10, No. of
ELIPMO	selected genes in crossover=8
HAS	HMS=50, HMCR=0.5 fixed, PAR=0.5
KHA	$N^{max}=0.01, V_f=0.02, D^{max}=0.005$
PSA	Only the common parameters (Fes and NP)
CSSA	rand-Random value between [0,1], $c=0.1$, $\varepsilon=0.001$
SSA	Only the common parameters (Fes and NP)
B-BBCO	$N_{pop}=100, k_{ls}=30, \alpha=0.8, N_s=5$
GBA	Only the common parameters (Fes and NP)

 w_{min} , w_{max} are respectively the min and max inertia weight 0.4, c_1 and c_2 are acceleration factors. HMS-Harmony Memory Size, PAR-Pitch Adjustment rate, HMCR-Harmony Memory Consideration rate, N_{pop} - Population size, K_{ls} - no. of non-improvement iteration, α - Reduction rate, N_s -no. of neighbours created in each generation, N^{max} - Maximum induced speed, V_f - The foraging speed, D^{max} - The maximum diffusion speed, c_1 , c_2 , c_3 - acceleration, ω - inertia weight, fl-length of the crow's flight, AP- perceptual probability of crow, V_{max} - upper limit of the particle update velocity.

Table 3. FEs number and the NP size for the algorithms

Problem	NP	t_{max}	Fes
Cone coupling	20	250	5000

Tables 3-6 and Figures 2-6 display the values of the outer radius (R_1) , the inner radius (R_2) , and the two constraints (g_1) and (g_2) . Table 7 and Figure 7 shows the values of volume minimization.

5.1 The inner radius R1

The inner radius if the cone coupling is minimized by optimizing for 20 trails with 10 different optimization methods.

5.2 The outer radius R₂

The outer radius if the cone coupling is minimized by optimizing for 20 trails with 10 different optimization methods.

5.3 Constraint g1

The outer radius is assumed to be equal to at least twice the inner radius.

5.4 Constraint g2

The torque of the shaft is minimized with 20 trails by using different types of optimization methods.

5.5 Volume minimization

Volume of the cone coupling is minimized by the optimization methods for 20 trails.

In Table 8, a comparison of results for design of cone coupling optimization problem are shown. Analysing the table results a conclusion has been drawn that the PSO gives better results in comparison to EHBMO, while in comparison to CSA and BBCO the results are nearly the same.



Figure 2. The inner radius R₁



Figure 3. The outer radius R₂



Figure 6. Volume Minimization fmin



Figure 7. The inner radius of the Coupling R₁



Figure 8. Constraint g1



Figure 9. The outer radius of the Coupling R₂





Figure 11. Volume minimization

Table 4. The inner radius R₁

Trial	PSO	EHDMO	HSA	CSA	CSSA	BBCO	GBA	KHA	PSA	SSA
1	4.2785	4.3256	4.3089	4.2871	4.2859	4.2984	4.3059	4.2985	4.2998	4.2987
2	4.2785	4.3265	4.3025	4.2871	4.2956	4.2984	4.3152	4.2981	4.2998	4.2989
3	4.2785	4.3256	4.3021	4.2871	4.2956	4.2984	4.3058	4.2965	4.2998	4.299
4	4.2785	4.3256	4.3025	4.2871	4.2969	4.2984	4.3056	4.2958	4.2998	4.2991
5	4.2785	4.3256	4.3025	4.2871	4.2989	4.2984	4.3059	4.2987	4.2998	4.2987
6	4.2785	4.3256	4.3056	4.2871	4.2965	4.2984	4.3059	4.2931	4.2998	4.2986
7	4.2785	4.3256	4.3052	4.2871	4.2986	4.2984	4.3059	4.2951	4.2998	4.2989
8	4.2785	4.3265	4.3089	4.2871	4.2963	4.2984	4.3059	4.2965	4.2998	4.2987
9	4.2785	4.3215	4.3052	4.2871	4.2958	4.2984	4.3058	4.2988	4.2998	4.2986
10	4.2785	4.3215	4.3021	4.2871	4.2965	4.2984	4.3058	4.2899	4.2998	4.2985
11	4.2785	4.3256	4.3025	4.2871	4.2936	4.2984	4.3058	4.2985	4.2998	4.2982
12	4.2785	4.3256	4.3025	4.2871	4.2965	4.2984	4.3058	4.2889	4.2998	4.2983
13	4.2785	4.3265	4.3025	4.2871	4.2956	4.2984	4.3059	4.2965	4.2998	4.2985
14	4.2785	4.3256	4.3025	4.2871	4.2986	4.2984	4.3059	4.2954	4.2998	4.2987
15	4.2785	4.3214	4.3025	4.2871	4.2989	4.2984	4.3059	4.2963	4.2998	4.2986

16	4.2785	4.3256	4.3021	4.2871	4.2969	4.2984	4.3058	4.2951	4.2998	4.2987
17	4.2785	4.3215	4.3021	4.2871	4.2965	4.2984	4.30587	4.2971	4.2998	4.2981
18	4.2785	4.3256	4.3025	4.2871	4.2965	4.2984	4.3059	4.2985	4.2998	4.298
19	4.2785	4.3266	4.3021	4.2871	4.2968	4.2984	4.3059	4.2985	4.2998	4.2888
20	4.2785	4.3256	4.3025	4.2871	4.2965	4.2984	4.3059	4.2951	4.2998	4.2889
Average	4.2785	4.3250	4.3035	4.2871	4.2962	4.2984	4.3063	4.2960	4.2998	4.2976
Max	4.2785	4.3266	4.3089	4.2871	4.2989	4.2984	4.3152	4.2988	4.2998	4.2991
Min	4.2785	4.3214	4.3021	4.2871	4.2859	4.2984	4.3056	4.2889	4.2998	4.2888
SD	0.0000	0.0018	0.0021	0	0.0027	0	0.0020	0.0027	0	0.0030
Fes	5000	5000	5000	5000	5000	5000	5000	5000	5000	5000

Table 5. The outer radius R2

Trial	PSO	EHDMO	HSA	CSA	CSSA	BBCO	GBA	KHA	PSA	SSA
1	2.1327	2.13426	2.1457	2.1344	2.1429	2.1468	2.1429	2.143	2.1489	2.1405
2	2.1327	2.1343	2.1424	2.1344	2.14299	2.1468	2.1427	2.1452	2.1489	2.1409
3	2.1327	2.13426	2.1456	2.1344	2.14563	2.1468	2.14285	2.1456	2.1489	2.1409
4	2.1327	2.1343	2.1457	2.1344	2.14296	2.1468	2.14283	2.1466	2.1489	2.1406
5	2.1327	2.13426	2.1452	2.1344	2.1457	2.1468	2.14285	2.1465	2.1489	2.1411
6	2.1327	2.1342	2.1497	2.1344	2.14563	2.1468	2.14287	2.142	2.1489	2.1415
7	2.1327	2.1343	2.1499	2.1344	2.14296	2.1468	2.1429	2.1452	2.1489	2.1416
8	2.1327	2.13426	2.149	2.1344	2.1457	2.1468	2.1429	2.14	2.1489	2.1402
9	2.1327	2.13429	2.1459	2.1344	2.1457	2.1468	2.1429	2.1456	2.1489	2.1452
10	2.1327	2.13425	2.1456	2.1344	2.1457	2.1468	2.1429	2.14	2.1489	2.1456
11	2.1327	2.13422	2.1456	2.1344	2.14563	2.1468	2.14292	2.143	2.1489	2.1458
12	2.1327	2.13425	2.149	2.1344	2.14524	2.1468	2.1459	2.1423	2.1489	2.1453
13	2.1327	2.13426	2.149	2.1344	2.1459	2.1468	2.14265	2.1432	2.1489	2.1442
14	2.1327	2.13426	2.1486	2.1344	2.1452	2.1468	2.14266	2.142	2.1489	2.1443
15	2.1327	2.13426	2.149	2.1344	2.1452	2.1468	2.14562	2.1432	2.1489	2.1436
16	2.1327	2.13426	2.1459	2.1344	2.14256	2.1468	2.14524	2.1403	2.1489	2.1463
17	2.1327	2.13425	2.1457	2.1344	2.12546	2.1468	2.14587	2.1431	2.1489	2.1456
18	2.1327	2.13425	2.1457	2.1344	2.1457	2.1468	2.14567	2.1426	2.1489	2.1432
19	2.1327	2.13426	2.1467	2.1344	2.1457	2.1468	2.14287	2.1452	2.1489	2.1452
20	2.1327	2.13426	2.149	2.1344	2.1457	2.1468	2.14567	2.1456	2.1489	2.1455
Average	2.1327	2.13426	2.1469	2.1344	2.14391	2.1468	2.14368	2.14351	2.1489	2.143355
Max	2.1327	2.1343	2.1499	2.1344	2.1459	2.1468	2.1459	2.1466	2.1489	2.1463
Min	2.1327	2.1342	2.1424	2.1344	2.12546	2.1468	2.14265	2.14	2.1489	2.1402
SD	0	2.3E-05	0.002	0	0.00451	0	0.00134	0.00209	0	0.002188
Fes	5000	5000	5000	5000	5000	5000	5000	5000	5000	5000

Table 6. Constraint g₁

Trial	PSO	EHDMO	HSA	CSA	CSSA	BBCO	GBA	KHA	PSA	SSA
1	2.006	2.0268	2.0082	2.0086	2	2.00224	2.0094	2.0058	2.00093	2.00827
2	2.006	2.0271	2.0083	2.0086	2.0045	2.00224	2.0139	2.0036	2.00093	2.00799
3	2.006	2.0268	2.0051	2.0086	2.002	2.00224	2.0094	2.0025	2.00093	2.00803
4	2.006	2.0267	2.0052	2.0086	2.0052	2.00224	2.0093	2.0012	2.00093	2.00836
5	2.006	2.0268	2.0056	2.0086	2.0035	2.00224	2.0095	2.0027	2.00093	2.00771
6	2.006	2.0268	2.0029	2.0086	2.0025	2.00224	2.0094	2.0042	2.00093	2.00728
7	2.006	2.0267	2.0026	2.0086	2.0059	2.00224	2.0094	2.0022	2.00093	2.00733
8	2.006	2.0272	2.0051	2.0086	2.0023	2.00224	2.0094	2.0077	2.00093	2.00855
9	2.006	2.0248	2.0063	2.0086	2.0021	2.00224	2.0094	2.0035	2.00093	2.00382
10	2.006	2.0249	2.0051	2.0086	2.0024	2.00224	2.0094	2.0046	2.00093	2.0034
11	2.006	2.0268	2.0053	2.0086	2.0011	2.00224	2.0093	2.0058	2.00093	2.00308
12	2.006	2.0268	2.0022	2.0086	2.0028	2.00224	2.0066	2.002	2.00093	2.00359
13	2.006	2.0272	2.0021	2.0086	2.0018	2.00224	2.0096	2.0047	2.00093	2.00471
14	2.006	2.0268	2.0025	2.0086	2.0038	2.00224	2.0096	2.0053	2.00093	2.00471
15	2.006	2.0248	2.0022	2.0086	2.004	2.00224	2.0068	2.0046	2.00093	2.00532
16	2.006	2.0268	2.0048	2.0086	2.0055	2.00224	2.0072	2.0068	2.00093	2.00284
17	2.006	2.0249	2.005	2.0086	2.0215	2.00224	2.0066	2.0051	2.00093	2.00322
18	2.006	2.0268	2.0052	2.0086	2.0024	2.00224	2.0068	2.0062	2.00093	2.00541
19	2.006	2.0272	2.0041	2.0086	2.0026	2.00224	2.0095	2.0038	2.00093	1.99925
20	2.006	2.0268	2.0022	2.0086	2.0024	2.00224	2.0068	2.0018	2.00093	1.99902
Average	2.006	2.0265	2.0045	2.0086	2.0039	2.00224	2.0089	2.0042	2.00093	2.00509
Max	2.006	2.0272	2.0083	2.0086	2.0215	2.00224	2.0139	2.0077	2.00093	2.00855
Min	2.006	2.0248	2.0021	2.0086	2	2.00224	2.0066	2.0012	2.00093	1.99902
SD	0	0.0009	0.0019	0	0.0044	0	0.0017	0.0018	0	0.00288
Fes	5000	5000	5000	5000	5000	5000	5000	5000	5000	5000

 Table 7. Constraint g2

Trial	PSO	EHDMO	HSA	CSA	CSSA	BBCO	GBA	KHA	PSA	SSA
1	5.011	5.056	5.0413	5.0195	5.0192	5.03149	5.0382	5.0312	5.03303	5.03112
2	5.011	5.0569	5.035	5.0195	5.0285	5.03149	5.0471	5.031	5.03303	5.03135
3	5.011	5.056	5.0349	5.0195	5.0288	5.03149	5.0382	5.0296	5.03303	5.03144
4	5.011	5.0561	5.0353	5.0195	5.0297	5.03149	5.0379	5.029	5.03303	5.03151
5	5.011	5.056	5.0353	5.0195	5.0319	5.03149	5.0382	5.0317	5.03303	5.03118
6	5.011	5.056	5.0386	5.0195	5.0297	5.03149	5.0382	5.026	5.03303	5.03113
7	5.011	5.056	5.0383	5.0195	5.0313	5.03149	5.0383	5.0282	5.03303	5.03142
8	5.011	5.0569	5.0417	5.0195	5.0294	5.03149	5.0382	5.029	5.03303	5.03109
9	5.011	5.0521	5.0379	5.0195	5.029	5.03149	5.0382	5.0317	5.03303	5.03151
10	5.011	5.0521	5.0349	5.0195	5.0297	5.03149	5.0382	5.0227	5.03303	5.03146
11	5.011	5.056	5.0353	5.0195	5.0269	5.03149	5.0382	5.0312	5.03303	5.03119
12	5.011	5.0561	5.0357	5.0195	5.0296	5.03149	5.0385	5.022	5.03303	5.03124
13	5.011	5.0569	5.0356	5.0195	5.0288	5.03149	5.0382	5.0293	5.03303	5.03131
14	5.011	5.0561	5.0356	5.0195	5.0316	5.03149	5.0382	5.0281	5.03303	5.03151
15	5.011	5.0521	5.0357	5.0195	5.0319	5.03149	5.0385	5.0291	5.03303	5.03134
16	5.011	5.056	5.0349	5.0195	5.0297	5.03149	5.0384	5.0277	5.03303	5.03172
17	5.011	5.0521	5.0349	5.0195	5.0275	5.03149	5.0385	5.0299	5.03303	5.03108
18	5.011	5.056	5.0353	5.0195	5.0297	5.03149	5.0385	5.0311	5.03303	5.03073
19	5.011	5.057	5.035	5.0195	5.0299	5.03149	5.0383	5.0314	5.03303	5.02222
20	5.011	5.0561	5.0357	5.0195	5.0297	5.03149	5.0385	5.0282	5.03303	5.02234
Average	5.011	5.0554	5.0364	5.0195	5.0291	5.03149	5.0387	5.0289	5.03303	5.03039
Max	5.011	5.057	5.0417	5.0195	5.0319	5.03149	5.0471	5.0317	5.03303	5.03172
Min	5.011	5.0521	5.0349	5.0195	5.0192	5.03149	5.0379	5.022	5.03303	5.02222
SD	0	0.0017	0.0021	0	0.0027	0	0.002	0.0027	0	0.00278
Fes	5000	5000	5000	5000	5000	5000	5000	5000	5000	5000

Table 8. Volume minimization

Trial	PSO	EHDMO	HSA	CSA	CSSA	BBCO	GBA	KHA	PSA	SSA
1	68.5698	71.2157	70.123	69.06997	68.8872	69.52422	69.9945	69.5822	69.57278	69.6277
2	68.5698	71.2651	69.817	69.06997	69.423	69.52422	70.5194	69.5297	69.57278	69.63328
3	68.5698	71.2157	69.749	69.06997	69.3883	69.52422	69.9934	69.4355	69.57278	69.63883
4	68.5698	71.217	69.771	69.06997	69.4989	69.52422	69.98	69.383	69.57278	69.6485
5	68.5698	71.2156	69.777	69.06997	69.5725	69.52422	69.9986	69.545	69.57278	69.61945
6	68.5698	71.2164	69.886	69.06997	69.4405	69.52422	69.9962	69.297	69.57278	69.6084
7	68.5698	71.2151	69.861	69.06997	69.5914	69.52422	69.9993	69.3635	69.57278	69.62366
8	68.5698	71.2699	70.081	69.06997	69.426	69.52422	69.9958	69.5127	69.57278	69.63182
9	68.5698	70.9861	69.918	69.06997	69.4008	69.52422	69.9924	69.563	69.57278	69.55741
10	68.5698	70.9866	69.748	69.06997	69.439	69.52422	69.9924	69.1477	69.57278	69.54634
11	68.5698	71.2168	69.771	69.06997	69.2775	69.52422	69.9925	69.5822	69.57278	69.52695
12	68.5698	71.2194	69.725	69.06997	69.4424	69.52422	69.9525	69.0609	69.57278	69.5394
13	68.5698	71.2667	69.724	69.06997	69.3871	69.52422	69.9979	69.4686	69.57278	69.56566
14	68.5698	71.2194	69.731	69.06997	69.5604	69.52422	69.9978	69.4243	69.57278	69.57537
15	68.5698	70.9812	69.725	69.06997	69.5777	69.52422	69.958	69.4576	69.57278	69.57948
16	68.5698	71.2157	69.745	69.06997	69.5043	69.52422	69.9606	69.431	69.57278	69.54776
17	68.5698	70.987	69.748	69.06997	69.7128	69.52422	69.9519	69.5032	69.57278	69.52417
18	68.5698	71.2158	69.77	69.06997	69.4391	69.52422	69.9563	69.5877	69.57278	69.55174
19	68.5698	71.2731	69.734	69.06997	69.4563	69.52422	70.0002	69.5519	69.57278	69.01539
20	68.5698	71.2176	69.725	69.06997	69.4396	69.52422	69.9563	69.358	69.57278	69.01677
Average	68.5698	71.1808	69.806	69.06997	69.4432	69.52422	70.0093	69.4392	69.57278	69.5289
Max	68.5698	71.2731	70.123	69.06997	69.7128	69.52422	70.5194	69.5877	69.57278	69.6485
Min	68.5698	70.9812	69.724	69.06997	68.8872	69.52422	69.9519	69.0609	69.57278	69.01539
SD	0	0.10246	0.1156	0	0.1615	0	0.12149	0.14237	0	0.179956
Fes	5000	5000	5000	5000	5000	5000	5000	5000	5000	5000

Table 9. Comparison of the best optimum solution for the cone coupling problem

Variables	PSO	EHBMO	HAS	CSA	CSSA	BBCO	GBA	KHA	PSA	SSA
R1 m	4.2786	4.32501	4.3035	4.2871	4.29622	4.2984	4.30636	4.29605	4.2998	4.29763
R2 m	2.1327	2.13426	2.1469	2.1344	2.14391	2.1468	2.14368	2.14351	2.1489	2.143355
g1 m	2.0062	2.02647	2.0045	2.00857	2.00393	2.00224	2.00886	2.00421	2.00093	2.00509
g2 m	5.0112	5.05543	5.0364	5.01948	5.02912	5.03149	5.03871	5.02891	5.03303	5.03039
Volume	68.57	71.1808	69.807	69.07	69.4432	69.5242	70.0093	69.4392	69.5728	69.5289

Table 10. Statistical result of the used algorithms for the cone coupling problem

Algorithm	Best	Mean	Worst	SD	Fes
PSO	68.57	68.57	68.57	0	5000
EHDMO	70.0071	70.2176	70.336	0.11403	5000
HSA	69.7241	69.8065	70.123	0.11559	5000
CSA	69.07	69.07	69.07	0	5000
CSSA	68.8872	69.4432	69.713	0.1615	5000
BBCO	69.5242	69.5242	69.524	0	5000
GBA	69.9519	70.0093	70.519	0.12149	5000
KHA	69.0609	69.4392	69.588	0.14237	5000
PSA	69.5728	69.5728	69.573	0	5000
SSA	69.0154	69.5289	69.649	0.17996	5000

6. RESULT AND DISCUSSION

6.1 Consistency

The consistency table gives the parameters that remain constant for all the trails. All the solvers give the value of PSO, CSA, BBCO and HSA for all the runs, which in turn indicates that the requirements are in the acceptable range.

- R₁ PSO (4.2785698567), CSA (4.2871), BBCO (4.2984)
- R₂ PSO (2.1326522330), CSA (2.13440), HSA (2.1490)
- g₁ PSO (2.0062201377), EHBMO (1.6366), HSA (2.00450)
- g_2 PSO (5.0112134936), HSA (5.036353), CSA (5.01948)

So, we see that the solvers PSO, CSA, BBCO, PSA remains constant throughout their runs.

6.2 Simplicity of algorithm

Of all the algorithm, we have taken PSO is the simplest followed by EHBMO, SSA, HSA, BBCO.

6.3 Minimum values of variables

The best optimal solution and statistical simulation results for the cone coupling problem are presented in Table 9, Table 10, and Figures 7-11. Table 8 shows that all of the methodologies used are capable of finding a globally feasible solution. However, with standard deviation values of 0, the PSO algorithm is the most robust in handling this problem, followed by EHBMO, SSA, HAS, CSA, CSSA, BBCO, PSA, GBA, and KHA.

- R₁ PSO (4.2786), CSA (4.2871), BBCO (4.2984)
- R₂ PSO (2.178655), CSA (2.13440), HSA (2.1490)
- g₁ PSO (1.962768), EHBMO (1.6366), HSA (2.00450)
- g₂ PSO (5.016092), HSA (5.036353), CSA (5.01948)

7. CONCLUSIONS

In this study, the volume of the cone coupling is optimized, and these optimized results are validated using ANSYS simulation. This volume minimized cone coupling will be very reachable for small scale industries and it gives profit and gives more manufactures. The following are some of the most common problems with classic gradient methods and traditional direct approaches:

- It converges to an optimal solution based on the original solution chosen.
- Most algorithms are prone to limiting themselves to a sun-optimal answer.
- A problem solved by one algorithm may not be efficient when applied to another.
- Algorithms are inefficient for solving problems with non-linear objectives, discrete variables, and a large number of restrictions.
- On a parallel computer, algorithms cannot be employed efficiently.

In general, standard techniques such as steepest descent, dynamic programming, and linear programming make it difficult to address large-scale issues with nonlinear objectives functions. Traditional algorithms cannot address nondifferentiable problems because they require gradient information. Some optimization problems have a large number of local optima. As a result of this issue, there is a need to build more powerful optimization approaches, and research has discovered our non-traditional optimization [16, 17].

In this paper, we compared 10 meta-heuristic algorithms to solve the cone coupling. The algorithms used are particle swarm optimization (PSO), crow search algorithm (CSA), enhanced honeybee mating optimization (EHBMO), Harmony search algorithm (HSA), Krill heard algorithm (KHA), Pattern search algorithm (PSA), Charged system search algorithm (CSSA), Salp swarm algorithm (SSA), Big bang big crunch optimization (B-BBBCO), Gradient based Algorithm (GBA). These algorithm's performance is evaluated statistically and subjectively.

By comparing these methods, we've proved that PSO is the best optimization method comparing with other nine methods which we discussed in the result analysis. To minimize the volume of the cone coupling, Particle Swarm Optimization (PSO) got the minimum value comparing with Enhanced Honey-Bee Mating (EHBMO) and Salp Swarm Optimization (SSA). Therefore, for cone coupling problem, Particle Swarm Optimization (PSO) is the best method. These results will be validated using simulation by ANSYS.

The original volume is reduced and this can be sent to the industries. So that will be very reachable for small scale industries and it gives profit and gives more manufactures.

ACKNOWLEDGMENT

The author would like to thank the Karunya Institute of Technology and Sciences for their assistance in carrying out this research.

REFERENCES

- Jovanović, D., Milenković, B., Krstić, M. (2020). Application of grasshopper optimization algorithm in mechanical engineering. YOURS 2020 Young Researchers Conference 2020.
- [2] Li, Y., Cohen, E.D., Qian, H. (2020). Rod and cone coupling modulates photopic ERG responses in the mouse retina. Frontiers in Cellular Neuroscience, 14: 566712. https://doi.org/10.3389/fncel.2020.566712
- [3] Muchungi, K., Casey, M. (2012). Simulating light adaptation in the retina with rod-cone coupling. In International Conference on Artificial Neural Networks, pp. 339-346. https://doi.org/10.1007/978-3-642-33269-2_43
- [4] Alizadeh, H.V., Helwa, M.K., Boulet, B. (2018). Modeling, analysis and constrained control of wet cone clutch systems: A synchromesh case study. Mechatronics, 49: 92-104.
 - https://doi.org/10.1016/j.mechatronics.2017.11.005
- [5] Vyrabov, R.V. (1991). Friction in a cone clutch and in a friction drive with wedge-type bodies. Journal of Tribology, 113: 681. https://doi.org/10.1115/1.2920679
- [6] Milenković, B. (2021). Application of particle swarm optimization for classical engineering problems. International Journal of Electrical Engineering and Computing, 5(1): 42-49. https://doi.org/10.7251/ijeec2101042m
- [7] Milenković, B., Jovanović, Đ. (2021). The use of the biological algorithm in solving applied mechanics design problems. Scientific Technical Review, 71(1): 38-43. https://doi.org/10.5937/str2101038m
- [8] Milenković, B., Bulatović, R., Atanasovska, I. (2021). Application of Grasshopper Algorithm for Solving Optimization Problems in Engineering. In X International Conference "Heavy Machinery-HM.
- [9] Cucullu, G.C., Mikhaylov, R., Forgette, D., Kwack, E. Y., Wang, G., Hoffman, P. (2014). SMAP (Soil Moisture Active and Passive) Cone Clutch Assembly (CCA)

Thermal Conductance Test. 44th International Conference on Environmental Systems. https://ttuir.tdl.org/bitstream/handle/2346/59604/ICES-2014-061.pdf.

- [10] Nguyen, L.N.P., Nguyen, Q., Nguyen, S.H. (2022). Optimization of fin with rectangular and triangular shapes by Levenberg – Marquardt method. Mathematical Modelling of Engineering Problems, 9(1): 245-250. https://doi.org/10.18280/mmep.090130
- [11] Chase, H. (1921). Practice and theory in clutch design. SAE Transactions, 357-396.
- [12] Fadah, I., Elliyana, A., Auliya, Y.A., Baihaqi, Y., Haidar, M., Sefira, D.M. (2022). A hybrid genetic-variable neighborhood algorithm for optimization of rice seed distribution cost. Mathematical Modelling of Engineering, 9(1): 36-42. https://doi.org/10.18280/mmep.090105
- [13] Rao, S. (2000). Engineering optimization, Theory and Practice. New Age International (P) Ltd.
- [14] Fan, Y., Shao, J., Sun, G., Shao, X. (2020). A modified salp swarm algorithm based on the perturbation weight for global optimization problems. Complexity, 2020: 6371085. https://doi.org/10.1155/2020/6371085
- [15] Askarzadeh, A. (2016). A novel metaheuristic method for solving constrained engineering optimization problems: Crow search algorithm. Computers & Structures, 169: 1-12. http://dx.doi.org/10.1016/j.compstruc.2016.03.001
- [16] Meichle, S., Krafft, R., Wolf, A. (2009). Double Cone friction clutch. In SAE 2009 Commercial Vehicle Engineering Congress & Exhibition (No. 2009-01-2931).
- [17] Pyoun, Y.S., Kim, H.T., Lee, Y.C., Gafurov, A., Kim, H., Jung, D.H. (2008). Development of evolutionary cone type LSD for SUV/RV utilizing the axiomatic approach and the ultrasonic nano crystal surface modification technology. International Journal of Automotive Technology, 9(1): 61-70. https://doi.org/10.1007/s12239-008-0008-7