

SPUR GEAR DESIGN VIA PARTICLE SWARM

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Abstract

This study aims to employ a nature inspired algorithm - Particle Swarm (PS) - to seek minimum center distance for desired life of a compact spur gear set to transmit a given power satisfying a number of constraints imposed. The PS, which is relatively recent heuristic search technique, imitates social behavior of birds flocking by sharing information among their members in multiple dimensions in space looking for the best food sources. The PS algorithm employs the generation of guided random positions when they search for the global optimum point. The algorithm does not require the evaluation of gradients of the objective functions since it is a derivative free optimization technique. Heuristic optimization techniques are used to overcome most of the limitations found in the traditional techniques. In this study, an algorithm which is a variant of the PS called the Repulsive Particle Swarm (RPS) is utilized. In this algorithm, each particle can make a wider search in its neighborhood to optimize itself due to stronger local search abilities. It is demonstrated that the PS performed and obtained better convergence reliability on the global optimum point than a more traditional method (Feasible Direction Gradient Search-FDGS).

Keywords: Particle swarm, Design optimization, Spur gear

1. Introduction

Many non-traditional optimization techniques such as the Genetic Algorithms and the Simulated Annealing have been employed to solve mechanical design problems [1]. Non-traditional optimization techniques do not need mathematical assumptions to the problems and have better search abilities over traditional optimization techniques. Spur gears are most widely used machine components in the industry. Such machine components design problems are complex activities in which computing capability are more and more required. Developments in computer technology have proved to be a great chance to the world of machine components design optimization. Any efficient optimization algorithm explores to investigate new and unknown areas in search space and exploits to make use of knowledge found at point previously visited to help find better solution point. The Particle Swarm (PS) can provide a remarkable balance between exploration and exploitation of the search space. The PS is a recent powerful performance algorithm used as an alternative to the genetic algorithms and the simulated annealing. From this point of view, this study provides use of the PS to seek a global optimum solution to problem in hand. The algorithm employs the generation of guided random positions when they search for the global optimum point. The PS does not require the evaluation of gradients of the objective functions.

2. The Particle Swarm Algorithm

The PS was proposed by Kennedy and Eberhart [2]. The PS is an optimization technique inspired by social behavior of animals such as birds flocking, fish schooling, and swarm theory [3]. The PS is developed through simulation of social behavior of bird flocking by sharing of information among their members in multiple dimension in space [4] and [5] looking for best food sources (global optimum).

A swarm consists of individuals, called particles, which change their position over time. Each individual of the swarm is assigned a velocity which is dynamically adjusted and updated according to the flying experiences of its own and companions [6]. The PS has well-balanced mechanism to enhance and adapt to the global and local exploration [7]. The PS algorithm is robust, well suited to handle continuous, discrete, and integer variable types with ease [5]. While the PS has ability to provide a balance between exploration and exploitation [8], it can be successfully used in engineering design optimization. The PS is initialized with a population of candidate solutions called particles. Each particle keeps track of its coordinated in the search space. Each particle moves in the search space with a velocity, v_i , according to its personal previous best, p_{best} , solution and previous best solution of the entire swarm, g_{best} , to update the current position, x_i , of each particle in the swarm. The position of each particle is updated by a new velocity calculated by

$$x_{i+1} = x_i + v_{i+1} \quad (1)$$

$$v_{i+1} = w v_i + c_1 r_1 (p_{best_i} - x_i) + c_2 r_2 (g_{best_i} - x_i) \quad (2)$$

where x_i and v_i are the current position and velocity of the individual particle, respectively. w is the inertial factor.

c_1 and c_2 are learning factor as social and cognitive components, respectively that show how much the particle is directed towards good positions. The larger inertia weight and the larger maximum velocity favor the exploration and smaller ones are suitable for the exploitation [9]. A suitable value for the inertia weight usually provides balance between global and local exploration which end up in a better solution. r_1 and r_2 are uniformly distributed random numbers in the range [0, 1]. p_{best} is the personal best position of a given particle so far. g_{best} is the global best seen by the swarm, population of algorithm. The algorithm general steps are constructed as follows:

Step 1: Initialize a population of particles with random positions and velocities in the problem space. The initial position and the velocity vectors randomly distributed throughout the design space using a uniform distribution for each particle of the swarm is obtained by Eqs. (3) and (4) [5].

$$x_o = x_{min} + r (x_{max} - x_{min}) \quad (3)$$

$$v_o = [x_{min} + r(x_{max} - x_{min})] / \Delta t \quad (4)$$

where x_{min} and x_{max} represents lower and upper bounds of the design variables respectively. r is a random number between 0 and 1. Δt is a time step value.

Step 2: For each particle, evaluate the objective function (fitness) values using the design space positions, x_i .

Step 3: Compare particle's fitness evaluation with particle's p_{best} . If current value is better than p_{best} then set p_{best} of each particle and its objective value equal to its current position and objective value.

Step 4: Compare fitness evaluation with the populations overall previous best. If current value is better than g_{best} , then set g_{best} and its objective value equal to the position and objective value of the best initial particle.

Step 5: Update the velocity and position of the particle as specified in Eqs. (1) and (2).

Step 6: Repeat Steps 2-5 until the stop criterion is met. The stopping criterion is usually based on the number of iterations reached or sufficiently good fitness which particles change their positions in search space until a relatively unchanged position has been encountered.

In this study, an algorithm which is a variant of the PS called the Repulsive Particle Swarm (RPS) is utilized. In this algorithm, each particle can make a wider search in its neighborhood to optimize itself due to stronger local search abilities [10]. In the RPS, v_{i+1} of a particle at position with current velocity, v_i , and the position of the particle are formulated by Mishra [10] as.

$$v_{i+1} = w v_i + a_1 r_1 (P_{best_i} - x_i) + w a_2 r_2 (x_h - x_i) + w a_3 r_3 z \quad (5)$$

where a_1, a_2, a_3 are constants, r_1, r_2, r_3 are random numbers [0,1], z is a random velocity vector, x_h is best position of randomly chosen other particle from the swarm.

In the literature, there are several guidelines for the selection of the key parameters of the PS algorithm. The typical range for the number of particle (individual) of the swarm is 10-200. In this work, a particle size of 100 is chosen. The velocity determines the direction in which a particle needs to move for improving the current position. The particles might fly past good solutions for too high velocity and may not explore sufficiently beyond locally good regions for too low velocity [8]. The inertia weight parameter, w , has control over the impact of the previous information of velocities on current velocity of a given particle. A larger inertia parameter favors a global optimum point and a smaller inertia parameter favors a local optimum point [11]. The weight parameter, $w = 0.5$, is used in this study. The learning parameters c_1 and c_2 represent acceleration terms that pull each particle toward p_{best} and g_{best} position as a cognitive and social learning respectively. These parameters usually are defined as constant and are problem dependent. The parameters values in the range [0.5, 2.5] are recommended by Engelbrect [12] and [1.5, 2.5] by Pulido and Coello [13]. For this study, $c_1 = 0.5$ and $c_2 = 0.5$ are used.

3. Problem Statement

In this study, the center distance, C , between the input and output shaft for a specified reliability life is minimized. Figure1 shows two spur gears in contact. For given combination of gear parameters, the design problem is formulated in terms of design variables: the number of pinion teeth, x_1 , the diametral pitch, x_2 , and the gear and pinion face width, x_3 . It should be noted that all constraints are of inequality type. The minimization of the center distance using the FDGS which is performed by Savage [14] will be a reference for the examination and validation of the RPS utilized in this study. The FDGS is a variant of the basic gradient search method. It checks the gradients in the inequality constraints as well as direction which improves the objective function while staying within the acceptable design region [15]. The formulations of the problem at hand are given in the following:

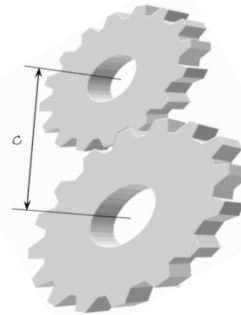


Figure 1 Spur gear couple.

Minimize

$$F_{obj} = C(x_1, x_2, x_3) = [(0.5 x_1 / x_2) + (1 + N)] \quad (6)$$

Subject to

$$g_1 = [\sin(\Phi / (180 / \pi)) / \cos(\Phi / (180 / \pi))] - AA > 0.001 \quad (7)$$

$$AA = [(\sqrt{R_{A2} R_{A2}}) - (R_{B2} R_{B2})] - R_2 \sin(\Phi / (180 / \pi)) / [(R_{B1}) (1)] \quad (8)$$

$$R_{A2} = [0.5 (\pi / x_2) (N x_1 / \pi)] + [(1 / x_2) + 1] \quad (9)$$

$$R_{B1} = [0.5 (\pi / x_2) (x_1 / \pi)] + [\cos(\Phi / (180 / \pi))] \quad (10)$$

$$R_{B2} = [0.5 (\pi / x_2) (N x_1 / \pi)] + [\cos(\Phi / (180 / \pi))] \quad (11)$$

$$R_1 = x_1 / (2 x_2) \quad (12)$$

$$R_2 = [0.5 (\pi / x_2) (N x_1 / \pi)] \quad (13)$$

$$g_2 = [(x_3) / (2 (0.5 x_1 / x_2))] < 0.5 \quad (14)$$

$$g_3 = (0.5 x_1 / x_2) (1 + N) > 0.0 \quad (15)$$

$$g_4 = Pw + Gw > 0 \quad (16)$$

$$Pw = \gamma \pi (R_1)^2 x_3 \quad (17)$$

$$Gw = \gamma \pi (R_2)^2 x_3 \quad (18)$$

$$g_5 = Hp 63025 / \omega > 0 \quad (19)$$

$$g_6 = [Hp 63025 / \omega] / [x_1 / (2 x_2)] > 0 \quad (20)$$

$$g_7 = [\omega (x_1 / 2 x_2) \pi] / 6 > 0 \quad (21)$$

$$g_8 = F_T V_F > 0 \quad (22)$$

$$F_T = [Hp63025 / \omega] / [x_1 / (2x_2)] \quad (23)$$

$$V_F = (A + \sqrt{V}) / A \quad (24)$$

$$A = 50 + 56[(1 - (12 - Q_v)^{2/3}) / 4] \quad (25)$$

$$V = [\omega(x_1 / 2x_2)\pi] / 6 \quad (26)$$

$$g_9 = [(Hp63025 / \omega)(x_2) / (x_3 Y_s)] < 40000 \quad (27)$$

$$Y_s = 2[(x_E)^2 / (R_C - Y_E)](x_2 / 3) \quad (28)$$

$$X_E = [(R1 - Y_B) \sin(\beta + \theta)] - (X_B \cos(\beta + \theta)) - [(0.3 / x_2) / R_B](Y_B \sin(\beta + \theta) + X_B \cos(\beta + \theta)) \quad (29)$$

$$Y_B = (1.25 / x_2) - (0.3 / x_2) \quad (30)$$

$$\beta = (\pi / x_1) - (\Delta / (x_1 / 2x_2)) \quad (31)$$

$$\Delta = (\pi / 2x_2) - ((\pi / x_2) / 2) - \quad (32)$$

$$(Y_B \sin(\Phi / (180 / \pi)) / \cos(\Phi / (180 / \pi))) - ((0.3 / x_2) / \cos(\Phi / (180 / \pi))) \quad (32)$$

$$X_B = (x_1 / (2x_2))\theta \quad (33)$$

$$R_B = \sqrt{(Y_B)^2 + (X_B)^2} \quad (34)$$

$$R_C = [(x_1 / (2x_2)) \cos(\Phi / (180 / \pi))] / \quad (35)$$

$$[(\cos(\Psi_A - (T_C / (2(x_1 / (2x_2)))) - F_{INV}(p) + F_{INV}(\Psi_A))] \quad (35)$$

$$\Psi_A = \text{Arc tan}[(g_1 + ((Z - P_B) / R_{B1})) + \quad (36)$$

$$((2P_B - Z) / R_{B1})] / (180 / \pi) \quad (36)$$

$$Z = C_1 + [C_2 - (C \sin(\Phi / (180 / \pi)))] \quad (37)$$

$$C = R_1 + R_2 \quad (38)$$

$$C_1 = \sqrt{(R_{A1} R_{A1}) - (R_{B1} R_{B1})} \quad (39)$$

$$C_2 = \sqrt{(R_{A2} R_{A2}) - (R_{B2} R_{B2})} \quad (40)$$

$$P_B = (\pi / x_2) \cos(\Phi / (180 / \pi)) \quad (41)$$

$$T_C = (\pi / x_2) / 2 \quad (42)$$

$$F_{INV}(P) = [\sin(\Phi / (180 / \pi)) / \quad (43)$$

$$\cos(\Phi / (180 / \pi))] - \Phi / (180 / \pi) \quad (43)$$

$$F_{INV}(\Psi_A) = [\sin(\Psi_A) / \cos(\Psi_A)] - \Psi_A \quad (44)$$

$$Y_E = [(R1 - Y_B) \cos(\beta + \theta)] + (X_B \sin(\beta + \theta)) + \quad (45)$$

$$[(0.3 / x_2) / R_B](X_B \sin(\beta + \theta) - Y_B \cos(\beta + \theta)) \quad (45)$$

$$g_{10} = (g_5 / R_1) / [(\cos(\Phi / \quad (46)$$

$$(180 / \pi))\pi x_3 S_{BB}] < 150000 \quad (46)$$

$$S_{BB} = \sqrt{[2(g_5 / R_1)] / \quad (47)$$

$$[(\cos(\Phi / (180 / \pi))\pi E_o x_3 CAP_2]} \quad (47)$$

$$E_o = E / (1 - \nu^2) \quad (48)$$

$$CAP_2 = 1 / [R_{OB}((1 - R_{OB}) / (((0.5 x_1 / x_2) + \quad (49)$$

$$(1 + N)) \sin(\Phi / (180 / \pi)) \quad (49)$$

$$R_{OB} = R_1 \cos(\Phi / (180 / \pi))(g_1 + BL_1) \quad (50)$$

$$BL_1 = (Z - P_B) / [R_1 \cos(\Phi / (180 / \pi))] \quad (51)$$

$$g_{11} = [(g_5 / R_1) / 3] / \quad (52)$$

$$[(\cos(\Phi / (180 / \pi))\pi x_3 S_{BA}] < 150000 \quad (52)$$

$$S_{BA} = \sqrt{[(g_5 / R_1) / 3] / \quad (53)$$

$$[(\cos(\Phi / (180 / \pi))\pi E_o x_3 CAP_1]} \quad (53)$$

$$CAP_1 = 1 / [R_{OA}((1 - R_{OA}) / (((0.5 x_1 / x_2) + \quad (54)$$

$$(1 + N)) \sin(\Phi / (180 / \pi)) \quad (54)$$

$$R_{OA} = R_1 \cos(\Phi / (180 / \pi)) g_1 \quad (55)$$

$$g_{12} = [g_{13} (V_{LG} - V_{LP}) / 12] / 1000000 < 100 \quad (56)$$

$$V_{LG} = (\omega 2\pi / N) R_{A2} \sin(p + AA_2) \quad (57)$$

$$AA_2 = [C_2 - (R_2 \sin(\Phi / (180 / \pi))] / R_{B2} \quad (58)$$

$$V_{LP} = \omega (R_{A2} \sin(AA_2) / \sin(AA_1)) \sin(p - AA_1) \quad (59)$$

$$g_{13} = T_b + TI < 275 \quad (60)$$

$$TI = [S_w(0.027(50) / (50 - R_{ms})) (1.75) X_G \sqrt{V}] / \quad (61)$$

$$[(0.5 x_1 / x_2) + (1 + N)]^{0.25} \quad (61)$$

$$S_w = [((g_5 / (x_1 / (2x_2))) V_F / 3) / x_3]^{0.75} \quad (62)$$

$$V_F = (A + \sqrt{V}) / A \quad (63)$$

$$X_G = 0.5 I \sqrt{(N + 1)(A_X / B_X)} \quad (64)$$

$$A_X = \sqrt{I + G_Y} - \sqrt{I - (G_Y / N)} \quad (65)$$

$$G_Y = ((C_1 / R_{B1}) / (\sin(\Phi / (180 / \pi))) / \quad (66)$$

$$\cos(\Phi / (180 / \pi)) - 1 \quad (66)$$

$$B_X = (1 + G_Y)(N - G_Y)^{0.25} \quad (67)$$

$$x_1^{lower} \leq x_1 \leq x_1^{upper} \quad (68)$$

$$x_2^{lower} \leq x_2 \leq x_2^{upper} \quad (69)$$

$$x_3^{lower} \leq x_3 \leq x_3^{upper} \quad (70)$$

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Table 1 Constant parameters

Constants	Value
Poisson Ratio (ν)	0.25
Elastic Modulus (E), <i>Psi</i>	30000000
Pressure Angle (Φ), <i>deg ree</i>	20
Gear Ratio (N)	1.50
Pinion Power (Hp), <i>Horse power</i>	10
Pinion Speed (ω), <i>Rpm</i>	4500
Material Weight Density (γ), <i>Lbs / in³</i>	0.283
Material Strength Constant (C_m) <i>Psi</i>	9800
Weibull Slope (b)	2.5
Load-life Factor (p)	8.93
Design Reliability (Re)	0.90
Oil Inlet Temperature (T_b), <i>deg rees F</i>	120
Tooth Surface Finish (Rms), <i>Rms</i>	32

Table 1 gives the constant parameters which define the problem in hand. The Poisson's ratio (ν), elastic modulus (E), pressure angle (Φ), gear ratio (N), transmitted (pinion) power (Hp), pinion speed (ω), material weight density (γ), material strength constant (C_m), Weibull

slope (b), load-life factor (p), design reliability (Re), oil inlet temperature (T_b), and tooth surface finish (Rms). The specified range of design variables used for finding the minimum center distance are: The number of teeth, $10 \leq x_1 \leq 100$, the diametral pitch, $4 \leq x_2 \leq 28$, and the gear and pinion face width, $0.5 \leq x_3 \leq 5$.

Constraints are conditions that must be met in the optimum design and include restrictions on the design variables value and the optimum design of the objective function. These constraints define the boundaries of the feasible and infeasible design space domain. The constraints considered for the optimum design of the spur gear are as follows: The involute interface angles, g_1 , should be greater than 0.001 (in radian) for the gear tooth tip to contact the pinion tooth on its involute surface and avoid interference. The face width to pinion diameter ratio, g_2 , should be less than 0.5. The center distance, g_3 , should be greater than 0.0. The pinion and gear weights, g_4 , should be greater than 0.0. The pinion torque, g_5 , should be greater than 0.0. The transmitted force, g_6 , should be greater than 0.0, the pitch line velocity, g_7 , should be greater than 0.0. The AGMA –ANSI-AGMA 2001-B88 standard- velocity factor model is used to estimate the dynamic load. The gear quality number, Q_v , may have a value between 6 and 11 with 11 corresponding to higher quality gear. For this study, the quality number used is 9. The dynamic load, g_8 , should be greater than 0.0. The AGMA bending stress, g_9 , should be less than 40000 psi. The contact pressure, g_{10} , should be less than 150000 psi. The gear tip hertz contact pressure, g_{11} , should be less than 150000 psi. The pressure times velocity factor, g_{12} , should be less than $100 \cdot 10^6$ psi-ft/min. The flash temperature, g_{13} , should be less than 275 (degree F).

The PS is an unconstrained optimization procedure. Therefore, the objective functions should be transformed into an unconstrained problem by setting an augmented objective function incorporating any violated constraint as penalty function. In case of any violation of a constraint boundary, the fitness of corresponding solution is penalized, and thus kept within feasible regions of the design space by increasing the value of the objective function when constraint violations are encountered. A unique static penalty function developed by Homaifar et al. [16] is employed with multiple violation levels set for each constraint in order to maintain a feasible population. Each constraint is defined by the relative degree of constraint penalty coefficient. The penalty coefficients, r_j , for the j -th constraints have to be judiciously selected.

$$F_{obj} = \begin{cases} C(x_1, x_2, x_3) & \text{if } (x_1, x_2, x_3) \text{ are feasible} \\ \text{otherwise} \\ C(x_1, x_2, x_3) + \sum_{j=1}^{NC} r_j (\max [0, g_j])^2 \end{cases} \quad (71)$$

where NC is number of constraints.

3. Results

Figure 2 shows the plot of normalized objective function value in each iteration as optimization proceeds. From the plot can be seen that the selected parameter set has converged to a stable solution with similar values after iterations 15.

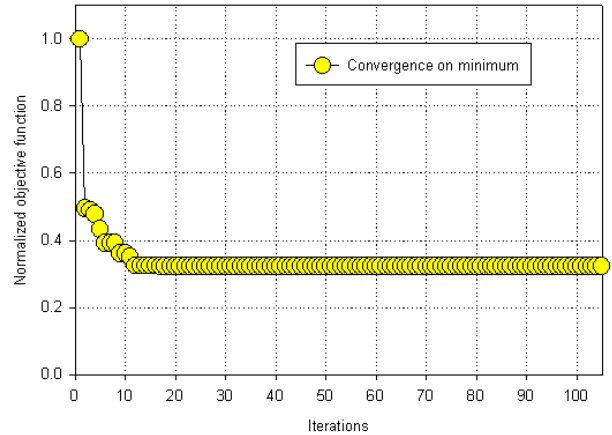


Figure 2 Convergence process of the PS for best results of objective function.

The inequality constraints versus the design variables are given in Figure 3 (a-m). Figure 3(a) gives the involute interference limit, Figure 3(b) gives the force width to diameter limit, Figure 3(c) gives the center distance limit, Figure 3(d) gives the gear and the pinion weight limit, Figure 3(e) gives the pinion torque limit, Figure 3(f) gives the transmitted force limit, Figure 3(g) gives the pitch line velocity, Figure 3(h) gives the total dynamic load limit, Figure 3(i) gives the AGMA bending stress limit, Figure 3(j) gives the full load contact stress limit, Figure 3(k) gives the gear tip hertz pressure, Figure 3(l) gives the PV factor, and Figure 3(m) gives the flash temperature limit. These constraints limits divide the design space in two regions; as feasible design region in which all design constraints are satisfied and infeasible design region in which at least one design constraint is violated. Figure 4 shows the plot of the design space for the objective function, center distance of two spur gears in contact, versus the design variables. It can be seen how the objective function varies for different design variables combination by visualizing the design space. Also the optimal point which satisfies the inequality constraints is marked on the plot. Table 2 shows a comparison of the best overall solution found for the central distance of the spur gears in contact by the RPS and the FDGS. As can be seen in Table 2, the FDGS gives good approximation to the global optimum but not the exact solution. So, better convergence reliability is obtained with the RPS. Using the FDGS, the objective function, center distance, of 1.832 in. (46.532 mm) was found with the pinion teeth of 20.39, the diametral pitch of 13.91 in^{-1} , and the face width of 0.732 in. in the study by Savage (1995) while the center distance, of 1.252 in. (31.800 mm) was found with the pinion teeth of 21.459, the diametral pitch of 21.416 in^{-1} , and the face width of 0.5003 in. by the RPS. Table 2 shows that the optimum design by the RPS has the minimum gear and pinion weight.

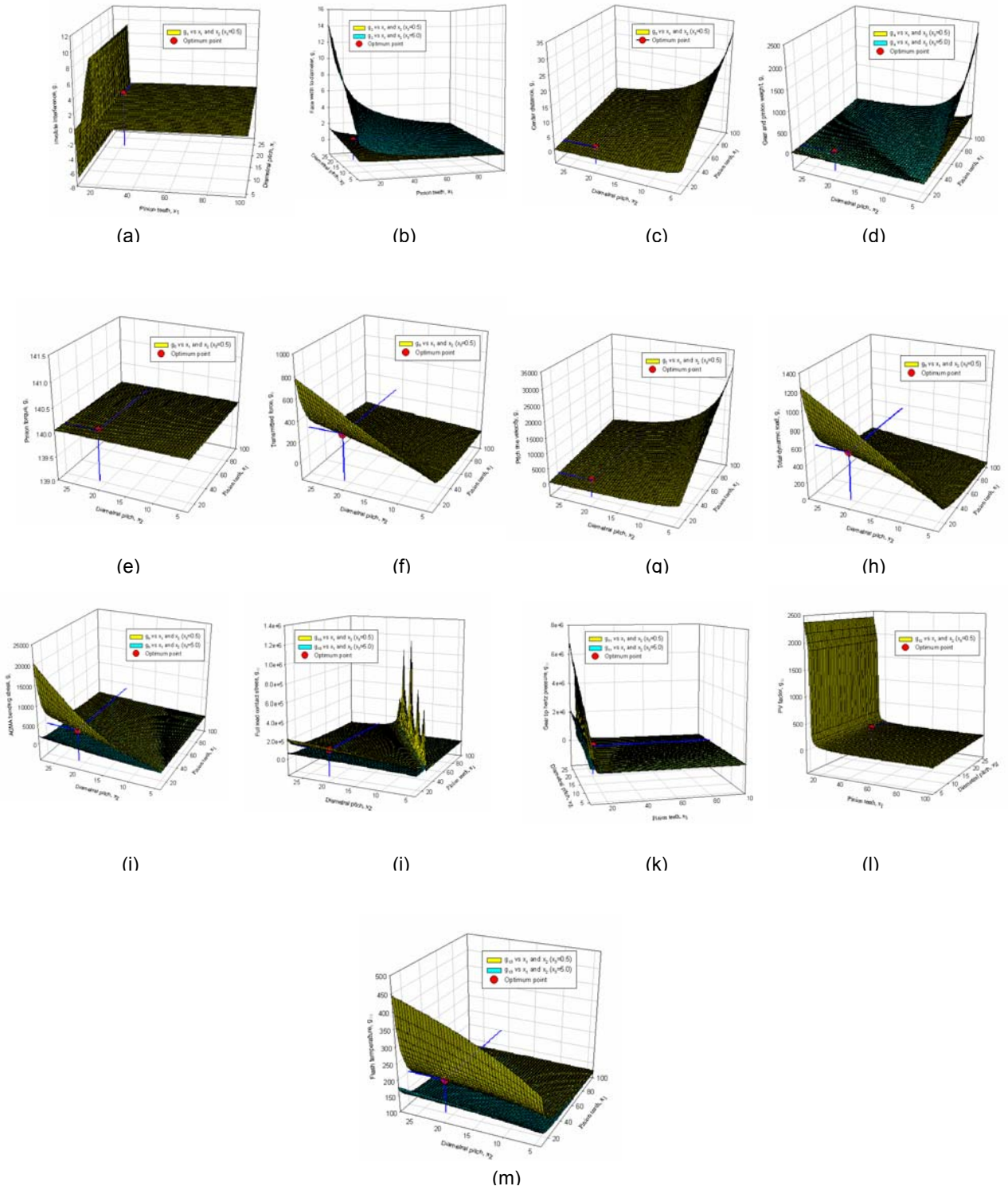


Figure 3. The design variables versus inequality constraints.

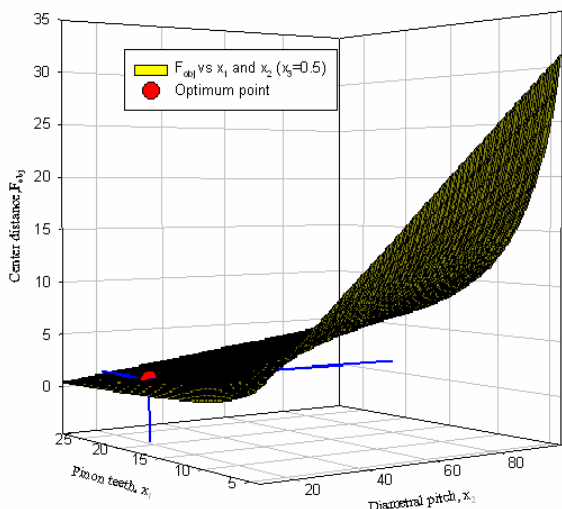


Figure 4 The objective function versus design variables with the optimum point.

Table 2 The best overall results.

	FDGS	RPS
Pinion Teeth	20.395	21.459
Diametral pitch, in. ⁻¹	13.910	21.416
Face width, in.	0.7320	0.5003
Center distance, in.	1.832	1.252
Involute interference, radians	0.1086	0.1196
Face width to diameter, ratio	0.4998	0.5006
Gear and pinion weight, pounds	1.1376	0.3629
Pinion torque, lb-in	140.06	140.055
Transmitted force, pounds	191.07	279.54
Pitch line velocity, ft/min.	1727.1	1180.47
Total dynamic load, pounds	418.72	471.64
AGMA bending stress, psi	25097	17411
Full load contact stress, psi	149990	103170
Gear tip hertz pressure, psi	125180	146632

4. Conclusion

Most machine components design problems are hard to solve using conventional optimization algorithms due to many specific constraints imposed. Handling such complex problems of machine components design with constraints is not easy task. Most traditional optimization techniques require at least first-order derivatives of both the objective function and constraints with respect to design variables. When continuity and existence of derivatives of the objective function are not assured, traditional methods lack robustness and may trap in local optima. To overcome these problems, this study utilized a nature inspired algorithm, the Repulsive Particle Swarm (RPS), to find minimum center distance for desired life of a compact spur gear set to transmit a given power with satisfying a number of constraints. The algorithm does not require the evaluation of gradients of the objective function since it is a derivative free optimization technique. It is worth trying to compare the results obtained by the RPS to the Feasible Direction Gradient Search (FDGS). It is observed that the RPS has been able to find a better solution than the FDGS. The RPS requires a greater number of function evaluations than the FDGS. This requires more

computational effort. However, it can be concluded that the RPS is proven to be robust and has capability to produce an efficient solution for machine components design.

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