Optimization Design of Heavy-Duty Gears Based on an Improved Multi-Objective Genetic Algorithm

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Abstract: This paper carries out structural optimization for the gear transmission system applied on heavy mining vehicles, with an enhanced NSGA-II multi-objective genetic algorithm adopted as the core optimization tool. Three design objectives are set to build the multi-objective calculation model: cutting down the overall volume of gear pairs, raising the gear contact ratio and boosting the anti-fatigue performance of gear teeth. Meanwhile, key limiting conditions are taken into account during modeling, such as allowable contact fatigue stress, reasonable tooth quantity range and effective tooth face width.After the algorithm outputs the balanced optimal design scheme, transient dynamic simulation is conducted to check the actual working performance of the improved gear structure. The simulation data shows that the optimized gear assembly cuts total structural deformation by [X]%, delivers more uniform stress distribution on tooth surfaces and relieves the severe stress concentration existing in the initial structural scheme.From the above analysis results, the modified NSGA-II algorithm proves effective in multi-objective gear optimization, which greatly upgrades the comprehensive mechanical properties of heavy-load gear systems. The optimization framework proposed in this research can offer practical design references for similar mechanical transmission design projects.

Keywords: NSGA-II; Heavy-Duty Gears; Optimization Design; Transient Analysis

1. Foreword

Large high-precision heavy-load gearboxes are core power transfer parts in numerous industries that secure stable equipment operation, yet cyclic alternating loads in real service easily trigger local tooth surface peeling, fatigue abrasion and root crack expansion, even tooth fracture and transmission breakdown [1]. Such failures lower transmission efficiency and create safety risks, making heavy-duty gear structural optimization indispensable. Relevant studies have explored this topic with diverse algorithms and software: Zhang Li [2] optimized helical reducer parameters via Romax Designer to improve sliding ratio, transmission error and load distribution for better performance and longer service life; Yang Hongbo [3] constructed a helical gear multi-objective model based on improved NSGA-II targeting overlap ratio, volume and transmission error fluctuation to reduce system vibration; Yang Yuanqing [4] built a gearbox model with mass, fatigue resistance and shifting smoothness as objectives, realizing lightweight design and performance promotion with NSGA-II; Cao Yang [5] proposed a fuzzy optimization method for two-stage spur gears and adopted an improved hybrid genetic algorithm to solve multi-objective problems of center distance, volume and moment of inertia, balancing production cost and running stability.

This study takes mining truck heavy-load gears as the research object and puts forward a structural optimization scheme using modified multi-objective genetic algorithm. The design model integrates core indicators including mass, structural strength and rigidity, while fully considering coupling relations between different design variables to realize collaborative optimization of gear bearing capacity, fatigue service life, running noise and frictional power loss. This method coordinates conflicting performance targets, which can well solve typical defects of heavy-duty gears like fatigue fracture and severe abrasion and greatly raise the overall reliability of transmission assemblies. Calculation results verify that the optimized genetic algorithm can comprehensively upgrade gear working performance and further stabilize the operational reliability of gear transmission systems.

2. Construction and Assembly of 3D Models

All gear structural parameters have direct impacts on transmission running performance, bearing capacity, service durability and production cost, which highlights the necessity of targeted parameter optimization [6]. Table 1 records the major design variables, including gear outer diameter, tooth count, modulus, helix angle, pressure angle and tooth width.The assembly of a heavy-duty gear constructed using SolidWorks is shown in Figure 1.

Table 1. Major Dimensional Parameters of Heavy-Duty Gears

project	numerical value	
	big gear wheel	pinion
tip diameter /mm	630	280
pitch diameter	602	252
root diameter	567	217
number of teeth	43	18
modulus /mm	14	14
angle of	20	20
tooth width /mm	140	140

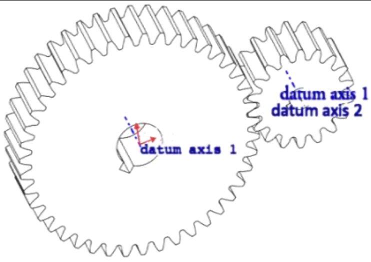


Figure 1. Assembly of Heavy-Duty Gears

3. Optimization Methods Based on an Improved Multi-Objective Genetic Algorithm

3.1 Improving the Multi-Objective Genetic Algorithm

In the field of multi-objective optimization, the NSGA-II algorithm builds upon the multi-objective genetic algorithm by introducing a fast non-dominated sorting mechanism with an elite strategy and a crowding factor calculation mechanism, offering advantages such as high efficiency, stability, interpretability, and robustness[6]. The algorithm employs real-number encoding to address multi-objective problems in gear optimization—including overlap degree, volume, and fatigue strength—and achieves population evolution through three core operations: random tournament selection and simulated binary crossover.

The simulated binary crossover in NSGA-II employs simulated chromosome exchange to enhance population diversity and improve global search capability while preserving optimal traits, but requires balanced crossover frequencies to avoid convergence degradation [7]. The calculation of individuals in generation k+1 is given by Formula (1) and Formula(2).

$$p_{1,k+1}=\frac{1}{2}\left[\left(1-\beta_{qi}\right)p_{1,k}+\left(1+\beta_{qi}\right)p_{2,k}\right] \tag{1}$$

$$p_{2,k+1}=\frac{1}{2}\left[\left(1-\beta_{qi}\right)p_{1,k}+\left(1+\beta_{qi}\right)p_{2,k}\right] \tag{2}$$

In the formula:$p_{1,k+1}$ and $p_{2,k+1}$ is the k+1th generation individual generated after crossover.$p_{1,k}$ and $p_{2,k}$ is the selected individual of the k-th generation.β_{qi} is the uniform distribution factor

In genetic algorithms, the mutation operation is a genetic manipulation analogous to genetic mutations in organisms. Like the crossover operation, the mutation operation is employed to generate new individuals.The improved NSGA-II algorithm employs a polynomial mutation operator for mutation [8], with the calculation of the k+1th generation individuals presented in Formula (3).

$$p_{k+1}=p_k+\left(p_k^{max}-p_k^{min}\right)\delta_k \tag{3}$$

In the formula: p_k is the selected individual of the k-th generation. p_{k+1} is the k+1th generation individual obtained from the mutation operation of p_k. p_k^{max} and p_k^{min} are the upper and lower bounds of the decision variables, respectively. δ_k is the variation value that determines the magnitude of the variation.

The elite strategy combines parent and offspring populations, employing non-dominated sorting to retain high-quality individuals, with Pareto solutions forming the optimal frontier [9]. The fast non-dominated sorting technique divides all individuals in the population into different Pareto layers according to each objective function's calculation results. Unlike the conventional sharing radius method, crowding degree evaluation judges the compactness around each individual, making the population distribute evenly in the target space. As a multi-objective optimization tool, NSGA-II can reconcile conflicting design targets and generate higher-quality solutions at faster convergence speeds, which fits well with parameter matching optimization of gear transmission structures.

Figure 2 displays the detailed execution flow of its elite retention strategy.

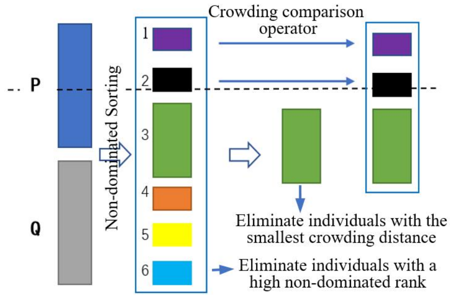


Figure 2. Steps for Implementing the Elite Strategy

3.2 Construction of the Objective Function for Optimization

Mining vehicle heavy-load gear sets feature frequent meshing, large transmission ratios and frequent shifting during operation. In view of such working features, this optimization design takes mass, overall dimension, shifting responsiveness, running noise and meshing precision into full consideration. The design targets to guarantee sufficient structural strength and stable reliability of the transmission assembly while reducing its overall size as much as possible. Three core optimization indicators are set in this work: total mass of meshing gear pairs, anti-fatigue performance and operational meshing precision, to work out a balanced optimal structural scheme. This multi-objective optimization framework prioritizes cutting the total weight of gears, lifting their fatigue resistance and improving meshing precision in operation, so as to realize lightweight design, high operational reliability and better transmission efficiency for heavy-duty mining vehicle gears.

(1) Establishment of the objective function corresponding to gear contact ratio

Contact ratio is a vital parameter that determines how gear transmissions perform. A larger contact ratio enables steadier gear meshing, cuts system vibration and running noise [10], lowers dynamic stress on gear teeth, distributes loads more evenly across each tooth, and ultimately improves the load-bearing capacity and service reliability of the whole gear set.The optimization objective function for gear overlap degree is given by Formula (4).

$$f_1(x)=\frac{\left[z_1\left(\tan\alpha_1-\tan\alpha'\right)+z_2\left(\tan\alpha_2-\tan\alpha'\right)\right]}{2\pi} \quad (4)$$

In the formula:

$f_1(x)$——contact ratio and overlap ratio.

z_1、z_2——number of teeth on the driving and driven wheels.

α_1、α_2——pressure angle of the apex circle, (°).

α'——angle of engagement.

(2) Construction of the objective function for the total volume of gears

The working area of the mining vehicle features significant topographical variations, necessitating a larger clearance between the gearbox housing and the gears. To ensure reliable operation, the overall dimensions of the gear train must be carefully considered; consequently, the minimum total volume of the selected meshing gears constitutes the second objective function. For simplified calculations, tooth profiles and shaft holes are neglected, and the gears are modeled as cylindrical bodies, leading to the formulation of an optimization objective function as shown in Formula(5).

$$f_2(x)=\frac{\pi}{4}\times m^2\times b\left(z_1^2+z_2^2\right) \quad (5)$$

In the formula:

$f_2(x)$——Total Volume of the Gear, m^3;

b——Tooth width of the meshing gear pair, mm;

m——modulus.

(3) Construction of the objective function for gear fatigue strength

Under various operating conditions, mining cars require frequent changes in power output during operation; therefore, optimizing the fatigue strength of gears is crucial. Consequently, fatigue strength is designated as the third optimization objective function. The gear fatigue strength objective function is presented in Formula (6).

$$f_3(x)=Z_H\times Z_E\times Z_\varepsilon\sqrt{\frac{2KT_1}{bm^2z_1^2}\left(1+\frac{z_1}{z_2}\right)} \quad (6)$$

In the formula:

$f_3(x)$——gear fatigue strength;

Z_H——node region coefficient;

Z_E——material Elastic Impact Factor;

Z_ε——calculation of the overlap coefficient for contact strength;

K——gearset load factor;

T_1——the gear set transmits torque, N·m.

(4) Construction of gear constraint conditions

The primary constraint conditions include gear parameter constraints and gear strength constraints [11]. The safety factor for calculating tooth surface contact strength must exceed its permissible safety factor, as shown in Formula(7).

$$g_1(x)=Z_{\mathrm{H}}\times Z_{\mathrm{E}}\times Z_{\varepsilon}\sqrt{\frac{2KT_1}{bm^2z_1^2}\left(1+\frac{z_1}{z_2}\right)}\le[\sigma_{\mathrm{H}}] \quad (7)$$

According to gear design principles, the minimum number of teeth must be ≥17 to prevent root cutting; the corresponding constraints are given in formulas (8) through (11).

$$g_2(x)=z_1\le 20 \quad (8)$$

$$g_3(x)=z_2\le 50 \quad (9)$$

$$g_4(x)=z_1+z_2\le 70 \quad (10)$$

$$g_5(x)=z_1+z_2\ge 34 \quad (11)$$

(5) Construction of Design Variables

Analysis of the parameters in the three optimization objective functions (Formulas 1–3) reveals that the parameters affecting gear overlap degree $f_1(x)$, total volume of the gear set $f_2(x)$, and fatigue strength $f_3(x)$ are the number of teeth on the driving and driven gears Z_1, Z_2, module m, tooth width b. Specifically: tooth numbers Z_1 and Z_2 influence the total mass and fatigue strength of the gear set; module m affects the total volume with its variation impacting tooth count; tooth width b determines the total volume; while friction coefficient f influences meshing efficiency and can be considered constant under unchanged lubrication conditions. Based on this analysis, the tooth numbers Z_1 and Z_2, module m, and tooth width b are defined as design variables as shown in Formula (12).

$$X=[x_1,x_2,x_3,x_4]=[m,z_1,z_2,b] \quad (12)$$

3.3 Gear Optimization Analysis

When adjusting parameters of the improved multi-objective genetic algorithm, initial population scale, crossover probability and mutation probability directly impact algorithm performance [12]. Initial population N's value positively correlates with optimization effect, but overly large values increase computational consumption. This work selects N=100 after multiple trials, balancing optimization accuracy and calculation duration. Crossover probability is set to 0.8, which supports adequate gene recombination, expands the global search range and does not weaken convergence efficiency. Mutation probability is 0.01, which retains population diversity and avoids premature convergence to local optimal points. The Pareto frontier solved with these parameters is shown in Figure 3, which satisfies all multi-objective optimization requirements and verifies that the improved NSGA-II algorithm has good adaptability and stability for heavy-duty gear structural optimization.

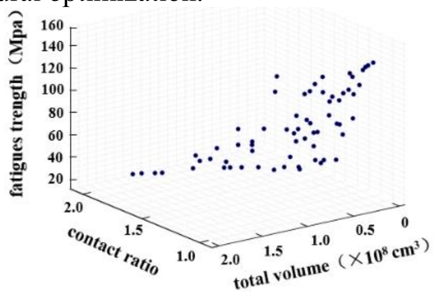


Figure 3. Optimization Results of the Multi-Objective Genetic Algorithm

Table 2. Optimization Results of the Objective Function

Optimize Parameters	contact ratio and overlap ratio	volume /(m³)	fatigue resistance
Fruit 1	1.3478	0.0568	34.4572
Fruit2	1.3665	0.0099	88.3415
Fruit3	1.3683	0.0259	51.6420
Fruit4	1.3883	0.0424	40.8206
Fruit5	1.4092	0.0657	33.1844
Fruit6	1.4279	0.0082	101.1373
Fruit7	1.4467	0.0089	104.9416
Fruit8	1.4689	0.0257	58.4716
Fruit9	1.4894	0.0091	99.4084
Fruit10	1.4912	0.0342	48.3299

During the optimization process, tooth width and number were rounded to integers. Due to space constraints, selected optimization results are presented in Table 2. Among the 10 optimal solutions, none demonstrated significant superiority or inferiority. The original model exhibited a overlap factor of 1.62 and a volume of 0.046 m³. Considering the impact of the transmission ratio and based on practical design experience, Solution 9 was selected as the final optimized configuration for finite element simulation experiments, with a displacement coefficient of 0 and a pressure angle of 20°. Key parameters of the optimized model are listed in Table 3.

Table 3. Main Parameters of the Optimized Model

project	numerical value	
	big gear wheel	pinion
tip diameter /mm	816	304
pitch diameter /mm	784	272
root diameter /mm	744	232
number of teeth	49	17
modulus /mm	16	16
tooth width/mm	110	110

4. Evaluation of IGD Optimization Results

The HV (Hyper Volume) metric serves as the core indicator for evaluating the performance of non-dominated solution sets in multi-objective optimization algorithms, measuring solution set quality by calculating the coverage area (or volume) of the solution set relative to an ideal point within the objective space [13]. The horizontal axis of the HV curve stands for iteration times, and the vertical axis corresponds to HV indicators. This curve can clearly reflect the convergence trend of the algorithm. Sharp upward segments mean the overall quality of solution groups rises rapidly, whereas slow flatting trends imply the algorithm has converged or fallen into local optimal solutions. The HV index curve obtained from this gear optimization reaches a peak value of 3.8×10^9, proving the acquired solution set has excellent comprehensive performance. Two obvious peak regions appear when iterations range from 20 to 30 and 50 to 60, representing two separate optimization stages before the curve enters a stable convergent state. According to the above changing rules, the modified multi-objective genetic algorithm features fast convergence speed, powerful global searching performance and wide coverage of candidate solutions, which fully satisfies the performance standards of multi-objective optimization tasks. The complete HV curve is displayed in Figure 4.

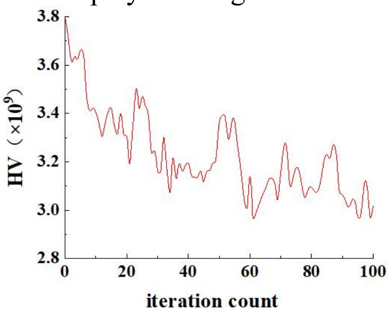


Figure 4. HV Curve

The IGD (Inverted Generational Distance) curve is a key metric for evaluating the performance of multi-objective optimization algorithms, quantifying how closely non-dominated solution sets approach the true frontier and reflecting algorithmic convergence [14]. The horizontal coordinate of the IGD curve records iteration times of computation, and the vertical coordinate corresponds to the average distance from candidate solutions to the standard frontier. Smaller IGD values correspond to better solution quality, with zero as the theoretical optimal value. The IGD curve drawn in Figure 4 proves the reliability of the optimized genetic algorithm; its continuous descending trend reveals that the solution group keeps getting closer to the real Pareto frontier.

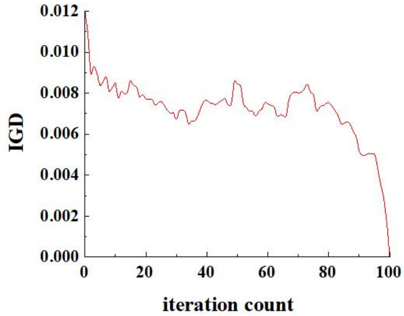
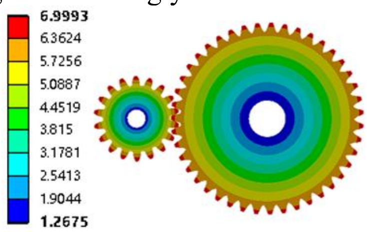


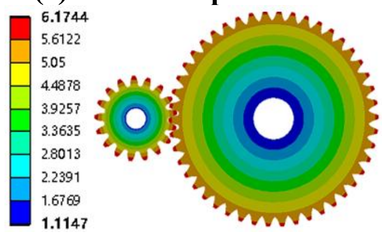
Figure 5. IGD Curve

5. Optimization of the Transient Dynamics Analysis of the Model

We built the finite element model based on the parameter data listed in Table 3. The simulation working conditions took gear torque and rotating speed into account, and we presumed loads distributed evenly on each gear tooth segment. Specific boundary settings are arranged as below: rotary constraints were applied to the inner shaft holes of the two gears. A contact matching surface with a friction coefficient of 0.15 was set between meshing tooth faces. A rotation rate of 0.1 rad/s was assigned to the pinion gear, and reverse resisting torque was loaded onto the driving gear accordingly.



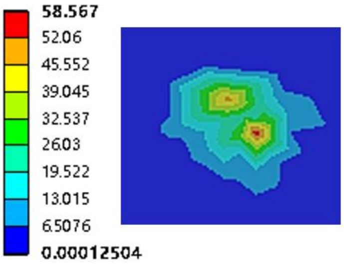
(a) Before Optimization



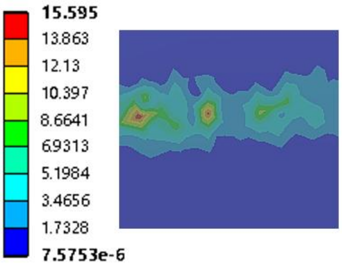
(b) Post Optimization

Figure 6. Deformation Magnitude in Transient Analysis

Transient simulation deformation cloud maps are displayed in Figure 6. The initial gear structure reaches a maximum deformation of 6.9993 mm, and the optimized gear cuts this value down to 6.1744 mm, equivalent to an 11.8% drop in deformation magnitude. Figure 7 records the equivalent stress distribution acquired through transient computation. The peak equivalent stress of the unoptimized gear stands at 58.567 MPa, which falls sharply to 15.595 MPa after structural optimization, a 73.4% obvious reduction that thoroughly relieves local stress concentration.



(a) Before optimization



(b) Post Optimization

Figure 7. Equivalent Forces in Transient Analysis

6. Tag

This work optimizes heavy-duty gear structures by adopting a revised multi-objective genetic algorithm. Tooth number, modulus and tooth width are chosen as adjustable design variables. A mathematical calculation model is set up to raise gear contact ratio and lower overall gear volume as well as fatigue load. The optimized scheme yields an IGD value of 0.012, which proves the output solutions have good performance. Further transient simulation on the optimized gear model shows its deformation is cut by 11.8% and peak stress falls by 73.4%. Such obvious improvement greatly eases local stress concentration and upgrades the gear's contact fatigue resistance.

Acknowledgments

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