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Knowledge-guided particle swarm optimization of multi-link systems for cold and warm forging presses

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Abstract. The performance of the multi-link system for mechanical press directly affects the performance of the press and the quality of the forgings. In order to improve the quality of forgings and enhance the design efficiency, a knowledge-guided particle swarm optimization design framework for multi-link systems is proposed, taking the cold and warm forging press as the research object. A knowledge database consisting of historical cases, rule knowledge and other knowledge was created. A reasoning machine consisting of retrieval and adoption was then built to determine the configuration of the multi-link system through case similarity calculations. A multi-link system optimization model was established for the selected configuration. To solve the optimization model, a knowledge-guided improved particle swarm optimization algorithm is developed, from which we obtain the optimized dimensions of the multi-link system. Comparing the results before and after optimization, we found that all the performance indexes have been improved to a certain extent, which proves the effectiveness of the knowledge-guided particle swarm optimization design framework for multi-link systems. Moreover, the framework facilitates the storage and reuse of design knowledge, which improves design efficiency and promotes design automation.

Introduction

Mechanical presses play a crucial role in forging and stamping processes. With the development of forging technology, in order to obtain near-net shape forgings, the development and use of cold forging technology has become the consensus of the manufacturing powerhouse. In the cold forging conditions, the fluidity of the metal is much lower than it in the hot forging conditions, so the cold forging forming is more sensitive to the forming speed, which requires “forming in accordance with the trend”, that is, the forming speed should be as low as possible, and the forming force should be much higher. Traditional crank-slide mechanical presses are difficult to meet the needs of current industrial production due to problems such as high speeds and difficulty in adjusting them [1]. Multi-link mechanical presses have received widespread attention and application in recent years due to their ability to approach the material being processed at slower, more uniform speeds and their quick-return characteristics. Their performance is mainly determined by the structural and dimensional parameters of the multi-link system. However, the multi-link systems for presses are complex and various. The conventional design methods depend on the experience of designers and a trial-and-error process, leading to low precision, extended design cycle and other problems.

With the advancement of computer technology, data-based optimization design methods [2,3] and knowledge-based design methods [4,5] are gradually maturing. In recent years, there have been many researchers using data-based optimization design methods combined with computer simulation for the optimal design of multi-link systems. Dong [6] proposed an improved optimization algorithm based on virtual prototype technology by considering the kinematics and dynamics performance indexes of the elbow-bar drive mechanism, and determined the optimal dimensions of the elbow-bar drive mechanism. Kütük [7] established an optimization model of a two-degree-of-freedom seven-link mechanism using a genetic algorithm to determine the optimal link lengths and applied kinetostatic approach to analyse crank torques and all the forces on the links. However, data-based optimization design methods require a large amount of data to support them. With the growing complexity of products, conventional intelligent optimization algorithms encounter challenges such as low efficiency and local optimization. Moreover, most of the studies have neglected the selection of the transmission configuration of the multi-link system, which is a difficult step to establish an optimization model. Selecting the most suitable transmission configuration requires more experience and theoretical knowledge of the designers.

Knowledge-based design methods are good at aggregating and reusing design knowledge (e.g., expert experience, design manuals, industry specifications, etc.) for reasoning, judging, and decision-making to achieve automation, and intelligence in product design. However, they are seldom applied to the design of multi-link system of mechanical presses, and knowledge-based design methods are difficult to apply in practice due to incomplete knowledge, difficulties in knowledge acquisition and characterization, and limited adaptability. Therefore, it is imperative to integrate and improve these two methods for better application in practice [8,9].

Aiming at the above problems, this paper builds a design knowledge base and a reasoning machine to realize the rapid selection of transmission configuration for cold and warm forging presses through the case similarity calculation, and establishes an optimization model based on the elbow-bar transmission configuration determined by the above. A knowledge-guided improved particle swarm optimization algorithm is proposed to solve the optimization model. Then the optimized dimensional parameters of the multi-link system are obtained. The purpose of improving design efficiency, press performance and product quality is achieved.

Rapid Selection of Transmission Configuration

The selection of the transmission configuration is not only the first step of press design, but also the most critical step. The types of configurations are complex and varied. In order to select the most suitable transmission configuration, the theoretical knowledge and design experience of the designers are required to a higher level. In this paper, knowledge engineering technology is used to create a knowledge base and a reasoning machine to store and reuse historical cases and design experience to realize the rapid selection of transmission configurations.

Knowledge base is to store the knowledge in some form of representation in the computer for subsequent recall. Multi-link systems design knowledge is varied and complex in form, which can be divided into case knowledge, rule knowledge and related information knowledge. The above knowledge is stored in an appropriate way to build a knowledge base for multi-link system design. The structure of knowledge base is shown in Fig. 1.

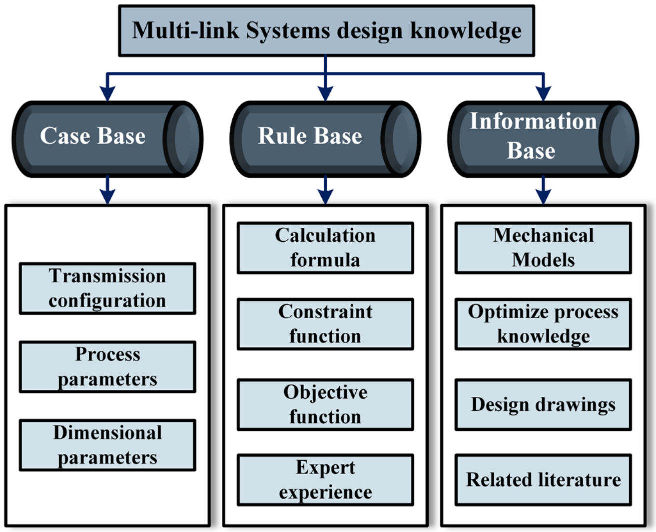

Fig. 1. Structure of multi-link systems design knowledge base.

The reasoning machine is a bridge between the knowledge base and the design requirements. In this paper, firstly, input the design demand parameters, the reasoning machine retrieves whether there are similar cases. If there is, then adopt the case with the highest similarity, follow its transmission configuration, and improve the design of partial size parameters according to the design demand to form a new case. If an identical case exists, the case is used directly. The reasoning process for the transmission configuration of the multi-link systems is shown in Fig. 2.

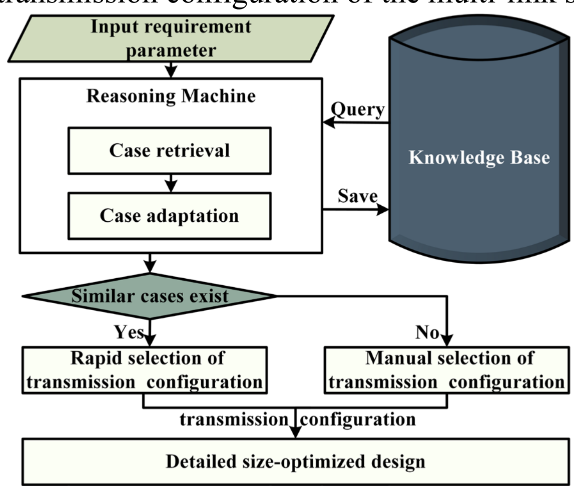

Fig. 2. Reasoning process for the transmission configuration of the multi-link systems.

The main technical parameters to be entered for case retrieval include: machine type, nominal pressure, slide stroke, nominal pressure stroke and process parameters. The case similarity formula based on the above parameters is as follows

$$S(A,B)=\sum_{i=1}^{n}\frac{\mu_i}{1+|a_i-b_i|}. \tag{1}$$

Where S represents the similarity of cases, A, B represents different cases, the set of attributes of these two cases is (a_1, a_2, ..., a_n), (b_1, b_2, ..., b_n), n represents the similarity of cases, and μ_i represents the weights, the effect of each attribute on the multi-link systems.

Considering the richness of the cases in the case base, we set the similarity threshold to 0.6. If there are cases with similarity more than 0.6, they are considered similar. If the similarity of all cases is lower than 0.6, it is considered that there is no similar case. So, the transmission configuration needs to be selected manually. With the continuous enrichment of the knowledge base, the accuracy and automation of the reasoning machine will be continuously improved.

Take the main technical parameters of a cold forging press for near net shape as an example: Nominal pressure, 12500 kN; Nominal pressure stroke, 10mm; slide stroke, 400 mm; Maximum stroke rate of slide is 25SPM. After the case retrieval and adoption, according to the highest similarity case, the reasoning obtained the transmission configuration should be the elbow-bar mechanism of bias driving, which is the same as the original transmission configuration of this press, proving the validity of this reasoning mechanism. The transmission sketch of the elbow-bar driving mechanism is shown in Fig. 3.

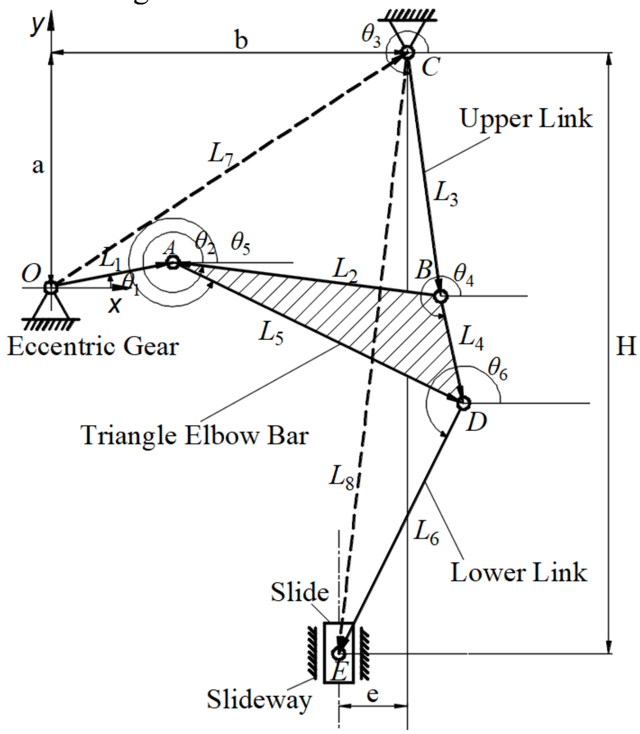

Fig. 3. Transmission sketch of the elbow-bar driving mechanism.

Optimization Model of Elbow-Bar Driving Mechanism

The kinematic model of the elbow-bar driving mechanism needs to be established firstly. Establish the coordinate system shown in Fig. 3. L_1~L_6 is the length of each link, and θ_1~θ_6 is the turning angle of each link. According to the closed vector method, three closed loops are selected as OABCO, ABDA and CBDEC, which can be obtained as:

$$\begin{cases} L_1\cos\theta_1 + L_2\cos\theta_2 = a + L_3\cos\theta_3 \\ L_1\sin\theta_1 + L_2\sin\theta_2 = b + L_3\sin\theta_3 \\ L_2\cos\theta_2 + L_4\cos\theta_4 = L_5\cos\theta_5 \\ L_2\sin\theta_2 + L_4\sin\theta_4 = L_5\sin\theta_5 \\ L_3\cos\theta_3 + L_4\cos\theta_4 + L_6\cos\theta_6 = e \\ L_3\sin\theta_3 + L_4\sin\theta_4 + L_6\sin\theta_6 = H \end{cases} . \tag{2}$$

From Eq. 2, Under the condition that the size of links is fixed, there exist θ_1, θ_2, θ_3, θ_4, θ_5, θ_6, H a total of 7 variables, of which θ_1 is the independent variable. In the limit of 6 equations, cancelling θ_2, θ_3, θ_4, θ_5, θ_6, we can get the equation of H about θ_1, denoted as $H(\theta_1)$.

Then we can get the kinematic equations of the elbow-bar driving mechanism are

$$\begin{cases} s = H_{\max} - H \\ v = \dfrac{\mathrm{d}s}{\mathrm{d}t} \\ a = \dfrac{\mathrm{d}^2 s}{\mathrm{d}t^2} \end{cases} . \tag{3}$$

where s, v, a are the displacement, velocity and acceleration of the slider, respectively.

Once the kinematic model of the mechanism is complete, the corresponding optimization model can be established. The optimization vector is as follows:

$$X = [x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8, x_9]^{\mathrm{T}} = [L_1, L_2, L_3, L_4, L_5, L_6, a, b, e]^{\mathrm{T}} . \tag{4}$$

In order to establish the constraint equations and objective functions, it is necessary to take into account the structure of the multi-link system, the transmission performance and the characteristics of the cold and warm forging process.

As can be seen from Fig. 3, there is a crank-rocker mechanism in the driving mechanism. The constraint functions for establishing the crank rock mechanism are

$$\begin{cases} g_1(X) = x_1 - x_2 \le 0 \\ g_2(X) = x_1 - x_3 \le 0 \\ g_3(X) = x_1 - x_7 \le 0 \\ g_4(X) = x_1 + x_7 - x_2 - x_3 \le 0 \\ g_5(X) = x_1 + x_2 - x_7 - x_3 \le 0 \\ g_6(X) = x_1 + x_3 - x_2 - x_7 \le 0 \end{cases} . \tag{5}$$

In order to ensure good transmission performance of the mechanism, it is necessary to limit the range of transmission angle between two limit positions. Establish the constraint functions $g_7(X)$, $g_8(X)$ for the pole drive angle.

$$\begin{cases} g_7(X) = x_2^2 + x_3^2 - (\sqrt{x_7^2 + x_8^2} - x_1)^2 - 2x_2 x_3 \cos\gamma_{\min} \le 0 \\ g_8(X) = -x_2^2 - x_3^2 + (\sqrt{x_7^2 + x_8^2} + x_1)^2 + 2x_2 x_3 \cos\gamma_{\max} \le 0 \end{cases} . \tag{6}$$

Where $\gamma_{\min}$, $\gamma_{\max}$ is the allowable minimum and maximum transmission angle between two limit positions, generally take $\gamma_{\min} = 45°$ and $\gamma_{\max} = 135°$.

Slider stroke is one of the main technical parameters of the press, which should be controlled within a certain error range at the design stage. Therefore, in this paper, the slider stroke error is constrained to be within ±1%, and the constraint functions $g_9(X)$, $g_{10}(X)$ are established.

$$\begin{cases} g_9(X) = H_{\max} - H_{\min} - 1.01s \le 0 \\ g_{10}(X) = 0.99s - H_{\max} + H_{\min} \le 0 \end{cases} . \tag{7}$$

The establishment of the optimization objective function needs to take into account the motion curve of the slider and the maximum input torque of the eccentric gear.

The low speed and smooth motion of the slide can make the material uniformly stressed during the forming process and improve the quality of forgings. In addition, lower slider speeds mean less input torque for the eccentric gear. Therefore, the minimization of the maximum speed and maximum acceleration of the slider within the nominal pressure stroke is taken as optimization objectives. The objective functions are

$$f_1(X) = |v|_{s=\mathrm{h}} \tag{8}$$

$$f_2(X) = \max |a|_{s\in[0,\mathrm{h}]} . \tag{9}$$

Where h is the displacement of the slide when it first contacts the workpiece, that is, the nominal pressure stroke.

At the same time, in order to increase the work efficiency, the return time should be reduced, that is, the quick-return characteristic should be strengthened. The objective function is

$$f_3(X) = t_{\mathrm{up}} . \tag{10}$$

Where t_{up} is the return time of slider.

Combining all objective functions and taking the constraint function as penalty terms, the total objective function is established as:

$$\min f(X) = \min\{\sum_{i=1}^{3} \mathrm{w}_i \frac{f_i(X)}{f_{i\min}} + \sum_{j=1}^{10} \gamma_j g_j(X)\} . \tag{11}$$

Where w_i are the weights of each optimization objective, and $\mathrm{w}_1+\mathrm{w}_2+\mathrm{w}_3 = 1$; $f_{i\min}$ are the estimated optimal values for each optimization objective, so that the values of the three optimization objectives are of the same order of magnitude; γ_j is the penalty factor

Any kinematic and optimization models of the transmission configuration will be stored as knowledge in the knowledge base. This avoids repeated modeling and improves the design efficiency in the subsequent similar case designs.

Knowledge-Guided Particle Swarm Optimization

In this paper, the particle swarm optimization algorithm is used to solve the optimization model, in order to improve the optimization efficiency, this paper proposes a knowledge-guided improved particle swarm optimization algorithm. And the following optimization strategies are proposed.

Firstly, this paper adopts a hierarchical case knowledge-guided particle population initialization strategy by making full use of historical similar cases. The aim is to reduce the number of iterations and to improve the local optimization accuracy while making the algorithm capable of global search.

For the characteristics of the transmission configuration combined with the actual production situation, set the upper and lower limits of each size parameter $x_{i\max}$, $x_{i\min}$ (i=1,2,3...9), to determine the global optimization space for the

$$\begin{aligned} D = [&x_{1\min}, x_{1\max}; x_{2\min}, x_{2\max}; x_{3\min}, x_{3\max}; x_{4\min}, x_{4\max}; x_{5\min}, x_{5\max}; \\ &x_{6\min}, x_{6\max}; x_{7\min}, x_{7\max}; x_{8\min}, x_{8\max}; x_{9\min}, x_{9\max};]^{\mathrm{T}} \end{aligned} . \tag{12}$$

According to the similar historical cases (similarity greater than 0.6), obtained in the transmission configuration reasoning stage, the maximum and minimum values of each design variable in the similar historical cases with the same transmission configuration are taken as $sx_{i\max}$, $sx_{i\min}$ (i=1,2,3...9), and thus the local optimization space is determined as

$$D_1 = [sx_{1\min}, sx_{1\max}; sx_{2\min}, sx_{2\max}; sx_{3\min}, sx_{3\max}; sx_{4\min}, sx_{4\max}; sx_{5\min}, sx_{5\max}; sx_{6\min}, sx_{6\max}; sx_{7\min}, sx_{7\max}; sx_{8\min}, sx_{8\max}; sx_{9\min}, sx_{9\max};]^{\mathrm{T}}. \quad (13)$$

If the number of similar historical cases is m and the particle swarm population size is n, the above m historical cases are used as m population initial solutions, and 0.6n-m population initial solutions are taken to be randomly generated in the local optimization space D_1, and the remaining 0.4n population initial solutions are randomly generated in D-D_1. So that the algorithm has global search capability while improving the local optimization accuracy.

If there are few similar cases in the case base to generate local optimization intervals or lack of practical reference value, it is necessary to judge whether to adjust the global optimization space by oneself, and carry out random initialization of all particle `populations in this global optimization space.

Then, the particle iteration process is guided by the sensitivity knowledge of each optimization variable. In the particle swarm optimization algorithm, the particles find the global optimal solution by continuously updating their position and velocity, and its particle iteration formula is

$$\begin{cases} v_i(t+1) = \lambda v_i(t) + c_1 r_1 (pb_i - x_i(t)) + c_2 r_2 (gb_i - x_i(t)) \\ x_i(t+1) = x_i(t) + v_i(t+1) \end{cases}. \quad (14)$$

Where v, x are the velocity and position of the particle, respectively; t is the number of iterations; λ is the inertia weight; c_1 is the self-learning factor; c_2 is the social learning factor; r_1, r_2 are the random numbers between (0,1); pb_{i} and gb_{i} are the positions of the individual and global guides for particle i.

According to the objective function and global optimization space of elbow-bar driving mechanism, the sobol method is applied to perform parameter sensitivity analysis. The parameter sensitivity vector is obtained as

$$V_{sen} = [S_{x1}, S_{x2}, S_{x3}, S_{x4}, S_{x5}, S_{x6}, S_{x7}, S_{x8}, S_{x9}]. \quad (15)$$

where $S_{x\mathrm{i}}$ is the sensitivity of the objective function to each optimization variable x_{i} (i=1,2,3...9).

Based on the above knowledge of parameter sensitivity, the particle iteration formula is dynamically updated to improve the search direction and step size. Firstly, the particles are guided to iterate in the direction of high sensitivity variables by updating the important parameters λ, c_1, c_2 as

$$\begin{cases} \lambda = \lambda_{\max} - \dfrac{V_{sen} \cdot v_i(t)}{\|V_{sen}\| \times \|v_i(t)\|} (\lambda_{\max} - \lambda_{\min}) \\ c_1 = c_{1\min} + \dfrac{V_{sen} \cdot (pb_1 - x_i(t))}{\|V_{sen}\| \times \|pb_1 - x_i(t)\|} (c_{1\max} - c_{1\min}) \\ c_2 = c_{2\min} + \dfrac{V_{sen} \cdot (gb_1 - x_i(t))}{\|V_{sen}\| \times \|gb_1 - x_i(t)\|} (c_{2\max} - c_{2\min}) \end{cases}. \quad (16)$$

Where $\lambda_{\max}$, $\lambda_{\min}$ are the maximum and minimum values of the inertia weights; $c_{1\max}$, $c_{1\min}$, $c_{2\max}$, $c_{2\min}$ are the maximum and minimum values of the corresponding learning factors, respectively.

Meanwhile, the particles should be made to search quickly in the direction of low sensitivity variables with a larger step size while reducing the step size in the direction of high sensitivity variables in order to improve the algorithm's optimization ability during iteration. the iteration method is as follows

$$x_i(t+1) = x_i(t) + (1.5 - \frac{V_{sen} \cdot v_i(t+1)}{\|V_{sen}\| \times \|v_i(t+1)\|}) v_i(t+1) \cdot \tag{17}$$

Fig. 4 shows the knowledge-guided particle swarm optimization process. The optimization process is as follows.

Step 1: Determine the global and local optimization intervals, and initialize the particle population hierarchically in different intervals, using the historical similar cases as a guide;

Step 2: Iterate according to the particle iteration strategy guided by the sensitivity knowledge to update the position and velocity of each particle. Then, calculate the fitness of each particle based on the knowledge of constraints and objective functions;

Step 3: update the historical optimal positions of particles themselves and population, as well as the main parameters of the algorithm, such as the inertia weight λ;

Step 4: Stop iteration when the end condition is met, the optimization results are processed and outputted. The design results are stored in the example knowledge base to further enrich and improve the knowledge base.

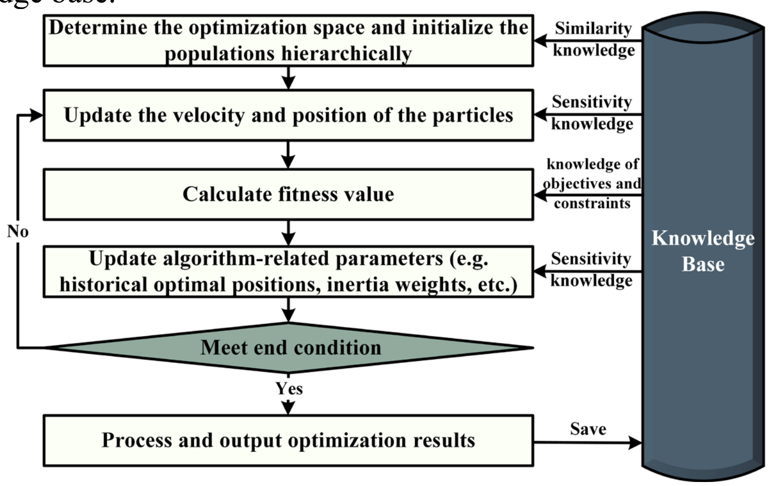

Fig. 4. Knowledge-guided particle swarm optimization process.

Optimization Result

Based on the above optimization model and the knowledge-guided particle swarm optimization algorithm, an optimization program is written in MATLAB to perform the optimization calculations. In order to facilitate the manufacturing and accuracy testing of the link system in engineering practice, the optimization results are rounded off and the optimized links system parameters are compared with the original links system parameters, as shown in Table 1 below.

Table 1. Optimization results of the elbow-bar driving mechanism [mm].

	L_1	L_2	L_3	L_4	L_5	L_6	a	b	c
Initial	205	1720	610	720	1930	845	570	1500	-15
Optimal	260	1725	705	545	1900	920	760	1550	-28

Through kinematic analysis, we can get different curves of the slider. Comparing the slider curves before and after optimization, the optimized results are better than the original parameters as shown in Fig. 5.

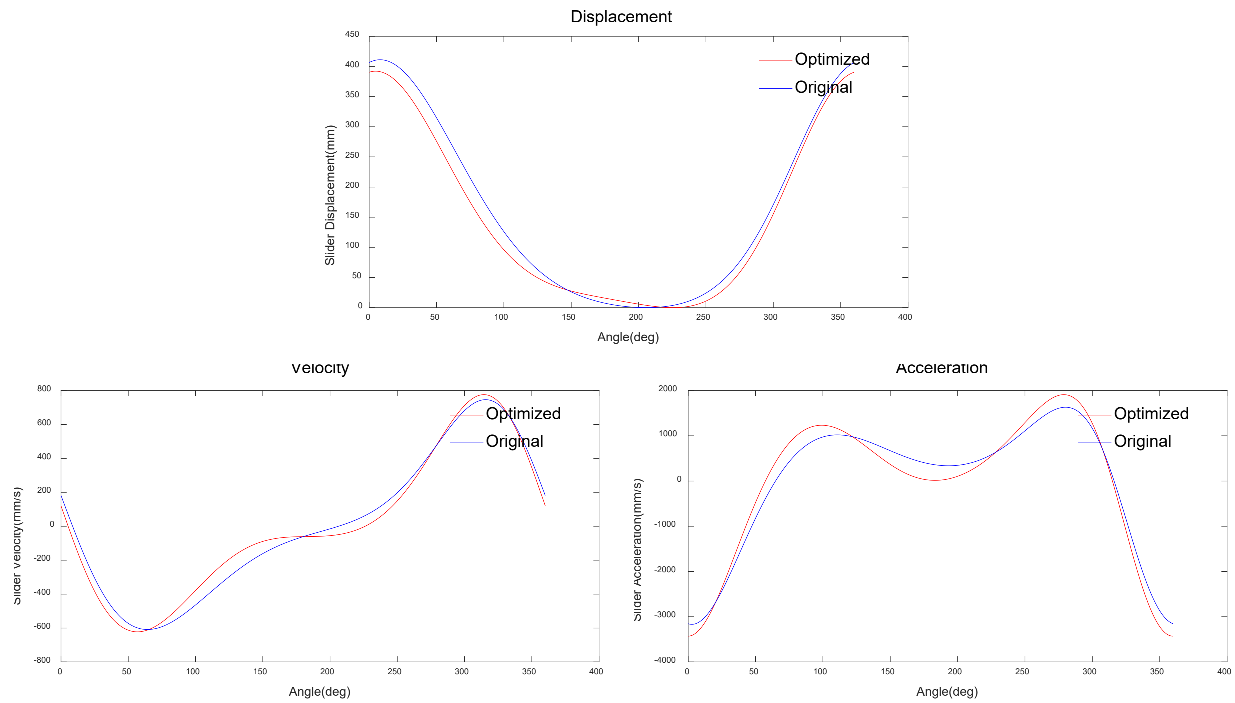

Fig. 5. Kinematics curve of slider.

The position of the lower dead center is shifted to the right, the motion curve is smoother in the forming stage. It meets the process requirements of low and smooth forming speed and long holding time for cold and warm forging, which is conducive to improving the quality of forgings.

The main technical indexes of the elbow-bar driving mechanism of the cold and warm forging press before and after optimization are shown in Table 2.

Table 2. Main technical indexes of the elbow-bar driving mechanism .

Main technical indexes	Initial	Optimal	optimzation rate
Stroke [mm]	411.11	392.12	29.07%
Total height [mm]	2212	2164	2.17%
Velocity on the height of 25 mm [mm/s]	152.58	79.06	47.83%
Maximum acceleration during the nominal stroke [mm/s^2]	645.40	576.93	10.61%
Eccentric gear input torque [N·m]	728584	377515	48.19%
Slider return time [s]	0.71	0.62	12.68%

As can be seen from Table 2, after the optimization of the knowledge-guided particle swarm algorithm, not only the motion curve of the mechanism is improved, but also its total height, the input torque of the eccentric gears is reduced, and the quick-return characteristics are also improved. The above analysis and data show that the knowledge-guided particle swarm algorithm can effectively optimize the size of the multi-link system to achieve the purpose of improving the performance of the press and the quality of forgings.

Summary

Based on the knowledge engineering technology, the knowledge base of multi-link systems design and the related reasoning machine are built, and the rapid selection of the transmission configuration for the designed press is realized. According to the elbow-bar driving mechanism obtained by reasoning, its kinematic model and optimization model are established, and the knowledge-guided improved particle swarm optimization algorithm is proposed to solve the optimization model. After optimization, all the kinematic performance indexes of the slider are optimized to different degrees and the maximum input torque is reduced. Meanwhile, the method presented in this paper facilitates the accumulation and transfer of design knowledge. The models and equations established for each design will be classified and stored in the knowledge base so that they can be used for subsequent design of similar cases to avoid repetitive work. With the gradual enrichment of the knowledge base, the accuracy and efficiency of the optimization design method proposed in this paper will be gradually improved.

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