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A Review of Optimization Methods for Sheet Metal Forming Processes

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Abstract

Sheet metal forming is a core manufacturing process in aerospace, automotive, and marine industries, where optimization of process parameters directly impacts product quality and production costs. This paper systematically reviews research progress in optimizing sheet metal forming process parameters, examining the current application status of traditional optimization methods, numerical simulation techniques, and intelligent optimization algorithms in this field. It focuses on exploring the principles and characteristics of typical optimization techniques such as finite element simulation, response surface methodology, genetic algorithms, neural networks, and multi-objective optimization. Furthermore, it provides an outlook on cutting-edge research directions like online monitoring and real-time control. Research indicates that intelligent optimization methods integrating digital twins, artificial intelligence, and big data will become a significant development trend in sheet metal forming process parameter optimization.

Keywords

Sheet Metal Forming; Process Parameter Optimization; Numerical Simulation; Intelligent Algorithm; Multi-Objective Optimization.

1. Introduction

Sheet metal forming technology is an indispensable fundamental process in manufacturing fields such as automotive, aerospace, and electronic appliances. The process parameters directly influence the mechanical properties, dimensional accuracy, and surface quality of the formed parts. As industrial products evolve toward lightweight, high-strength, and complex configurations, higher demands are placed on the precision and efficiency of sheet metal forming. The selection and optimization of process parameters have become key factors determining forming quality. Unreasonable parameter settings can lead to defects such as springback, cracking, and wrinkling, resulting in material waste and increased costs.

Traditional design of process parameters for sheet metal forming mainly relies on empirical trial-and-error methods, which suffer from long cycles, high costs, and low efficiency. In recent years, with the development of computer technology, numerical simulation techniques and intelligent optimization algorithms have provided new approaches for process parameter optimization. CAD/CAM/CAE integration technology has shifted process design from "experience-driven" to "data-driven" approaches, significantly improving optimization efficiency and accuracy. This paper aims to systematically review the research methods for process parameter optimization in sheet metal forming, analyze the advantages and limitations of various techniques, and provide a reference for related research and engineering applications.

2. Overview of Sheet Metal Forming Processes

2.1 Classification of Major Forming Processes

Sheet metal forming mainly includes processes such as stamping, bending, stretch forming, hydroforming, and deep drawing. Among these, stamping uses rigid dies to apply mechanical force to the sheet, causing plastic deformation that conforms the sheet to the die cavity shape. This process is suitable for high-efficiency, mass production of parts with relatively regular geometries. Bending applies a bending moment through dies, inducing plastic bending in specific regions of the sheet to obtain precise angles and straight edges. It is suitable for diversified, small-batch production, offering high precision and high flexibility. Stretch forming applies tensile forces to the sheet edges via grippers, inducing biaxial tensile plastic deformation over a punch, which effectively forms large-sized, low-curvature smooth surfaces and significantly suppresses springback. Hydroforming employs a flexible medium, using high-pressure liquid as a force-transmitting medium to uniformly and compliantly push the sheet against a rigid die from one side. Its advantage lies in the sheet conforming to the die under hydrostatic pressure, resulting in uniform stress distribution, enabling the formation of complex spatial curved surfaces while preserving surface quality. Deep drawing primarily controls material flow: under the constraint of a blank holder, the punch drives the sheet material in the flange region to flow radially into the die cavity and undergo significant plastic deformation. This process is suitable for manufacturing deep-cavity parts but requires precise control to prevent wrinkling and tearing [1-4].

2.2 Key Process Parameters

The core parameters vary across different forming processes. For stamping, the main parameters include blank holder force, stamping speed, die clearance, punch and die radii, and lubrication conditions. For bending, the key parameters are bending force, bending speed, holding time, and die angle compensation. For stretch forming, the key parameters include clamping force, total stretching amount, and punch rising speed. For hydroforming, the key parameters are peak hydraulic pressure, pressure loading path, back pressure value, and pre-filling pressure in the fluid chamber. For deep drawing, the key parameters include the magnitude and distribution of blank holder force, drawbead geometry, die surface compensation amount, punch stroke–pressure curve, and the distribution of forming steps in multi-stage drawing. These process parameters are coupled with one another and collectively influence material flow, stress distribution, and the final forming quality [5-9].

2.3 Common Forming Defects

Improper process parameters can easily lead to three typical types of defects: (1) Springback–shape deviation caused by recovery of elastic deformation. After forming, the elastic strain stored inside the sheet is released, causing the part dimensions and geometry to deviate from the die. This defect is common in bending, hydroforming, etc. (2) Wrinkling–due to excessive compressive stress in the tangential (or other) directions, the sheet undergoes instability buckling, forming wavy wrinkles. This mainly occurs in deep drawing and stretching of complex curved surfaces. (3) Cracking–local tensile stress exceeds the tensile strength of the sheet material, leading to fracture. This is commonly seen in the fillet transition zones of complex parts. In engineering practice, these three defects are often coupled with one another, exhibiting trade-off relationships, which constitute the core difficulty in process tuning. For example, increasing the blank holder force or reducing the die clearance to suppress wrinkling may cause excessive material flow resistance and lead to cracking. Conversely, reducing the blank holder force or enlarging the die radius to prevent cracking may induce wrinkling. Such contradictions are particularly pronounced in the forming of complex parts such as automotive body panels, and defect control is the central objective of parameter optimization [10].

3. Process Parameter Optimization Methods

3.1 Traditional Optimization Methods

(1) Empirical methods

These refer to a general class of practices that rely on long-term accumulated intuition, know-how, rules of thumb, and simple calculations of craftsmen and engineers for process design and problem solving, prevailing in periods when complete theoretical models or efficient computational tools were lacking. Their core is to simplify the complex nonlinear forming process into qualitative rules and quantitative mnemonics derived from direct observations of phenomena and repeated trial-and-error. Empirical formulas also belong to this category.

(2) Design of Experiment (DOE)

DOE is a methodology based on statistical principles. By scientifically arranging experimental schemes and systematically analyzing data, it efficiently reveals the causal relationships between process parameters and forming quality, thereby achieving process optimization. Through full factorial or orthogonal experiments, the parameter-quality response relationship is established. This method is intuitive but often requires a large number of experiments. The Taguchi method reduces the number of experiments using orthogonal arrays and combines signal-to-noise (S/N) ratio analysis to obtain robust process parameters. It is widely used in small-sample optimization [11].

3.2 Numerical Simulation-Based Optimization Techniques

Finite element method (FEM) simulation uses mathematical approximations to model real physical systems (geometry and loading conditions). By employing simple yet interacting elements, it approximates a real system with infinite unknowns using a finite number of unknowns. The solution domain is discretized into many small, interconnected subdomains called finite elements. For each element, an appropriate approximate solution is assumed, and then the overall conditions for the entire domain are derived and solved, thereby obtaining the solution to the problem. In sheet metal forming, FEM can be used to establish a finite element model of the forming process, predicting the stress–strain distribution, thickness variation, and defect formation mechanisms. Combined with springback compensation algorithms, it enables iterative optimization of die surfaces and process parameters, significantly reducing the number of die tryouts [12].

3.3 Surrogate Models

In traditional forming process design, process parameters are often adjusted based on experience and experimental methods. The results obtained in this way are not only imprecise but also require substantial time, financial, and material resources. Therefore, actual forming processes are frequently replaced by finite element simulations, which significantly reduce the consumption of equipment and other resources. However, evaluating multiple process parameter combinations via finite element simulation still incurs high time costs. Consequently, the application of surrogate models becomes very important. By using only a small number of experimental samples for training and learning, a mapping relationship between process parameters and stamping forming quality can be established, thereby approximating and replacing the finite element simulation process and providing great convenience for engineering optimization problems [13]. Common surrogate models include the following:

(1) Response Surface Methodology (RSM)

Response surface methodology constructs an approximate mathematical model based on experimental data, using polynomial fitting to represent the nonlinear relationship between process parameters and response values. The optimal parameter combination is then obtained through gradient-based optimization. This method offers high computational efficiency, but its accuracy is significantly influenced by the model order and the distribution of sample points. RSM typically adopts a quadratic polynomial model, which can be expressed as:

$$Y=\beta_0+\sum_{i=1}^{k}\beta_i x_i+\sum_{i=1}^{k}\beta_{ii}x_i^2+\sum_{i<j}^{k}\beta_{ij}x_i x_j+\epsilon \quad (1)$$

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where Y represents the response variable; x_i represent the input variables; β represent the regression coefficients; and ϵ represents the random error.

(2) Kriging Model

The fundamental idea of the Kriging model originated from the South African mining engineer Krige, who first presented it in his master's thesis in 1951. Subsequently, through gradual development and refinement by the French mathematician Matheron, a complete theoretical framework was established, and in 1963 it was named "Krigeage" (later referred to as the Kriging model) [14].

The Kriging model consists of two parts: a fitted regression term and a stochastic distribution. Its expression is as follows:

$$y(x) = F(\beta, x) + z(x) = f^T(x)\beta + z(x) \tag{2}$$

Where $f^T(x)$ represents the regression model, β represents the coefficients of the regression model, and $z(x)$ represents the random deviation, which satisfies the following statistical properties:

$$E[z(x)] = \mathbf{0} \tag{3}$$

$$D[z(x)] = \sigma_z^2 \tag{4}$$

$$Cov[z(x), z(w)] = \sigma_z^2 R(x, w) \tag{5}$$

where $E[z(x)]$ denotes the expectation, $D[z(x)]$ denotes the variance; $Cov[z(x), z(w)]$ denotes the covariance; and $R(x,w)$ represents the variogram between sample points x and w.

(3) Radial Basis Function (RBF) Neural Network Model

The RBF neural network uses RBF as the basis functions of the hidden layer. It can directly map the input vector to the hidden layer units without necessarily performing weighted processing on the information from the input units. The architecture of the RBF neural network model is shown in Fig. 1.

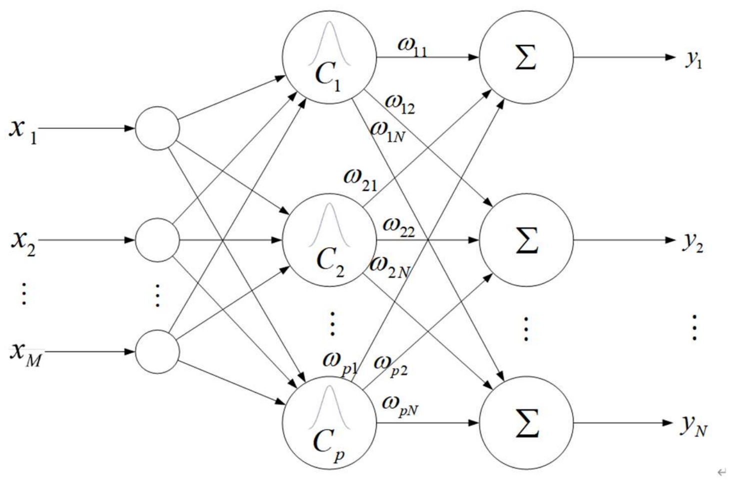

Fig. 1 RBF neural network model

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The radial basis function typically adopts a Gaussian function. Taking the M -th sample point as an example, its expression is as follows:

$$R(x_M - c_i) = \exp(-\frac{1}{2\sigma^2}\|x_M - c_i\|^2) \quad i = 1, 2\cdots P \tag{6}$$

Where σ denotes the width parameter, x_M denotes the sample point, c_i denotes the center of the kernel function, and $\|x_M - c_i\|$ denotes the distance from x_M t o the i -th center. Therefore, the output of the RBF neural network model can be expressed as:

$$y_N = \sum_{i=1}^{P} w_{ij} R(x_M - c_i) \quad j = 1, 2\cdots N \tag{7}$$

(4) BP Neural Network Model

The Back Propagation Neural Network (BPNN) possesses capabilities of self-learning, self-adaptation, and strong nonlinear mapping. In theory, a three-layer BPNN can achieve mapping from an n-dimensional space to an m-dimensional space. The structure of a single-hidden-layer BPNN model is shown in Fig. 2.

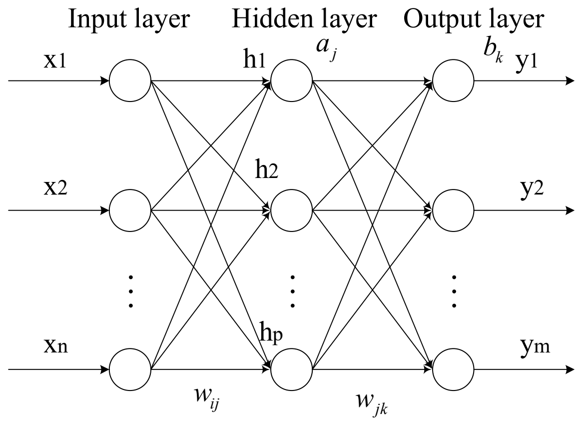

Fig. 2 BP neural network model

In Fig. 2, $\mathrm{X_n}$ denotes the input of the n-th input layer neuron; $\mathrm{h_p}$ denotes the output of the p -th hidden layer neuron; y_m denotes the output of the m -th output layer neuron, w_{ij} denotes the connection weight between the i -th input layer neuron and the j -thhidden layer neuron; w_{jk} denotes the connection weight between the j -th hidden layer neuron and the k -thoutput layer neuron; a_j denotes the bias of the j -th hidden layer neuron; b_k denotes the bias of the k -th output layer neuron.

Assume the transfer function from the input layer to the hidden layer is f, and the transfer function from the hidden layer to the output layer is g. The forward propagation in BPNN can be expressed as follows:

$$h_j = f(\sum_{i=1}^{n} w_{ij} x_i - a) \tag{8}$$

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$$y_k = g(\sum_{j=0}^{p} w_{jk} h_j - b) \tag{9}$$

Where $a = (a_1, a_2, \cdots, a_p)^T$ represents the hidden layer bias; $b = (b_1, b_2, \cdots, b_m)^T$ represents the output layer bias. The error function of BPNN is defined as:

$$\varepsilon = \frac{1}{2} \sum_{k=1}^{m} (t_k - y_k)^2 \tag{10}$$

where t_k denotes the true value of the k -th target, and y_k denotes the predicted value of the k -th target.

3.4 Single-Objective Optimization Algorithms

For complex engineering problems, surrogate models can be constructed to transform practical problems into expressible proxy models, thereby reflecting the influence relationships between process parameters and forming quality in engineering problems. In the surrogate model, this is manifested as the mapping relationship between model parameters and the loss function. Optimization algorithms, through specific computational steps and rules, identify the solution that minimizes or maximizes the loss function among a large number of possible solutions. Here, the loss function represents the predefined forming quality indicator, quantifying the evaluation criterion among different process parameter combinations.

Common single-objective optimization algorithms include gradient descent, Genetic algorithm (GA), and Particle swarm optimization (PSO), etc. Gradient descent updates the parameters by computing the gradient of the loss function with respect to the model parameters and then moving the parameters in the opposite direction of the gradient (i.e., the steepest descent direction). In each iteration, the loss function value decreases (at least locally), thereby gradually approaching the minimum of the loss function. GA is an optimization algorithm that simulates the biological evolution process in nature. It was proposed by American scholar John Holland together with his students and colleagues in 1975. Its core idea originates from Darwin's theory of natural selection. By simulating biological evolution processes such as natural selection, crossover, and mutation, GA searches for the optimal solution in the solution space. PSO is an iterative optimization method based on swarm intelligence. It was proposed by Kennedy and Eberhart in 1995, inspired by the study of bird flock foraging behavior. Imagine a flock of birds randomly searching for food in an area where only one piece of food exists. The simplest and most effective strategy to find the food is to search in the vicinity of the bird currently closest to the food. Through group collaboration and information sharing, PSO performs a search in the parameter space. Its convergence speed is faster than that of GA, making it suitable for continuous variable optimization [15-17].

3.5 Multi-Objective Collaborative Optimization

When a problem involves multiple objectives that conflict with and are incomparable to each other, a solution may be optimal in terms of one objective but poor in others. When optimizing such objectives, an improvement in one objective inevitably leads to the deterioration of at least one other objective. In this case, the obtained solution is called a Pareto solution. When a solution X_1 is superior to another solution X_2 in all objective values, then X_1 is said to dominate X_2. If X_1 is better than X_2 in some objectives while X_2 is better than X_1 in others, then X_1 and X_2 are said to be non-dominated with respect to each other. The set of mutually non-dominated solutions is called the Pareto set, and the curve formed by these solutions in the objective space is termed the Pareto front.

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In practical production, it is often necessary to simultaneously consider multiple objectives such as forming quality, production efficiency, energy consumption, and material utilization. For example, in stamping forming, optimizing both the maximum thinning rate and the maximum thickening rate simultaneously accounts for the risks of cracking and wrinkling. Through multi-objective optimization algorithms, a set of non-dominated solutions can be obtained, allowing decision-makers to select the appropriate solution according to actual requirements.

Common multi-objective optimization algorithms include Nondominated Sorting Genetic Algorithm II (NSGA-II), Strength Pareto Evolutionary Algorithm 2 (SPEA2), Multi-Objective Evolutionary Algorithm based on Decomposition (MOEA/D), Multi-Objective Particle Swarm Optimization (MOPSO), etc. NSGA-II is an improved multi-objective algorithm proposed by Deb et al. based on the nondominated sorting genetic algorithm (NSGA) [18]. SPEA2 was proposed by Zitzler et al. in 2001 as an enhancement of SPEA. To overcome the shortcomings of SPEA [19], SPEA2 employs a modified fitness assignment scheme that takes into account both the number of individuals dominated by each individual and the number of individuals that dominate it. In SPEA, individuals dominated by the same individual are assigned the same fitness value, placing all such individuals at the same level. Consequently, when the archive contains only a single individual, all individuals have the same rank regardless of whether they are dominant. This reduces the selection pressure and, in such an extreme case, renders the algorithm equivalent to random search. Furthermore, SPEA2 employs the nearest neighbor for density estimation and adopts a new archiving method, which ensures the preservation of boundary solutions. MOEA/D was proposed by Zhang et al. in 2007, primarily employing the concept of decomposition [20]. MOPSO was proposed by Coello et al. in 2004 based on particle swarm optimization, aiming to extend PSO to multi-objective optimization [21].

4. Future Development Trends

With the deep penetration of Industry 4.0, next-generation artificial intelligence, and green manufacturing concepts, process optimization for sheet metal forming is gradually shifting from traditional offline trial-and-error and single-physics simulation toward a new paradigm driven by the fusion of physics and data, whole-process intelligent decision-making, and sustainable collaboration. Future research will achieve breakthroughs around the following core directions.

4.1 Digital Twin and Physics-Data Fusion Closed-Loop Optimization

By constructing a high-fidelity mirror image of the forming process in virtual space, digital twin technology enables the dynamic integration of real-time sensor data with mechanistic models, thereby achieving online adaptive adjustment of process parameters and early intervention of defects. At present, the application of digital twins in sheet metal forming remains mainly at the level of condition monitoring and offline validation [22]. In the future, digital twins for forming processes will deeply integrate multi-source heterogeneous data and combine surrogate models with optimization algorithms to establish a closed-loop optimization system encompassing "sensing-prediction-decision-execution." This will significantly improve the consistency of forming quality and process robustness for complex parts .

4.2 Breakthroughs in Deep Learning and Multi-Fidelity Surrogate Models

Surrogate models serve as computational accelerators for process optimization, but their predictive capability has long been constrained by the high simulation cost of high-dimensional, strongly nonlinear forming responses. Multi-fidelity surrogate models perform collaborative modeling by combining a small amount of high-fidelity finite element data with a large amount of low-fidelity simulation or theoretical model data, thereby significantly reducing the demand for high-fidelity samples. Meanwhile, deep-structured surrogate models such as deep neural networks, convolutional neural networks, and long short-term memory networks can automatically capture the complex mapping relationships between defects (e.g., springback and wrinkling) and geometric features or material parameters. In addressing large-deformation path-dependent problems, these deep models

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demonstrate potential superior to traditional Kriging or radial basis functions. In the future, the integration of physics-informed deep learning with adaptive multi-fidelity strategies will enable surrogate models to maintain reliable extrapolation capability even with very few high-cost samples, promoting "few-sample, high-precision" development in process optimization [23].

4.3 Robust Optimization Considering Multi-Source Uncertainties

The sheet metal forming process inherently involves multi-source uncertainties, including fluctuations in material properties, variations in friction conditions, die wear, and positioning errors. The optimal parameters obtained from traditional deterministic optimization often become suboptimal or even lead to high rejection rates in actual production. Therefore, robustness optimization and reliability optimization for process stability have become unavoidable issues. Current research commonly employs polynomial chaos expansion, adaptive sampling, or Bayesian methods to propagate and quantify parameter uncertainties, and uses algorithms such as nondominated sorting genetic algorithms to find designs that are insensitive to fluctuations. A future trend is to integrate data-driven robust optimization with online process monitoring, achieving a transition from batch-level robust design to part-by-part traceable real-time reliability closed-loop control [24].

4.4 Real-Time Optimization and Control Based on Knowledge and Reinforcement Learning

Facing the flexible manufacturing demands of multi-variety, small-batch production, the traditional paradigm of relying on empirical adjustments or fixed optimized parameters is unsustainable. Reinforcement learning and its combination with surrogate models offer new pathways for self-learning control of forming processes. By defining reward functions related to forming quality, energy consumption, and efficiency, an agent can autonomously learn optimal control strategies (e.g., die actions and blank holder force trajectories) in a continuous action space and continuously evolve in real environments or digital twins. In the future, knowledge-and data-driven autonomous process learning systems will endow sheet metal forming equipment with "human-in-the-loop" or "fully autonomous" process decision-making capabilities, substantially reducing die change and parameter tuning time, and achieving near-zero-defect manufacturing [25-26].

4.5 Multi-Objective Collaborative Optimization for Full Process Chain and Sustainable Manufacturing

Forming quality is determined not only by the stamping process itself but also by upstream operations such as blank profile design and nesting, as well as downstream operations such as springback compensation and trimming. Isolated optimization of a single process can easily fall into local optima, neglecting the coupling effects among processes. Consequently, full-process-chain integrated optimization covering blank-forming-springback compensation is becoming key to improving final part geometric accuracy and material utilization. Meanwhile, under the macro-level goals of carbon peak and carbon neutrality, sustainability indicators such as energy consumption, material recyclability, and environmental load are increasingly becoming important dimensions in process evaluation. In the future, simultaneously incorporating forming quality, production efficiency, and environmental impact into a multi-objective optimization framework, developing high-dimensional preference-driven multi-objective decision-making algorithms, and integrating life cycle assessment will constitute the core connotation of next-generation green sheet metal forming process optimization.

5. Conclusion

The optimization of sheet metal forming process parameters is undergoing a profound shift from empirical trial-and-error to intelligent decision-making. Numerical simulation techniques have established the foundation for virtual optimization, intelligent algorithms have provided efficient solution tools, and digital twin along with big data technologies have opened a new chapter of full-process intelligence. Future research should concentrate on high-fidelity and high-efficiency modeling methodologies, robust optimization under uncertainty, multi-physics and multi-scale coupling analysis, and the automated acquisition and reuse of process knowledge. For engineering applications, it is imperative to strengthen the development of standardization systems and promote the adoption of advanced optimization technologies among small and medium-sized enterprises, thereby comprehensively raising the level of intelligence in China's sheet metal manufacturing industry.

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