Frontiers in Computing and Intelligent Systems
ISSN: 2832-6024 | Vol. 11, No. 2, 2025

Application of Adaptive Mutation Particle Swarm Optimization Algorithm in Roller Optimization

Min Xu *

School of Mechanical Engineering, Anhui University of Engineering, Wuhu, Anhui 241000, China

*** Corresponding author Email:** 2716487652@qq.com

Abstract: To solve the problems of excessive volume and weight of the double roll granulator, a volume function model was established with the key parameters of the double roll structure, which is the main component of the granulation mechanism, as variables. Through the Matlab software platform, combined with five constraint conditions including tooth surface contact fatigue, gear root cutting restriction, tooth root bending fatigue, straw particle cross-sectional size and surface area, the adaptive mutation particle swarm algorithm is used for iterative constraint optimization design. Compared with the original double roll structure model, the optimized design achieves more compact volume parameters while satisfying the constraints, effectively reducing the problems of excessive volume and weight of the double roll granulator.

Keywords: Particle Swarm Optimization; Roller; Optimized Design; Matlab.

1. Introduction

The squeezing process of the roller can be regarded as the transmission process of multiple rows of gears, so optimizing the roller can be transformed into optimizing a single row of teeth on the roller. With the emergence of intelligent algorithms, new methods have been provided for the design optimization of rollers. Particle swarm optimization is a type of evolutionary algorithm that starts from a random solution and iteratively seeks the optimal solution by adjusting fitness. This algorithm has a concise concept, easy implementation, fast convergence speed, and few parameter settings.

In the research on gear optimization design, many scholars at home and abroad have analyzed it through different algorithms. Wang Chun et al. [1] introduced the contraction factor and linearly decreasing inertia weight into the particle swarm optimization algorithm to optimize the design of gear coincidence and volume; Ma Honggang et al. [2] optimized helical gears using a dual population genetic particle swarm algorithm; Liu Longjie et al. [3]optimized gear volume based on genetic algorithm with strength and reliability as constraints.; RV Rao et al. [4]conducted comparative experiments on the weight minimization of gear systems using the Rao algorithm with particle swarm optimization (PSO), genetic algorithm (GA), simulated annealing algorithm (SA), and grey wolf optimization algorithm (GWO).

This article focuses on the optimization design of roller volume. A particle swarm optimization algorithm based on adaptive mutation is run using Matlab software, with five forms of roller failure as constraints. The main parameters of the roller part, which is the main component of the granulation mechanism, are used as variables to solve the volume optimization function. Comparing the results with the original design parameters and volume, it can be concluded that the algorithm has achieved the goal of optimizing the volume to a certain extent.

2. Adaptive Mutation Particle Swarm Algorithm

2.1. Basic Principles of Algorithms

The core idea of PSO algorithm is to randomly generate particle swarm and set initial velocity, then optimize the objective function in multiple loops, and find the best solution to the objective function through continuous iteration process. During each iteration, each particle updates its variable values based on its individual optimal solution, which is the particle's own optimal solution, as well as the global optimal solution, which is the current optimal solution of the entire community, in order to reach the convergence optimal position at a faster convergence speed. The iterative solving process of the adaptive mutation particle swarm algorithm can be regarded as E ecological communities distributed in a G-dimensional exploration space, each community consisting of M particles, where the position of the i-th particle can be represented by a G-dimensional vector, denoted as

$$X_i = (x_{i1}, x_{i2}, \cdots, x_{iG}), \quad i = 1,2,\cdots,M$$

Use a G-dimensional vector to represent the velocity of the i-th particle and label it as:

$$V_i = (v_{i1}, v_{i2}, \cdots, v_{iG}), \quad i = 1,2,\cdots,M$$

Using a G-dimensional vector to represent the current optimal position of the i-th particle is the individual extremum of the i-th particle, denoted as:

$$p_{best} = (p_{i1}, p_{i2}, \cdots, p_{iG}), \quad i = 1,2,\cdots,M$$

The global optimal solution can be represented by a G-dimensional vector, which is the optimal position of the particle swarm:

$$g_{best} = (p_{g1}, p_{g2}, \cdots, p_{gG})$$

According to formulas (1) and (2), particles update their velocity and position parameters through individual and global extremum:

$$x_{iE} = x_{iE} + v_{iE} \tag{1}$$

$$v_{iE} = w * v_{iE} + c_1 r_1 (p_{iE} - x_{iE}) + c_2 r_2 (p_{gE} - x_{iE}) \tag{2}$$

C1 and c2 are learning parameters, and r1 and r2 are random values in the range of 0 to 1.

The adaptive mutation particle swarm algorithm draws on the principle of biological genetic mutation and integrates it into the iterative process of particle swarm optimization. By introducing the biological mutation mechanism into the particle swarm optimization algorithm, that is; by resetting some parameters probabilistically at each iteration to escape from the original extremum region, the particle search space is expanded to seek better solutions for the global optimization function. Although resetting some parameters increases computation time, it can effectively solve the problem of traditional PSO algorithms being prone to getting stuck in local optima during iteration, resulting in only obtaining local optima rather than global optima.[5]

2.2. Basic Flow

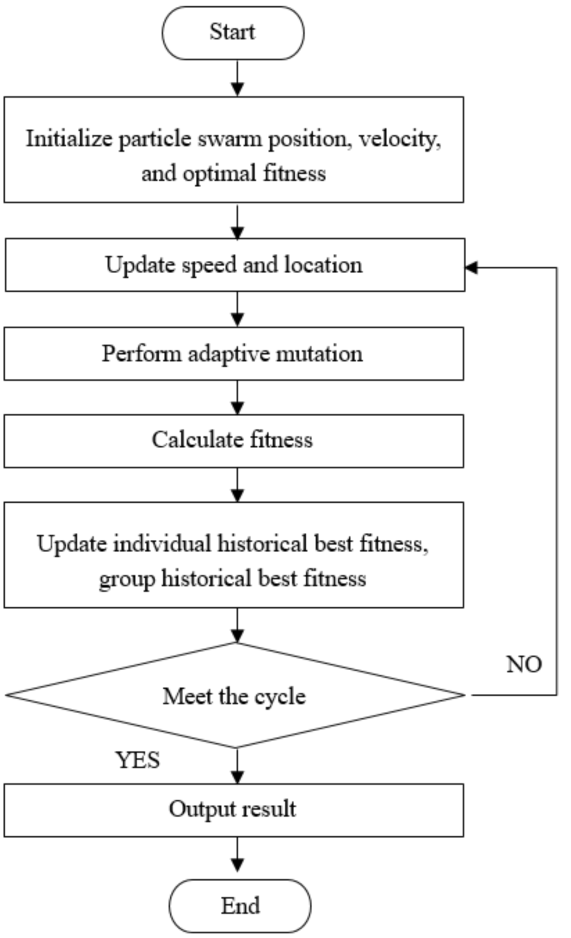

Figure 1. Flow Chart of Adaptive Mutation Particle Swarm Optimization Algorithm

1. Firstly, clarify the solution objective, establish the objective function in the adaptive mutation particle swarm algorithm based on the functional relationship, explore the variable constraints of the objective function, and list the corresponding constraint functions;

2. Set the initial state of the particle swarm, configure particle swarm parameters such as size M, position coordinates χ_i, and velocity direction v_i;

3. Set the optimal fitness value fitness_gbest (j) in individual records and determine the optimal fitness value fitness_zbest in group records;

4. Adjust the particle swarm velocity and limit its range, correct the population position coordinates and constrain the boundary of its population development;

5. Implement adaptive mutation particle swarm iteration to develop convergence calculation;

6. Evaluate the positional fitness in the individual records of the new population after iteration and perform constraint judgment

7. Compare the current individual fitness with the optimal value in the individual record. If fitness_pop (j) is less than fitness_gbest (j), update fitness_gbest (j) to fitness_pop (j);

8. Compare the optimal fitness value in individual records with the optimal fitness value in group records. If fitness_gbest (j) is less than fitness_zbest, update fitness_zbest to fitness_gbest (j);

9. Terminate when the error meets the standard or the number of iterations is exhausted, otherwise continue with step 4, as shown in the diagram 1.

3. Roller Optimization Design

3.1. Construction of Objective Function

The roller system can be regarded as consisting of 50 sets of gear units, with a spacing of 10mm between each unit and evenly spaced through holes on the tooth surface. When establishing an overall volume optimization model, it is necessary to deduct 40% of the pore volume of the roller system and the compression space between the gear sets. The roller model variables include gear geometric parameters and pore characteristic parameters. Denoted as X= $\{x_{1,}x_2\}$ = $\{m, z\}$, where m is the module of a single row gear and z is the number of teeth of the single row gear. The objective function of the roller, i.e. the roller volume function, is:

$$V = 0.6 * \pi * \frac{(mz)^2}{4} * 1010 - d^2 * m * z * 0.3 * z * 50 \tag{3}$$

$$V = 151.5\pi * {x_1}^2 * {x_2}^2 - 1500 * x_1 * {x_2}^2 \tag{4}$$

3.2. Constraints

The main forms of gear failure are tooth surface wear, tooth breakage, etc. In this analysis, the calculation is based on the constraint conditions of ensuring the bending fatigue strength of the tooth root and the contact fatigue strength of the tooth surface.

3.2.1. Tooth Root Bending Fatigue

The bending fatigue performance of gears can be represented by formula (5), where k_F represents the load factor, T_1 represents the load-bearing load, Y_{Fa} is the tooth profile parameter, Y_{sa} is the tooth tip stress adjustment factor, $Y_\varepsilon$represents the coincidence coefficient, and $\emptyset_d$ is the tooth width coefficient.

$$\sigma_F = \frac{2 \times k_F \times T_1 \times Y_{Fa} \times Y_{sa} \times Y_\varepsilon}{\emptyset_d \times m^3 \times \mathrm{Z}^2} \tag{5}$$

The roller material is 45 steels with a hardness of 230 HBS. The squeezing operation process is maintained in a stable state and driven by an electric motor. According to the table calculation, the value of K_F is 1.61, and the load is set to 1E+6 N * mm. According to the graph, the value of Y_{Fa} is selected as 2.35, Choose 1.7 for Y_{sa}. According to the calculation of Y_ε, it can be found to be 0.677. Please refer to the table and select $\emptyset_d$ as 1.

The fatigue condition for tooth root bending is $\sigma_F \leq [\sigma_F]$, and the calculation formula (6) for $[\sigma_F]$ is as follows [6]. K_{FN} is the bending fatigue life coefficient, and according to the graph, K_{FN}=0.95, σ_{Flim} is the tooth root bending fatigue limit of 485MPa, and the bending fatigue safety factor S=1.3. The calculation shows that the allowable stress for bending fatigue $[\sigma_F]$ is 354.42MPa.

$$[\sigma_F] = \frac{K_{FN}\sigma_{Flim}}{S} \quad (6)$$

Therefore, by combining formulas (5) and (6), the fatigue condition formula (7) for tooth root bending can be obtained as follows:

$$\sigma_F = \frac{2 \times 1.61 \times 10\text{^}6 \times 2.35 \times 1.7 \times 0.677}{1 \times m^3 \times Z^2} \leq [\sigma_F] = 354.42\text{MPa} \quad (7)$$

3.2.2. Tooth Contact Fatigue Strength

The contact fatigue strength of the gear is shown in equation (8). K_H is the load coefficient for contact fatigue strength, u is the gear ratio, Z_H is the zone coefficient, Z_E is the elastic influence coefficient, and Z_ε is the coincidence coefficient.

$$\sigma_H = \sqrt{\frac{2 \times K_H \times T_1}{\emptyset_d \times d_1^3} \times \frac{u+1}{u}} \times Z_H \times Z_E \times Z_\varepsilon \quad (8)$$

By calculating $K_H = K_A K_V K_{H\alpha} K_{H\beta}$, it can be obtained that K_H is 1.61. The specifications of the upper and lower rollers are the same, so u is 1. The regional coefficient can be calculated to be Z_H=1.96. For 45 steel, the Poisson's ratio μ is 0.3, the elastic modulus E is 2E+5 Mpa, and the elastic influence coefficient Z_E is calculated to be 187.0 $\text{MPa}^{1/2}$. The coincidence coefficient is Z_ε=0.87.

The condition for the fatigue strength of tooth surface contact is $\sigma_H \leq [\sigma_H]$,where $[\sigma_H]$ is the allowable stress for contact fatigue. The calculation formula (9) is as follows. K_{HN} is the contact fatigue life coefficient, and according to the graph, K_{HN}=0.91. The tooth root contact fatigue limit is 540MPa, with a failure probability of 1% and a contact fatigue safety factor S=1. The calculation shows that the allowable stress for contact fatigue is $[\sigma_H]$=527.8MPa.

$$[\sigma_H] = \frac{K_{HN}\sigma_{Hlim}}{S} \quad (9)$$

Therefore, formulas (8) and (9) provide the condition for tooth contact fatigue strength, and formula (10) is

$$\sigma_H = \sqrt{\frac{2 \times 1.61 \times 10\text{^}6}{1 \times m^3 \times z^3} \times \frac{1+1}{1}} \times 1.96 \times 187 \times 0.87 \leq [\sigma_H] = 527.8MPa \quad (10)$$

3.2.3. Other Conditions

In this analysis, in addition to the wear of the roller tooth surface and the failure mode of tooth breakage, the roller also needs to consider the constraints of gear shape root cutting, granulation machine particle forming section, and surface area size. The specification of a single row gear is a standard gear with an angle of α=20°, h=1, To avoid cutting off the root involute during gear machining, the number of teeth z in a single row of rollers should be ≥ 17[7]. Considering that the cross-sectional size of extruded straw particles is related to the tooth pitch, which is determined by the modulus, the modulus m is set to be greater than or equal to 10. The mechanism for squeezing straw requires a certain surface area, and the diameter of the dividing circle is set to be greater than or equal to 450 and less than or equal to 600.

In summary, there are five constraints on the objective function of the adaptive mutation particle swarm algorithm:

1. $x_1 \geq 10$
2. $x_2 \leq 17$
3. $450 \leq x_1 \times x_2 \leq 600$
4. $\frac{2\times1.61\times10\text{^}6\times2.35\times1.7\times0.677}{1\times{x_1}^3\times{x_2}^2} \leq 354.42\text{MPa}$
5. $\sqrt{\frac{2\times1.61\times10\text{^}6}{1\times{x_1}^3\times{x_2}^3} \times \frac{1+1}{1}} \times 1.96 \times 187 \times 0.87 \leq 527.8MPa$

4. Optimal Results

In the initial plan, the roller adopts a single row gear structure with a module set to 10, 50 teeth, and a tooth width of 10 millimeters. A total of 50 rows are arranged, with a total length of 1010 millimeters. After calculation, the total volume of the design is 8.15E+7 mm ^ 3. Using the Matlab platform, an adaptive mutation particle swarm optimization algorithm is implemented. After inputting the objective function and constraint conditions, the initial population size is set to 500, the maximum number of iterations is 1000, the inertia weight is 0.8, the individual and population learning coefficients are both 0.5, and the mutation coefficient is 0.85[8]. Calculated as x_1 =10.0073, x_2 =44.9678, The maximum volume is 66028410.4294 mm ^ 3. After rounding, m=10, z=45, V= 6.6E+7 mm^3.

Through continuous optimization using the adaptive mutation particle swarm algorithm, the volume parameter of the objective function quickly decreased to the range of 6.6-6.7E+7 mm ^ 3 within 100 iterations. After 200 iterations, the convergence process tends to be stable, and the volume parameter of the objective function result has approached V=6.6E+7 mm ^ 3. Based on the adaptive mutation particle swarm optimization algorithm, the volume parameter obtained from the objective function volume was reduced by 19.02% compared to the original design volume.

5. Conclusion

This study explores the roller structure in depth and derives its volume calculation formula. Under the original design parameter framework, considering factors such as tooth root bending fatigue, gear root cutting restriction, tooth surface contact fatigue strength, and straw particle cross-sectional size, constraints were established in five volume optimization algorithms, and a mathematical model was developed with the goal of minimizing the roller volume. To solve the mathematical model, an improved adaptive mutation particle swarm algorithm was adopted, which incorporates an adaptive mutation mechanism on the basis of traditional PSO, effectively avoiding the problem of local optimal solutions.

Through 200 rounds of adaptive mutation particle swarm optimization, the volume convergence process of the roller model tends to be stable, reducing the roller volume by 19.02% compared to the initial design, thereby achieving lightweight improvement of the overall double roller structure and effectively reducing production costs and energy consumption in industrial manufacturing when manufacturing double roller granulators.

References

[1] Wang Chun, Han Jiahao, Jiqing. Research on Optimization Design of Gear Transmission Based on Improved Particle Swarm Optimization Algorithm [J]. Mechanical and Electrical Engineering,2021,38(02):239-244.

[2] Ma Honggang, Liu Huan, Lei Wenjun, etc. Optimization design of helical gears based on dual population genetic particle swarm algorithm [J]. Internal Combustion Engine and Parts, 2021 (11): 22-24.

[3] Liu Longjie, Liu Xiangzhen. Reliability optimization design of gear transmission based on genetic algorithm [J]. Agricultural Equipment and Vehicle Engineering, 2021, 59 (06): 101-103+108.

[4] Rao R V ,Pawar R B . Optimal Weight Design of a Spur Gear Train Using Rao Algorithms[M]. 2020.

[5] Chen Bowen, Zou Hai. Summative Adaptive Mutation Particle Swarm Optimization Algorithm [J/OL]. Computer Engineering and Applications: 1-11 [2021-07-23].

[6] Mao Tianyu, Yu Yong, Liu Huaiju, etc. Dynamic reliability analysis of gear transmission system for flying cars [J]. Mechanical Transmission, 2021, 45 (06): 96-103+176.

[7] Huang Xiaoping, Zhao Linlin. Root cutting analysis of cylindrical helical arc gears [J]. Mechanical Transmission, 2019, 43 (06): 29-36+54.

[8] Xu Guosheng, Xu Zuyong, Zhou Junjie, etc. Research on Path Planning Algorithm for Inspection Robots Based on Genetic Algorithm [J]. Mechanical Design and Manufacturing Engineering, 2021, 50 (06): 93-98.

[9] Min Xu. Analysis of Double Roll Granulation and Extrusion Forming Process [D]. Anhui University of Engineering, 2023.