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Lithium Battery Shell Mould Design and Process Parameter Optimization Method Based on Digital Technology

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Abstract. The research object of this article is the processing process of new energy vehicle battery shells. In order to achieve digital design and process optimization of lithium battery shells, this article first analyzes the structural characteristics, material properties, and process parameters of battery shells. Then, based on the processing process of battery shells, the model structure of the mold is designed and completed, and simulation analysis is conducted. In the process of mold design, based on the establishment of a digital model of the mold, artificial intelligence algorithms were used to assist in the optimization of the model structure. According to the actual usage process of the mold, deep belief networks were used to optimize the parameters of the mold. Finally, an improvement plan for the mold structure was obtained through experimental simulation, and an example optimization analysis was conducted on the structure optimization of the mold's edge pressing ring.

Keywords: mould design, digitalize, artificial intelligence

1 Introduction

With the increasingly fierce competition in the domestic and international automotive industry, traditional automotive design, production, and power methods have been impacted and cannot be ignored. Consumers are paying more attention to the functionality, cost-effectiveness, and exterior design of cars. Therefore, traditional automotive design, production, and processing methods are changing with changes in consumer attitudes. The development trend of industries that rely on traditional energy sources such as oil, coal, and other non renewable energy sources is gradually showing signs of decline. With the gradual emergence of energy shortages and the requirements of national policies for enterprise transformation, the development of new energy vehicles will inevitably become a new growth pole for China's economic development. At the same time, with the increasing number of fuel vehicles year by year, the environmental pollution and thermal effects caused by automobile exhaust emissions should not be underestimated. The dual pressure of energy security and environmental pollution has forced many countries around the world, including China, to vigorously develop new energy vehicles. New energy vehicles are highly praised worldwide for their low-carbon and environmentally friendly features, fast start-up, low noise, and excellent performance. In summary, the transformation and upgrading of the automotive industry is undoubtedly a very important strategic opportunity for China to move from a major automotive country to a strong automotive nation [1].

In the production process of new energy vehicles, die casting is a new means of improving the overall performance of vehicles. How to achieve lightweight die casting parts has become the development trend of automotive die casting components today. New energy vehicles generally include a three electric system, in which the power battery serves as the power core of the new energy vehicle. During assembly, it is generally necessary to package the lithium battery and add a protective device to form a battery pack, which is installed at the bottom of the vehicle. Among the components that make up a power battery, the battery case is one of the core components, and its size, shape accuracy, and position accuracy play a key role in the safe operation of the power battery.

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The production of battery cases generally requires customized molds, and the rationality of mold design determines the quality of battery cases. Therefore, in the trend of widespread popularity of electric vehicles, in order to ensure the safety of power batteries, the research and development of battery case processing technology is particularly important. Therefore, as an essential process equipment in die-casting production, the product quality of battery case production molds directly affects the efficiency and results of die-casting production. With the rapid development of science and technology and the maturity of computer technology, various mold enterprises in China have gradually adopted injection molding CAD/CAE technology to assist mold design and production. Using mold CAD technology to design molds for different products, reducing manufacturing costs and shortening the development cycle of new molds [2].

In summary, the main work of this article is as follows:

1) Firstly, the production process of battery casing was analyzed, and corresponding moulds were designed based on its process characteristics. The mould design was combined with the material and mechanical properties of the die-casting object.

2) In the design phase, artificial intelligence algorithms were used for auxiliary design, and Mouldflow CAD Doctor 2015 software was used to pre repair the 3D model of the product and conduct simulation analysis.

3) In the process of optimizing mould parameters, a deep belief network was used to optimize the mould parameters, and the optimization of the pressure edge ring structure in the mould was ultimately taken as the experimental object.

2 Related Work

Many scholars have conducted relevant research on mould design and optimization of mould parameters. The following is a summary:

1) In terms of mould design, the application of digital methods has improved the efficiency of mould development.

Quanjun Li, in order to achieve rapid and accurate design of hydraulic forging dies for automotive wheel rims, integrated Access database with Pro/E software based on C++language and VC++development environment. Through further development of Pro/E, a CAD design system for “5 ° automotive wheel rim hydraulic forging dies” was constructed, which can quickly and accurately develop and design various types of hydraulic forging dies for wheel rims, greatly shortening the design cycle of hydraulic forging dies [3].

Lichang Zhang, using UG software and actual production conditions, completed the modeling of precision forging moulds, processing technology design, tool path planning, and CNC machining program development for non-standard parts widely used in mining machinery equipment, and produced qualified precision forging moulds. Production practice has proven that the components produced by this mould have high precision, good physical properties, can meet usage requirements, high production efficiency, and are suitable for large-scale production [4].

Guanghua Zhao, taking the intelligent toilet injection water mould as the research object, optimized the design of a conformal cooling water channel for one of the inserts with narrow and thin-walled forming characteristics. Using SLM 3D printing technology, an injection mould insert with conformal cooling water channel and cavity integrated was manufactured. Compared with the original insert processed by linear drilling, its temperature uniformity and cooling efficiency were effectively improved [5].

Mari Zhang used ABS as the injection moulding material for the heat exchanger sandwich, combined with the structural characteristics of the heat exchanger plastic parts. Based on Pro/E software, a heat exchanger sandwich injection moulding mould was designed. The mould injection moulding process parameters were input into a convolutional neural network model to predict the buckling results of the heat exchanger sandwich injection moulding. The minimum buckling result was taken as the objective function, and the optimal injection moulding process parameters were obtained through genetic algorithm. Input the heat exchanger sandwich injection mould designed by Pro/E software and the optimal injection moulding process parameters obtained from solving into the Mouldflow platform to achieve process simulation and visualization analysis during the heat exchanger sandwich injection moulding process. The optimized process parameters have completed the sandwich injection moulding of the heat exchanger, improving its load-bearing capacity [6].

2) In terms of optimizing mould parameters, digital technology also assists in optimizing mould design parameters.

Qiming Cheng, taking the injection molding of a computer case CD-ROM cover as an example, used UG software for 3D modeling and Moldflow analysis software for simulation analysis of injection performance parameters. Orthogonal experiments were designed to select parameters such as melt temperature, mold temperature, holding pressure, holding time, cooling time, etc. as independent variables, and the warpage deformation of injection molded products as the dependent variable. The process parameters were optimized to obtain the optimal parameter combination [7].

Yu Zhu optimized the arc additive process parameters of H13 mold steel based on response surface methodology, and established a mathematical model of process parameters (welding current, welding speed, and wire feeding speed) and forming dimensions (excess height coefficient and forming coefficient) using Box Behnken design principles and quadratic regression experiments. The results showed that the model fit was good, and there were interactions between the various parameter variables. The order of influence on the forming size was wire feeding speed>welding current>welding speed. The wire feeding speed was significantly correlated with the excess height coefficient ($r=-0.84$) and forming coefficient ($r=0.68$) [8].

Yaren Chen, taking rectangular aluminum alloy profiles as the research object, optimized the mould structure using HyperXtrude software with the objectives of the mean square deviation of the exit velocity of the profile section and the equivalent stress of the mould. The results showed that after optimizing the mould structure, the velocity distribution at the exit of the profile section was more uniform, and the mean square deviation of the exit velocity was reduced by 61.59%, improving the uniformity of the displacement distribution at the exit of the profile; The maximum equivalent stress of the mould decreased by 40.13%, extending the service life of the mould [9].

Guicheng Yu from Wuhan University of Science and Technology proposed the use of roll forging and die forging technology to produce slender variable cross-section non axisymmetric sword bars, and analyzed the forging process of the sword bars using finite element method. The study focuses on the forging process of the most complex cross-section of a sword bar, and compares the flow patterns of metal materials during one pass forging and two pass forging processes. The results show that during the one-time forging process, the deformation of the metal material is large and unevenly distributed. The maximum principal stress in the area of maximum equivalent strain is tensile stress, which is prone to cracking; After two passes of pre forging and final forging, the maximum equivalent strain and standard deviation of equivalent strain in the forging section are significantly reduced. The optimization of the pre forging die structure was carried out through orthogonal experiments, and the results showed that the depth of the upper die groove had the most significant effect on the distribution of equivalent strain in the cross-section of the forging. Compared with single pass forging, the maximum equivalent strain and standard deviation of equivalent strain of the secondary forging after optimizing the pre forging die are significantly reduced. The above optimization method was applied to the design of other sections of the sword bar forging die, and a forging die that meets actual production needs was manufactured [10].

Taking a certain shaped switch component as an example, analyze its external structural characteristics. Moldflow software was used to design the gating system and cooling system of the first mock examination with four cavities, and the filling time, warpage deformation, weld line and flow front temperature during the injection process were analyzed. Detailed design of the parting surface, core, cavity, and ejection mechanism of the mold was carried out using UG software, and the working process of the mold was introduced. The mold parting adopts a split type Haff block structure, which solves the problem of side core pulling demolding and interference with part features. Based on the narrow space inside the part, it is impossible to install inclined tops and top pins, and a push plate pushing mechanism is adopted. This provides a solution for demolding and pushing out this type of part. This set of molds has been verified through actual production, with a reasonable structure and a high yield of finished parts [11].

In summary, based on the research of the scholars mentioned above, this article has completed the design of the mould for the lithium-ion battery shell coating of new energy vehicles, and analyzed the mould design process and structural parameter optimization using digital methods, improving the efficiency and quality of mould design.

3 Structural Analysis of Parts and Mould Design

In order to improve the range of new energy vehicles, lightweight parts are generally used. In addition to selecting cool materials, the more important thing is the lightweight design of the structure. The battery shell structure of the new energy vehicle studied in this article is shown in Fig. 1. The workpiece is a typical thin walled box type part, which is often processed by stamping forming technology [12].

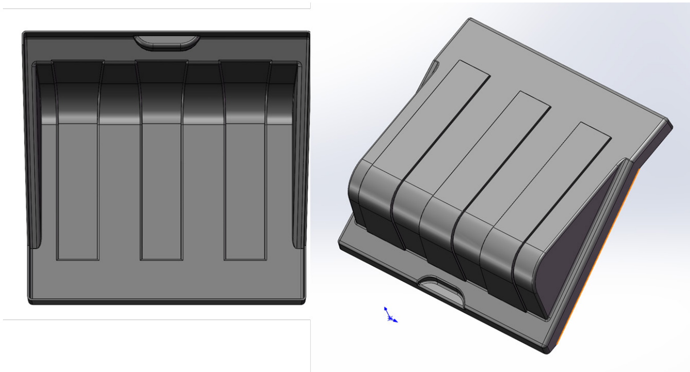

Fig. 1. Battery shell structure

3.1 Structure and Performance Analysis of Battery Cover Shell

During the stamping process of battery cases, the stress and strain experienced by the sheet metal in different regions vary. The stress and strain at a certain moment during the stamping process are shown in Fig. 2. According to the different stress and strain experienced by the sheet metal, the sheet metal in the forming process is divided into five regions, namely the radial strain and stress of the sheet metal, ε_2 and σ_2 are the strain and stress in the thickness direction of the sheet metal, and ε_3 and σ_3 are the tangential strain and stress of the sheet metal [13].

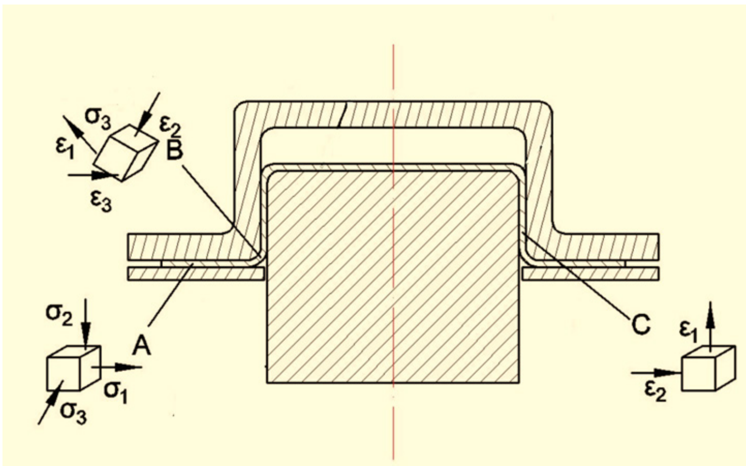

Fig. 2. Force analysis during compression process

1) Area A is the most significant deformation zone during the stamping process, which is subjected to tangential compressive stress σ_3 and radial tensile stress σ_1, causing plastic deformation of the sheet metal. When subjected to edge pressure, a compressive stress σ_2 is generated in the thickness direction of the plate. In general, the absolute values of radial tensile stress σ_1 and tangential compressive stress σ_3 are much greater than the compressive stress σ_2 in the thickness direction, causing the sheet metal to flow in both radial and thickness directions, resulting in an increase in sheet metal thickness. When ε_2 is positive, the thickening becomes more pronounced and the hardening becomes more severe in the area closer to the outer edge.

2) The B area is the transition zone during the stamping process, and the deformation of the sheet metal is very

complex. In region B, the sheet metal not only experiences the same tangential compressive stress σ_3 and radial tensile stress σ_1 as the flat flange region, but also bears the compressive stress σ_2 generated by the pressure and bending action of the concave die fillet. The B area sheet metal will undergo thinning and a small amount of compression deformation in the tangential direction.

3) The C area is the force transmission area during the stamping process, and the shape change has been completed. Only a small amount of adjustment and trimming is needed, and there will be no significant deformation again. In the subsequent forming process, the main focus is on transmitting the drawing force to the punch, resulting in a small amount of longitudinal drawing and thinning. Therefore, the C region only bears unidirectional tensile stress.

During the forming process of battery casing components, the circumferential area of the flat flange region is subjected to tangential and radial normal stresses, while the straight edge region is subjected to transverse and longitudinal normal stresses, all of which are unevenly distributed. In order to improve the die-casting capability, 3003 aluminum alloy was selected as the stamping material in this article [14]. The material composition and mechanical properties of the alloy are shown in Table 1.

Table 1. The material composition and mechanical properties of alloys

Component	Percentage	Parameter	Parameter values
S_i	0.6%	Tensile strength	142-178 MPa
F_e	0.7%	Yield strength	$\geq 115 MPa$
C_u	0.05-0.2%		
M_n	1%		
Z_n	0.1%		
Other	0.15%		

3.2 Mould Design

The overall structure of the mould is shown in Fig. 3.

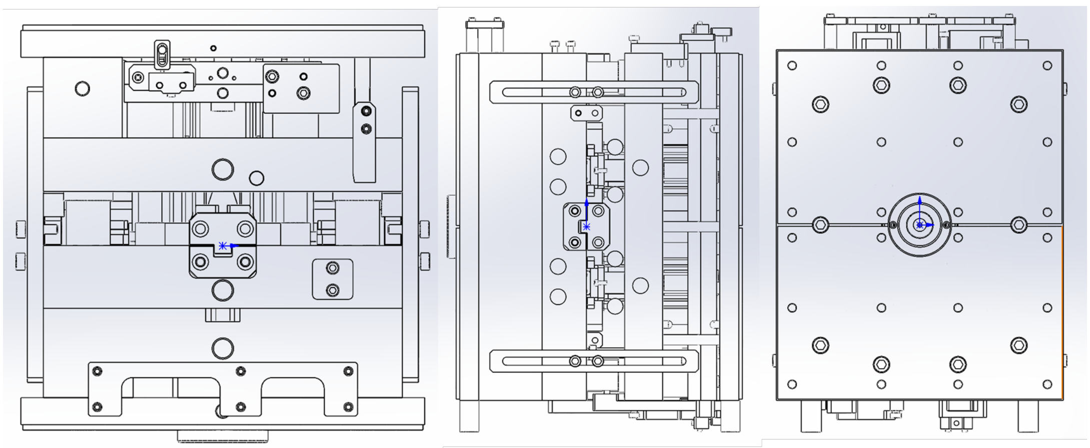

Fig. 3. Overall structure of the mould

Before designing the mould, it is necessary to input the three-dimensional structure of the lithium battery casing into the simulation software. In this paper, Mouldflow CAD Doctor 2015 software [15] is used to pre repair the 3D model of the product and conduct simulation analysis. The battery casing structure is designed using SolidWorks, as shown in Fig. 1. After transferring the 3D model of the product to x_t format, open it using Mouldflow.

The size of the battery pack accessory is 229 × 92 × 133 (unit: mm), with an average wall thickness of 1.05mm, which belongs to thin-walled products. At the same time, the automotive battery case has the characteristics of large shape and size, complex surface, and high processing difficulty. Using multiple forming methods will affect the quality of the workpiece, increase processing costs, and reduce production efficiency. Therefore, in this article, single deep drawing forming is adopted. In this article, two-dimensional shell elements are used, which generally have quadrilateral meshes and triangular meshes. Triangular meshes are usually used in complex areas of the surface. When different cell grid shapes are used, there will be significant differences in the calculation results. The efficiency and accuracy of quadrilateral grids are significantly higher than triangular grids, but the applicability of quadrilateral grids is poor, and bad cells often occur. Therefore, this article adopts a combination of two types of grids for grid division, with quadrilaterals as the main and triangles as the auxiliary. According to the three principles of grid division, the maximum cell size of the mould is set to 19 mm and the minimum size is 0.5 mm. Local grid refinement is carried out in areas with significant structural changes, such as raised and rounded corners. The sheet size is set to 10 mm.

The main structure of the mould consists of a static mould, a dynamic mould, and a edging ring. In the drawing process, the reference surface is determined as the static mould, and the offset of the convex dynamic mould surface is 0.6mm. The closing height of the mould set is 1427mm. The static model surface is determined by the drawing surface, and the static mould guide selects the appropriate guide depth based on the drawing depth. The pressure plate groove is selected at the appropriate position according to the press model. The static mould material is high-strength cast iron, and after a detailed modeling process, the complete model of the static mould is obtained as shown in Fig. 4.

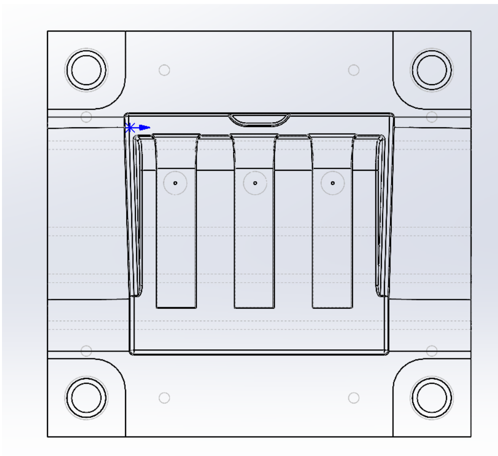

Fig. 4. Overall structure of the mould

The mould contains a safety platform, which is a necessary structure in each set of moulds. Each set of large pool pressure moulds is equipped with a safety platform, which serves as the safety of the mould work. In the stamping operation, if there is an inappropriate setting in the stamping process, this platform can ensure the safety of the mould. The selection of the safety platform has strict specifications. The size of the safety platform selected for the mould set designed in this article is. The pressure plate groove is a device used to fix the mould on the pressure equipment worktable and slider. The design of the pressure plate groove must match the structure in the press. The processing benchmark is the reference for the later mould processing surface, and the later mould maintenance is also based on this benchmark for alignment. The mould lifting lug is used in conjunction with the lifting rod for mould lifting and flipping. The upper and lower mould seats in each set of moulds must be designed with flipping lifting lugs, and the press can be equipped with lifting screws [16].

The layout of the mould mouth line and hydraulic top rod is a key link in the design of the dynamic mould. The position of the drawing mould on the press worktable is determined, and after careful arrangement, the mould and press worktable are offset by 50mm (the maximum allowable offset is 75mm), and the highest point of the dynamic mould surface is 625mm. The material of the dynamic mould seat is cast iron, and the setting of different materials can save costs. In the later stage, the working part of the mould is severely worn and easy to maintain. Install a mounting platform on the moving mould and secure it to the lower mould base with screws. After selecting and assembling the standard components required for the dynamic mould, the complete structure of the dynamic mould is obtained as shown in Fig. 5.

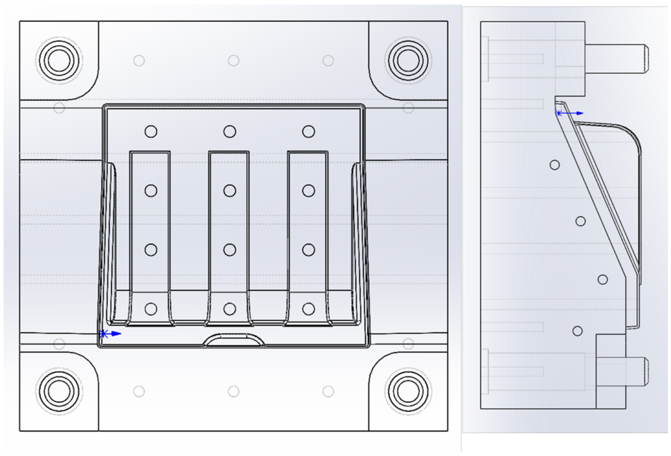

Fig. 5. Overall structure of the mould

Based on the analysis of the material characteristics of the battery shell and the structural characteristics of the battery, this section has completed the core structure design of the mold. The design content includes the static mold, dynamic mold, and edge pressing ring of the main structure of the mold. In the design process, digital 3D software was used for assistance, and design schemes were also provided for various subtle structures in the model structure. The final edge pressing ring structure serves as the basis for subsequent optimization, and this section provides a more detailed introduction to its design process.

4 Optimization Design of Mould Structure

This section mainly introduces the use of digital artificial intelligence methods to optimize mold structural parameters, and then designs a mold intelligent optimization system, introducing the system's composition framework.

The current common design situation in mold enterprises is that the mold design and optimization work, which is the core technical position of the enterprise, is mainly undertaken by mold designers. The different levels of experience of the designers result in different quality of mold design, making it difficult to control the cost of mold design. The successful cases of mold design accumulated by the enterprise over the years have been in a "dormant" state, and the excellent design experience and rules hidden in them have not been effectively explored and utilized, and the mold improvement plan has not been continued. For mold companies, there are frequent changes in design personnel. Once experienced designers leave, their valuable experience will also be lost. The overall technical level of the company is prone to fluctuations, and the design quality of products cannot be continuously guaranteed [17].

The combination of digital technology and mold structure optimization has led to the development of Computer Aided Mold Design (CAMD) technology, which is an important progress in the methodology of mold design. With the rapid development of artificial intelligence and computer technology, many technologies and methods, including neural networks, expert systems, group technology, feature modeling, feature recognition, etc., have been widely applied in the process of mold design and mold structure optimization. The application of these technologies and methods has to some extent improved the intelligence level of the design system, reduced the serious dependence on the experience of designers, and also improved the design efficiency and quality of products. Up to hundreds of functional parts in a mold are gathered in a relatively small space, which results in a certain degree of uniqueness in mold design. Its design not only considers the difficulty and manufacturing cost of part processing, but also needs to ensure the forming quality of plastic parts. Introducing artificial intelligence technology into mold optimization engineering can maximize the use of intelligent design technology to improve mold quality and enterprise production efficiency.

This section is based on deep learning theory to optimize the structural parameters of stamping dies. The process of optimizing mold structural parameters is shown in Fig. 6.

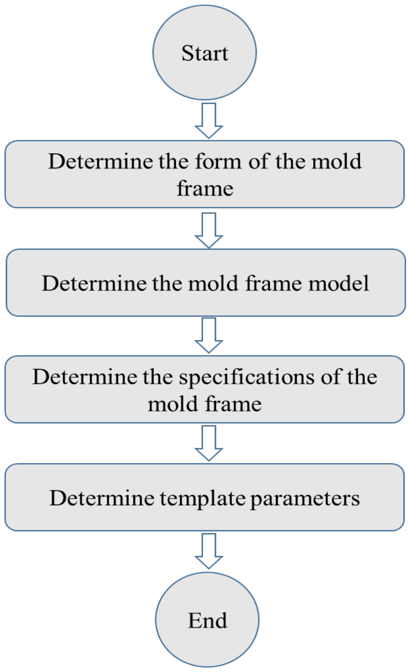

Fig. 6. Optimization process of mold structure parameters

Rule based reasoning, also known as search based reasoning, refers to reasoning that expresses knowledge based on production rules [18]. Production rules are used to express knowledge with causal relationships, and they are a way to describe problems that are relatively close to people's habits. The basic meaning of the rules is: if the preconditions are met, the specified operation of the conclusion is executed. Based on the semantic description method, if the condition matching values on both sides of AND are both true, then the IF premise holds; If the conditions on both sides of the OR in the premise are true, then the IF premise also holds. If the premise contains both AND and OR logical operators, logical operations are performed on both sides of OR first. When the matching value is TRUE, logical operations are performed on AND conditions. Only when both matching values are TRUE, the premise holds true. The conclusion of the rule is derived from one or more conclusions using the keyword THEN. The conclusions are expressed in the form of equations. Each equation has variables on one side and corresponding values on the other, connected using the matching operator '='. This reasoning method generally does not specify fixed reasoning steps in advance, and the actual reasoning steps are given based on the antecedent situation and search process. This reasoning process is very in line with people's natural thinking habits. By adding heuristic rules, its reasoning chain is easier to track and can be well explained. Therefore, rule-based reasoning is a relatively mature reasoning model in artificial intelligence technology and one of the most commonly used reasoning methods in knowledge-based expert systems.

In practical engineering, stamping dies are designed by designers based on their own design experience and reference to previous cases. The mold frame design system does not have the function of assisting decision-making and has a low degree of intelligence. In fact, the correct selection of each mold frame requires a clear understanding of the specific form and model of the mold, the specifications of the mold, and the parameters of each board. The form and model of the mold (the structural form of the mold frame) are non numerical parameters, and their selection requires a series of empirical rules to determine; The specifications of the mold and the parameters of each plate (key parameters of the mold template) are numerical parameters, and their values are determined by selecting the optimal value within a certain range of selectable values. It can be seen that relying solely on rule-based reasoning to determine specific molds will not be accurate and will result in significant errors compared to actual engineering selection. By comparing and analyzing the characteristics of rule-based reasoning and deep learning, this paper proposes a stamping die optimization method based on deep learning and rule-based reasoning. The basic idea is to first determine the model and category of the die through rule-based reasoning, and then switch to deep learning to determine key parameters such as template thickness that are not suitable for rule-based reasoning, in order to obtain the specifications of the die. Then, a parameterized design based on graphical templates is used to quickly generate the stamping die optimization model. As shown in Fig. 7, the stamping die optimization process is based on deep learning and rule-based reasoning.

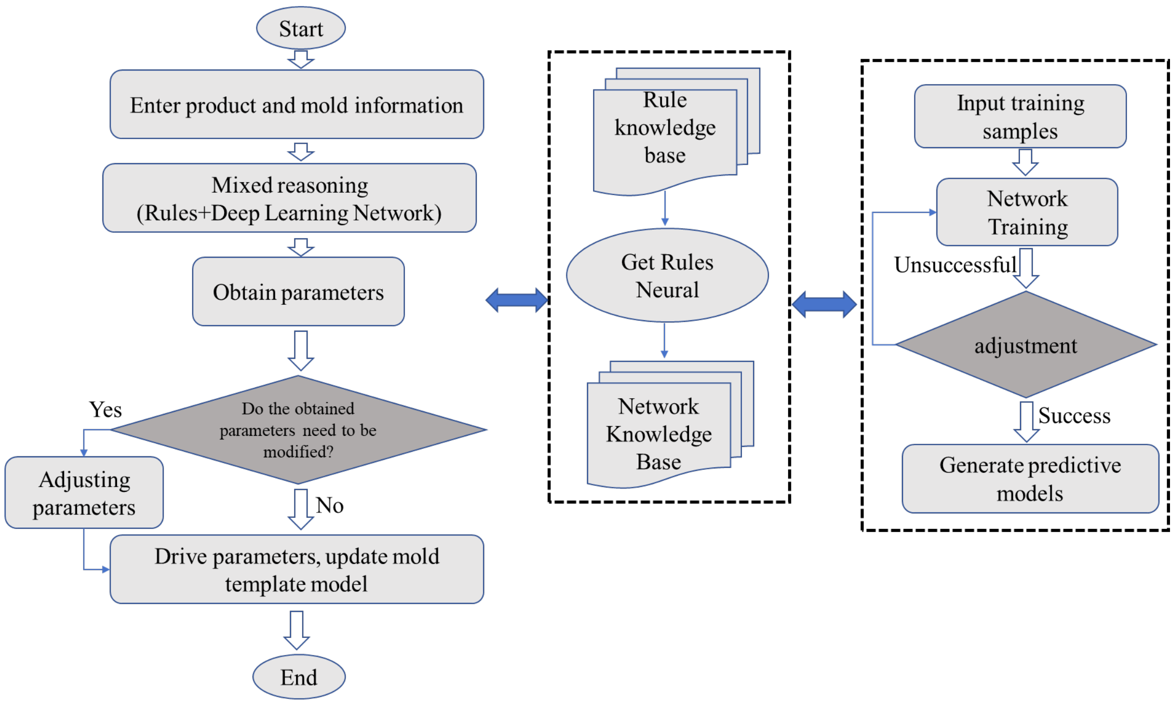

Fig. 7. Network architecture diagram

Knowledge representation is a set of conventions made to describe objects or phenomena, which transforms knowledge into a form of representation that can be accepted and processed by computers. At present, the knowledge representation methods commonly used in intelligent mechanical design systems include production rule representation and predicate logic representation. In the design of formwork, the selection of formwork form and type involves some engineering or empirical rules and knowledge, and the application of production rules can meet the requirements. This article reviews relevant literature and combines the experience and knowledge of mold enterprise designers to input basic information of plastic parts (including gate type, ejection method, etc.) into the human-computer interaction interface. These basic information will be extracted as the precursor of the rule through the program and sent to the system's mold frame rule library. According to the forward reasoning strategy, the inference machine searches the rule library for matching based on the provided rule precursor. If the matching is successful, the rule is triggered, the corresponding conclusion is drawn, and it is added as the inference result to the comprehensive database. Other inferences are continued, and this inference process is repeated until the entire inference is completed.

The process is shown in Fig. 8.

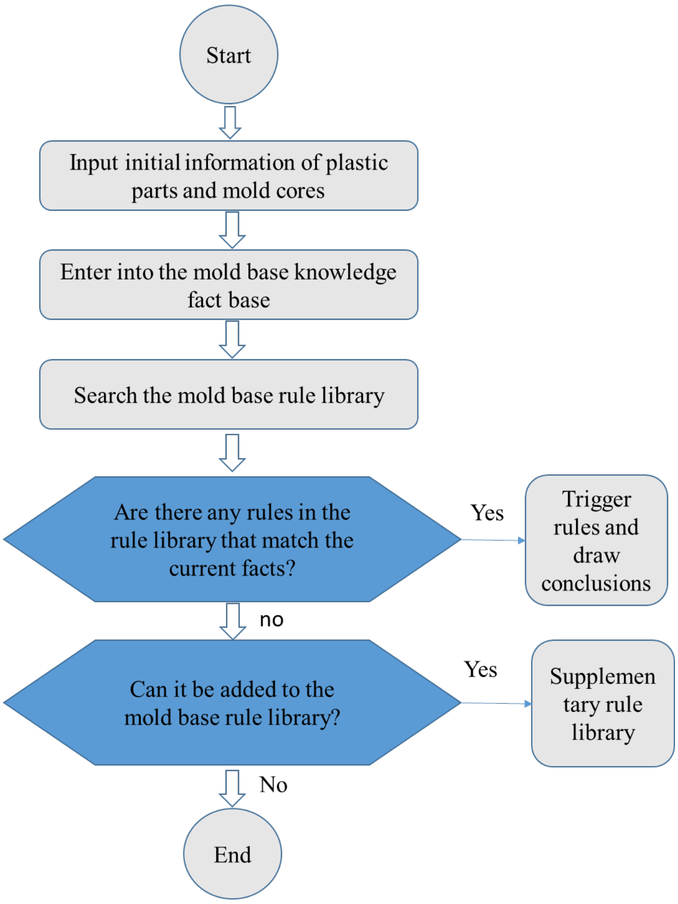

Fig. 8. Optimize the flowchart

Optimization of key parameters of molds [19], based on production rules, has a simple knowledge expression form, strong reasoning ability, and is easy to implement. It is widely used in expert systems. This article uses rule-based reasoning technology to determine the mold frame model. However, as mentioned in the preface, it is not appropriate to use rule-based reasoning to determine relevant numerical parameters, including the thickness of the fixed template, in the process of mold optimization. For parameter optimization, this article mainly focuses on the length, width, and thickness of the mold, the thickness of the moving template in the mold, and the thickness of the C-plate in the mold frame. This article uses deep belief networks to optimize parameters.

The mathematical expressions for each parameter are:

1) Mold frame length:

$$L_{mj} = L_{mr} + 2H_{jmj}. \tag{1}$$

2) Mold frame width:

$$W_{mj} = W_{mr} + 2H_{jmb2}. \tag{2}$$

3) Thickness of static template

$$H_{jm} = H_{mrj} + H_{jmd}. \tag{3}$$

4) Thickness of moving template

$$H_{dm} = H_{dmr} + H_{dmd}. \tag{4}$$

Deep Belief Network (DBN) is a typical deep learning method consisting of multiple layers of Restricted Boltzmann Machines (RBM) and a supervised network, which can learn nonlinear mapping relationships between input and output data from a large number of samples. DBN, as a generative model, improves prediction accuracy by training the weights between neurons to generate training data with maximum probability. This article uses the DBN algorithm to establish a mold frame design parameter prediction model based on the characteristics of the mold design process and mold frame selection operation. Based on the above analysis, this article determines the length L_{mr}, width W_{mr}, concave mold thickness H_{jm}, dynamic mold thickness H_{dm}, and product height H_{cp} of the mold core in the mold frame design as input parameters for the prediction model; The length L_{mj} of the mold frame, the width W_{mj} of the mold frame, the thickness H_{jmb} of the fixed template, the thickness H_{dmb} of the moving template, and the thickness H_C of the C plate are used as the output parameters of the model. Due to the different physical meanings or orders of magnitude of variables in sample data in engineering, in order to avoid the impact of this situation on the prediction accuracy of neural networks, sample data is usually preprocessed before training the neural network.

Due to the different physical meanings or orders of magnitude of variables in sample data in engineering, in order to avoid the impact on the prediction accuracy of neural networks, sample data is usually preprocessed before training the neural network. One important preprocessing method is normalization, which restricts the data to be processed within the [0,1] interval or smaller. The commonly used linear function conversion method in engineering, and the data normalization processing formula are shown in the following equation [20].

$$A' = \frac{A - A_{\min}}{A_{\max} - A_{\min}} \times 0.85 + 0.12. \tag{5}$$

In the formula, A' and A represent the sample values of each variable data in the mold sample after and before conversion, respectively. $A_{\max}$ and $A_{\min}$ are the maximum and minimum values of each data in the mold frame sample variables, respectively. The calculated data is between [0,1]. The predicted value of the mold frame data is obtained by the following inverse normalization formula:

$$A = \frac{\left(A' - 0.12\right) \times \left(A_{\max} - A_{\min}\right)}{0.85} + A_{\min}. \tag{6}$$

The prediction model is shown in Fig. 9.

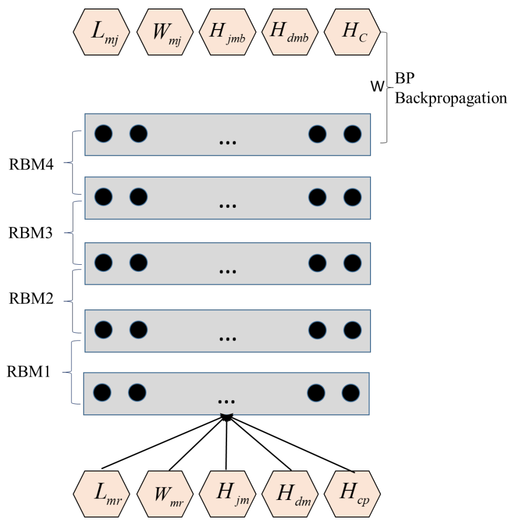

Fig. 9. Schematic diagram of prediction model

Determination of output layer weights. Finally mapped to the output layer. The excitation function of the output layer is the softmax function, expressed as follows. By comparing with the data label, the output layer weight w is randomly initialized.

$$h(\alpha_i)=\frac{e^{\alpha_i}}{\sum_{i=1}^{n}e^{\alpha_i}},i=1,2,\cdots,N. \tag{7}$$

The training process of the model is shown in Fig. 10.

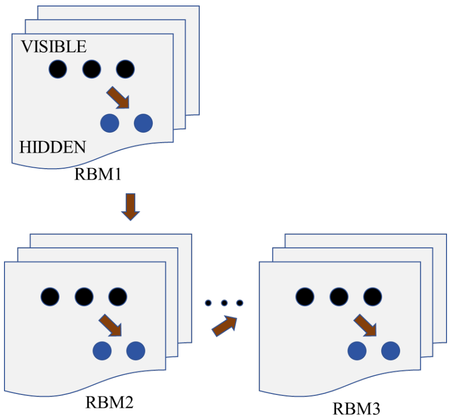

Fig. 10. The training process of the model

After the first step of pre training, the initial weights of the network are obtained: W_1, W_2, W_3, W_4, W. A BP network is established in the last layer of the deep belief network. Adjust the initial weights through backpropagation under supervision based on the sample data labels. During the fine-tuning process, use the following objective function.

$$h(\theta)=-\sum_{n}S_n^T\log S_n^y. \tag{8}$$

Among them, $\theta=\{W_1,W_2,W_3,W_4,W\}$ is the weight that needs to be fine tuned, S_n is the sample label, and S_n^y is the prediction result. Since W is randomly initialized, during the fine-tuning process, starting from the last layer of the DBN network, adjust the value of W and gradually fine tune the value of model parameter W_1,W_2,W_3,W_4 to lower layers using known labels.

Each layer of RBM network can only ensure that the weights within its own layer achieve optimal mapping of the feature vectors for that layer, not for the entire DBN. Therefore, the backpropagation network also propagates error information from top to bottom to each layer of RBM, fine-tuning the entire DBN network. The process of training the RBM network model can be seen as initializing the weight parameters of a deep BP network, which overcomes the disadvantages of BP network being prone to local optima and long training time due to random initialization of weight parameters.

Through the above process, the optimization of mold structural parameters can be achieved. The above process provides parameter optimization methods and processes, and the optimization results will be demonstrated in simulation experiments.

5 Simulation Experiment and Conclusion Analysis

This article uses Python language to implement a deep confidence network for predicting mold design parameters. After multiple debugging and comprehensive consideration of prediction accuracy and training time, the DBN parameter design is as follows: design 4 layers of RBM, set the number of nodes in each hidden layer to 4, and set the number of iterations to 100; The batch size is 80; Set the learning rate to 0.1; The incentive function is selected as the softmax function that is more suitable for multi classification. After the parameter design of the DBN model was completed, 378 successful cases of mold frame design were adopted by sorting and analyzing the mold frame design cases of a domestic mold enterprise in the past two years. After necessary screening, non-standard mold frames and mold frame cases with duplicate data were removed, resulting in 282 sets of sample data. Extract the input and output parameters of each mold case mold frame design one by one as sample data. Using the optimization of edge banding as an example for description.

The force on the edge press ring mainly comes from two aspects. One is the reaction force of the sheet metal contact flow on the edge press ring insert during the forming process, which is transmitted from the insert to the edge press ring body; The second is the edge pressing force provided by the machine tool air cap, which is transmitted to the edge pressing ring through the air cap. Therefore, the optimization of the direct force bearing part can be considered from the following perspective: according to the actual process of mold design in engineering, the formability analysis step is before the structural design, that is, the structural design of the edging ring must follow the process documents of formability analysis. Therefore, the structural adjustment of the edging ring cannot affect the flow of the sheet metal. Optimizing contact force through controlling the flow of sheet metal during the structural design phase is difficult to achieve. The optimized contour line of the edge banding ring is shown in Fig. 11.

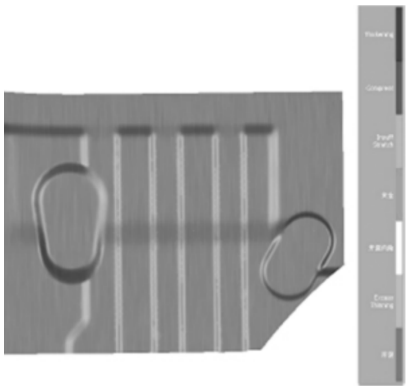

Fig. 11. Optimized rendering

The curve of the maximum equivalent stress of the edge ring structure before and after the stamping process modification over time is shown in Fig. 12. According to the simulation results, it can be seen that after structural optimization, the maximum equivalent stress peak of the edge ring is reduced to 241MPa. The stress concentration phenomenon at the inner corner of the edge pressing ring has been effectively controlled. During the entire stamping process, the average maximum equivalent stress has significantly decreased compared to before optimization, and the pressure change is shown in Fig. 12.

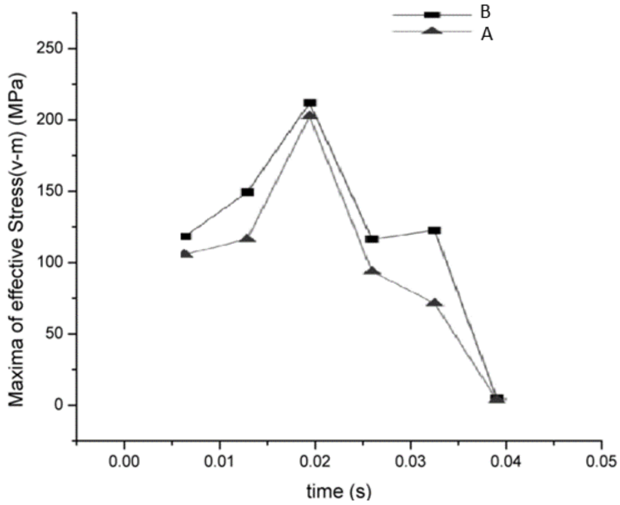

Fig. 12. Comparison before and after optimization

In the above figure, B represents before optimization, and A represents after optimization.

Through simulation, this section mainly completed the optimization of the edge pressing ring structure, and improved the efficiency of model design through optimization.

6 Conclusion

This article focuses on the die-casting process of battery casings. Firstly, the structure, materials, and production process characteristics of the target parts are analyzed. The developed mold frame design system allows designers to input relevant mold frame parameters based on knowledge and experience, and the system can automatically generate a 3D model of the mold frame.

Simulation design and intelligent optimization both belong to digital technology, which participates in the application of modeling and design tools in mold manufacturing processes, such as parametric modeling technology and design optimization methods, providing more accurate and flexible mold design methods. Meanwhile, the adoption of integrated manufacturing systems has accelerated the manufacturing process and reduced production cycles. In addition, simulation and virtual manufacturing technology have played a key role in reducing errors and costs. Although this greatly saves designers the time to build their own mold frames and reduces modeling errors, a new injection mold frame selection scheme was designed by analyzing the specific experience and methods of mold factory designers when designing mold frames. The selection and design knowledge of injection mold frames were sorted out and summarized, and an integrated reasoning mode based on deep learning and rule-based reasoning was used to infer the key parameters that determine mold frame selection. By combining neural networks and RBR, the advantages of both were utilized to improve the decision-making efficiency and accuracy of the mold frame design system. The introduction of artificial intelligence has accelerated the mold development cycle and improved the optimization performance of mold parameters.

At the same time, the research results of this article are not the focus of this study. For further research directions, this article has made the following plans:

1) Numerical simulation technology can effectively simulate the stamping process and obtain accurate impact loads, but using uniform loading method for the analysis of the convex die force of the mold may result in finite element results that do not fully match the actual situation. In subsequent research, load mapping and other methods can be used to analyze the force on convex molds to obtain more accurate results.

2) This article only uses the nominal stress method and linear fatigue cumulative damage theory to analyze

the fatigue of the convex mold. In subsequent research, different fatigue life analysis methods and cumulative damage theory can be adopted to analyze the fatigue of the convex mold, in order to obtain more accurate fatigue life.

3) Split mold design is the core of mold design and the beginning of mold design. This article proposes an automated parting design method based on materialization to address the shortcomings of existing mold design technologies. This method can successfully solve the mold design problems for the vast majority of plastic parts in engineering, such as common shell and flat plate types. Although we have not encountered the problem of plastic part parting during the system application testing process, it is not difficult to imagine that in real engineering, the shape of plastic parts can sometimes be extremely special, and the corresponding mold structure may suddenly be different from normal. Using existing design methods may still encounter difficult problems to solve. Therefore, further deepening the research on solid parting design technology to make the system adapt to the mold design of all plastic parts as much as possible is the ultimate goal of this study.

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