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Injection Molding Process Optimization Based on Weighted Optimization Twin Network

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Abstract. *Optimisation of injection moulding process parameters traditionally relies on empirical experimental methods and a single optimisation algorithm, which performs poorly in dealing with complex nonlinear relationships and multivariate interactions, resulting in limited productivity and part quality. In order to solve this problem, this paper proposes an injection moulding process parameter optimization model based on Seagull Optimization Algorithm (SOA) and Weighted Twin Neural Network (WTNN). Firstly, through a detailed analysis of the moulding mechanism and process parameters of injection moulded parts, six key process parameters affecting warping deformation are identified, including melt temperature, holding pressure, holding time, mould temperature, cooling time and injection time. Then, combining the global search capability of SOA and the efficient feature extraction capability of WTNN, the accurate optimisation of the above six process parameters is achieved. The experimental results with a thin-walled injection moulded part of a car as the research object show that compared with the traditional optimization method, the SOA-WTNN model significantly improves its performance in optimizing the injection moulding process parameters, with the optimal warping deformation reduced to 0.172, the computation time shortened to 100 seconds, and the convergence speed increased to 30 iterations. The performance of the model is particularly significant in reducing warping deformation and improving part quality, which has high potential for application.*
Keywords: injection moulding process; SOA; twin neural network; process parameter optimisation; warping deformation

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1. **Introduction.** The study of injection molding process optimization holds significant research value and necessity in the field of manufacturing. Injection molding is a widely used manufacturing process for producing plastic parts, ranging from small components to

large body panels of automobiles [1, 2]. The quality of injection molded parts is heavily influenced by various process parameters such as melt temperature, packing pressure, and cooling time. Optimizing these parameters is crucial to reduce defects like warping deformation and shrinkage, enhance the mechanical properties of the molded parts [3, 4], and improve overall production efficiency. Moreover, with the increasing demand for precision and high-quality products in industries such as automotive [5], aerospace [6], and consumer electronics [7], there is a continuous need for advanced techniques to optimize the injection molding process and ensure consistent product quality.

Neural networks have shown great potential in the optimization of injection molding process parameters [8, 9, 10]. By leveraging their capability to model complex, non-linear relationships between input parameters and output quality metrics, neural networks can effectively predict and optimize the performance of the injection molding process. Specifically, models like the Twin Neural Network (TNN) [11, 12] can be utilized to analyze the impact of multiple process parameters simultaneously and identify optimal settings. The integration of neural networks with optimization algorithms, such as the Seagull Optimization Algorithm (SOA) [13, 14], further enhances the optimization process by combining global search capabilities with efficient feature extraction. This approach not only improves the accuracy of the optimization but also reduces computational time, making it a promising solution for industrial applications. The purpose of this paper is to optimize the injection molding process parameters through the model based on SOA and TNN, so as to reduce warping deformation and improve the product quality and production efficiency.

1.1. **Related work.** Traditional methods for optimising injection moulding process parameters mainly include empirical test method, response surface method, orthogonal experimental design and Taguchi method [15, 16]. These methods have improved the quality and efficiency of the injection moulding process to a certain extent, but there are also some non-negligible problems.

The empirical test method is the most common optimisation method, in which the process parameters are continuously adjusted through operator experience and trials. However, this method depends on the experience and skill level of the operator, and the test process is time- consuming and laborious, and it is difficult to ensure the consistency and repeatability of the results. Costa et al. [17] proposed an optimisation method based on the empirical test method for injection moulding and found that this method is inefficient and difficult to optimise comprehensively under the complex combinations of process parameters.

Response surface methodology describes the relationship between process parameters and quality characteristics by constructing a mathematical model to optimise the process parameters. Chen et al. [18] used response surface methodology to optimise the injection moulding process, and achieved certain results, but this method shows some limitations when dealing with multivariate interactions, and it is easy to fall into the local optimum.

Orthogonal Experimental Design (OED) is an effective multifactorial and multilevel experimental method to obtain as much information as possible through a small number of trials. Taguchi method further simplifies the OED, but its optimisation effect is limited when dealing with nonlinearities and process parameters with significant interactions. Oktem et al. [19] used Taguchi method to optimise the injection moulding process and although the product quality was improved, the optimisation effect was not satisfactory under complex combinations of process parameters. improved the product quality, but the optimisation effect was not satisfactory under complex process parameter combinations.

Traditional methods often rely on a large amount of experimental data in the optimisation process, and it is difficult to comprehensively consider the nonlinearities and interactions between process parameters. With the complexity of the injection moulding process, the limitations of the traditional methods become more and more obvious, and new optimisation techniques are urgently needed to improve the efficiency and effectiveness of process parameter optimisation.

Neural networks have been gradually applied in the optimisation of injection moulding process parameters due to their powerful nonlinear modelling and parallel processing capabilities. Neural network-based optimization methods can effectively alleviate the limitations of traditional methods, especially when dealing with complex multivariate interactions and nonlinear relationships, Yin et al. [20] proposed a Back Propagation Neural Network (BPNN)-based optimization method for injection moulding process parameters, and the optimization results are better than the traditional methods by training the network model to predict the quality of the parts under different combinations of process parameters. The optimisation results are better than the traditional methods. However, BPNN suffers from the problems of long training time and easy to fall into local optimisation. In order to improve the optimisation results, researchers have introduced advanced neural network models such as multilayer perceptron (MLP) and Convolutional Neural Network (CNN). Ha and Jeong [21] used a CNN model to optimise the injection moulding process, and found that this method has significant advantages in dealing with large-scale datasets and complex nonlinear relationships, but there is still a risk of overfitting.

In recent years, the application of TNN in practical engineering has gradually increased.TNN is able to effectively capture the similarities and differences between process parameters through a dual network structure with shared weights. Nolte and Pyrak-Nolte [22] applied TNN to monitor crack saturation, and achieved good results, but it did not perform well when dealing with unbalanced data sets. In order to further improve the optimization effect, researchers try to combine meta-inspired optimization algorithms, such as Genetic Algorithm (GA) and Particle Swarm Optimization (PSO), to optimize the weights and structure of neural networks. Wahjudi et al. [23] used GA to optimize the weights of the BPNN model, which significantly improves the efficiency and accuracy of the optimization of the injection moulding process parameters, but the optimization process is complicated and the computational cost is higher .

1.2. **Motivation and contribution.** Existing optimisation methods for injection moulding process parameters usually focus on traditional experimental design and single optimisation algorithms, which are difficult to deal with complex multivariate interactions and nonlinear relationships effectively. The process parameters in the injection moulding process, such as melt temperature, holding pressure and cooling time, have significant nonlinear relationships with each other, which makes the traditional optimisation methods perform poorly in practical applications. In addition, existing neural network-based optimisation methods often face the problems of long training time, high computational cost and easy to fall into local optimums when dealing with large-scale datasets and complex nonlinear relationships. In order to solve the above problems, this paper proposes a model based on SOA optimization weighted TNN for optimising injection moulding process parameters.

The main innovations and contributions of this work include:

1. Aiming at the complexity of the moulding mechanism of thin-walled injection moulded parts, through the detailed discussion on the influences of holding pressure, temperature and multiple effects, this paper systematically reveals the influences of each process parameter on the quality of the parts, and provides a scientific basis for the

subsequent optimization of process parameters. In particular, through orthogonal experimental design and

ANOVA method, this paper effectively identifies the key process parameters affecting warping and deformation, and lays a solid foundation for the establishment of the optimisation model.

2. Aiming at the limitations of traditional methods in dealing with complex nonlinear relationships and multivariate interactions, the SOA-WTNN model proposed in this paper achieves accurate optimisation of injection moulding process parameters by combining the global search capability of SOA and the efficient feature extraction capability of WTNN. The model performs particularly well in reducing warping deformation and improving part quality.

2. Analysis of the moulding mechanism and process parameters of injection moulded parts.

2.1. Analysis of warping deformation mechanism of thin-walled injection moulded parts.

Warp deformation of thin-walled injection moulded parts is one of the important factors affecting their moulding quality, and its causes are complex, involving a variety of process parameters and their interaction. This paper will take a car thin-walled injection moulding parts as the research object, to discuss the pressure holding, temperature and the influence of multiple effects on the warping deformation of thin-walled injection moulding parts. The parts are shown in Figure 1, with length, width and height dimensions of 1678mm×350mm×335mm, and average wall thickness of 4.5 mm.

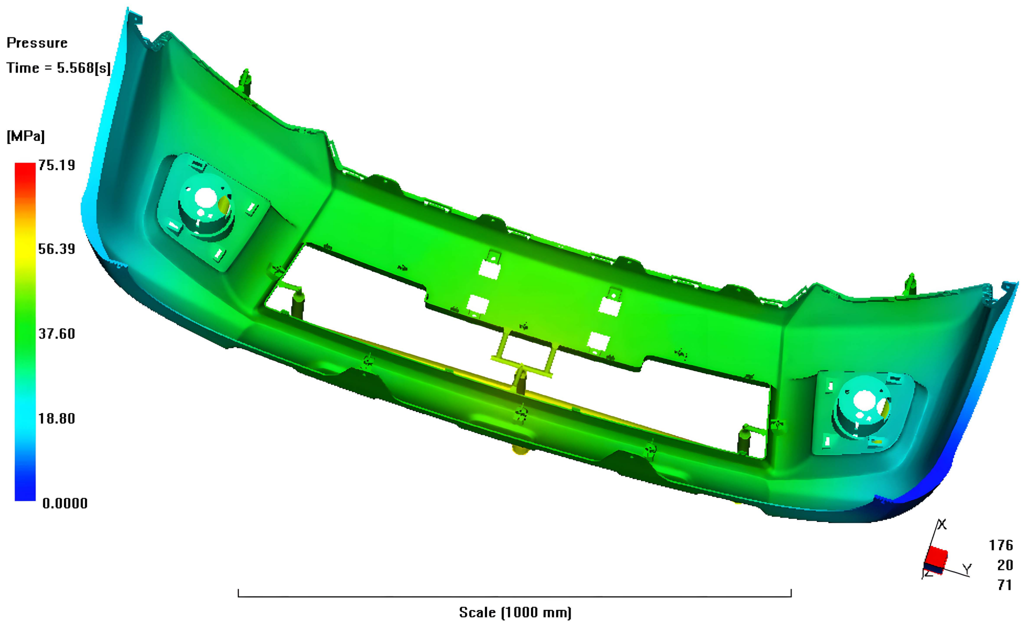

Figure 1. FIGURE 1. Thin-walled injection moulded parts for a car

2.1.1. *Effect of holding pressure.*

The holding pressure stage is a critical part of the injection moulding process, where pressure is applied to the polymer melt in the cavity to compensate for the volume shrinkage of the polymer during the cooling process, thus improving the denseness and quality uniformity of the part. In an ideal moulding process, the filling stage ends when the melt reaches the end of the cavity and switches smoothly to the holding pressure stage to provide optimum part quality.

The holding pressure and holding time have a significant effect on the quality characteristics of the parts such as shrinkage, warping deformation, flying edge, geometry and residual stress. According to the study, the relationship between the pressure drop in the cross- section of the mould cavity and the melt flow front is shown below:

$$\Delta P = \frac{12\,Q\,\eta\,l}{w\,h^3} \tag{1}$$

where ΔP is the pressure drop; Q is the volume flow rate; η is the melt viscosity; l is the flow length; w and h are the width and thickness of the cross-section respectively. Thin-walled injection moulded parts have higher pressure loss due to the smaller thickness of the cavity cross-section, and the increase in melt viscosity due to an increase in flow length or a decrease in temperature will also significantly increase the pressure drop.

The pressure is high around the gate and begins to decrease rapidly away from the gate. Too high a holding pressure can lead to flying edges and excessive internal stresses, while too low a holding pressure can cause insufficient part density and surface defects. The length of the holding time determines the cooling time of the melt in the mould cavity. Too long a holding time will prolong the cycle time, while too short a holding time will not adequately compensate for shrinkage. Optimising the parameters of the holding pressure stage is essential to improve part quality and productivity.

2.1.2. *Effect of temperature.* Temperature is another important factor affecting the warping and deformation of injection moulded parts. After the melt enters the cavity, its heat is rapidly dissipated through the cavity surface, resulting in rapid cooling of the part. In the thin-wall injection moulding process, due to the thinner wall thickness, the melt heat loss is faster, and the temperature decreases rapidly, resulting in an increase in melt viscosity and resistance to flow.

During the filling stage, the melt temperature is higher near the gate area and lower at the end of filling, and this temperature gradient leads to inconsistent shrinkage in different areas, which causes warping deformation [24].

2.1.3. *Influence of multiple effects.* Warp deformation is usually the result of multiple effects. In injection moulding, after the melt is injected from the gate to both sides, the pressure and temperature decrease along the flow direction. The pressure is higher in the area near the gate and lower at the end of the fill away from the gate; at the same time, the temperature is higher in the area near the gate and lower at the end of the fill. This double effect of pressure and temperature leads to complex warping deformation.

For example, non-uniform pressure distribution will cause the filled end of the part to shrink towards the centre, resulting in warping deformation around it, while non-uniform temperature distribution will result in saddle warping deformation of the part. In practice, these effects can be accurately simulated and predicted through numerical simulation and experimental analysis, so that the process parameters can be optimised and the warping deformation can be reduced.

2.2. **Analysis of process parameters.**

2.2.1. *Orthogonal experimental design.* In the process of injection moulding, the influence of process parameters on the quality of final parts is crucial. Reasonable process parameters can effectively reduce warping deformation and improve the mechanical properties and dimensional accuracy of the parts. In this paper, we will take a thin-walled injection moulding part as the research object, and use the orthogonal experimental design method to analyse and optimise the main process parameters.

Through orthogonal experimental design and Moldflow simulation, the influence of each process parameter on the warping and deformation of injection moulded parts can be systematically investigated so as to provide scientific basis and data support for the subsequent optimization work. In order to obtain reliable data in the simulation, Moldflow software is selected for numerical simulation. A two-level meshing model is used, and the mesh matching rate reaches more than 90%. The material used for the product is polypropylene (PP), and its main characteristic parameters are shown in Table 1.

Table 1. Main characteristics of the material

Parameter name	Numerical value
Solid density (g/cm^3)	0.916
Melt density (g/cm)	0.762
Modulus of elasticity (MPa)	1216
Poisson's ratio	0.367
Maximum permissible shear stress (MPa)	0.24
Maximum permissible shear rate (1/s)	23100

Orthogonal experimental design is an effective multifactorial and multilevel experimental method to obtain as much information as possible through a smaller number of trials. In this study, melt temperature (T_{melt}), holding pressure (P), holding time (t_p), mould temperature (T_{mold}), cooling time (t_c) and injection time (t_{inj}) six main process parameters, respectively, set three levels, the specific parameter range is shown in Table 2.

Table 2. Range of process parameters

Parameters	Numerical value
T_{melt}	200–300 °C
P	20–60 MPa
t_p	4–12 s
T_{mold}	30–90 °C
t_c	10–30 s
t_{inj}	0.5–3 s

In order to verify the interaction between factors and obtain the optimal combination of process parameters, L27 (3^{13}) orthogonal test table (13 factors at 3 levels) was used. The header design of the orthogonal table is shown in Table 3, with each factor occupying one column, each interaction factor occupying two columns, and the remaining empty columns storing the error terms.

Table 3. Orthogonal table headers

1	2	3	4	3	6	7	8	9	10	11	12	13
T_{melt} (A)	P (B)	A×B	A×B	t_p (C)	A×C	A×C	B×C	T_{mold} (D)	blank	B×C	t_c (E)	t_{inj} (F)

Twenty-one sets of tests were carried out according to the scheme of orthogonal experimental design. Each set of tests was carried out at different combinations of process parameters, and the amount of warping distortion (W_z) of the fabricated parts was recorded and analysed. By comparing and analysing the data from each set of tests, it was possible to determine which process parameters had the most significant effect on warping distortion. Table 4 shows the results of the orthogonal tests.

Table 4. Orthogonal test results

No.	T_{melt} (A)	P (B)	t_p (C)	T_{mold} (D)	t_c (E)	t_{inj} (F)	W_z
1	230	25	5	40	15	0.6	0.6086
2	230	25	6	60	20	1	0.4098
3	230	25	7	80	25	1.4	0.3931
4	230	35	5	60	25	1.4	0.8626
3	230	35	6	80	15	0.6	0.7671
6	230	35	7	40	20	1	0.2117
7	230	45	5	80	20	1	0.6261
8	255	45	6	40	25	1.4	0.2363
9	255	45	7	60	15	0.6	0.2525
10	255	25	5	60	20	14	0.8319
11	255	25	6	80	25	0.6	0.6267
12	255	25	7	40	15	1	0.2398
13	255	35	5	80	15	1	0.6517
14	255	35	6	40	20	14	0.3301
15	275	35	7	60	25	0.6	0.3857
16	275	45	5	40	25	0.6	0.9801
17	275	45	6	60	15	1	0.7967
18	275	45	7	80	20	14	0.6864
19	275	25	5	80	25	1	0.5675
20	275	25	6	40	15	14	0.4743
21	275	25	7	60	20	0.6	0.5353

From the test results, it can be seen that the combination of process parameters has a significant effect on the warping deformation of injection moulded parts. It can be concluded from the analysis that the effect of holding time and holding pressure on the amount of warping deformation is particularly significant, indicating that these two parameters need special attention in the optimisation process. At the same time, melt temperature and mould temperature also have a greater effect on warping deformation, while the cooling time and injection time have a relatively small effect.

2.2.2. *Process analysis.* After completing the orthogonal test design and experimental data collection, the next step is to carry out a detailed process analysis of these data to determine the degree of influence of each process parameter on the warping and deformation of the injection moulded parts and to provide a basis for optimising the process parameters.

In order to determine the significance of each process parameter on the amount of warping deformation W_z, the results of the orthogonal tests were statistically processed using analysis of variance (ANOVA). ANOVA is able to quantify the effects of the factors and their interactions on the response variable to identify the most significant process parameters. Table 5 demonstrates the results of the ANOVA.

It can be seen that the holding time (C), mould temperature (D) and melt temperature (A) have a significant effect on the warping deformation of the injection moulded parts, and the effect of holding time is the most prominent. This is consistent with the results of the previous mechanism analysis, indicating that these process parameters should be given priority in the optimisation process. The holding pressure (B), injection time (F) and cooling time (E) have a weaker effect on the warping deformation of injection moulded

Table 5. ANOVA for warping deformation

Source of variables	Square sum	Degrees of freedom	Mean square	F-value	Significance level
A	0.1586	2	0.0793	13.47	**
B	0.0690	2	0.0345	5.86	*
C	0.5668	2	0.2834	48.15	***
D	0.1936	2	0.0968	16.45	**
E	0.0204	2	0.0102	1.73	
F	0.0609	2	0.0305	5.18	*

Note: * indicates the level of significance, the higher the number of *, the stronger the significance.

parts. The influence magnitude of each factor is shown as follow:

$$C > D > A > B > F > E \tag{2}$$

3. SOA weighted optimisation of twin networks.

3.1. Principle of SOA.. In the optimisation of injection moulding process, traditional optimisation algorithms are often difficult to achieve the desired optimisation effect due to the complex multi-factor interaction. SOA is an emerging meta-inspired optimisation algorithm inspired by the complex and efficient foraging behaviours of seagulls in the foraging process. The algorithm achieves a comprehensive search of the solution space and the location of the optimal solution by simulating the random search and global localisation behaviours of seagull colonies during foraging.

The fundamentals of SOA consist of two main phases [25]: the search phase and the predation phase. The search and predation behaviour of seagulls is shown in Figure 2.

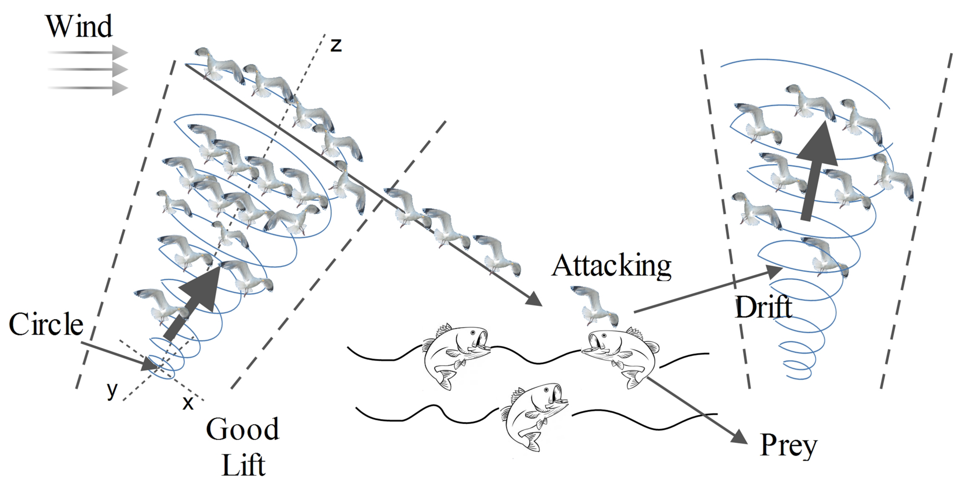

Figure 2. Search and feeding behaviour of seagulls

(1) **Search phase:** In this phase, the gull colony conducts an extensive search within the solution space to discover potential food sources (i.e., high-quality solutions in the solution space). The position of each gull is determined by its current position and velocity, and is updated by the following method:

$$\boldsymbol{X}_i(t+1) = \boldsymbol{X}_i(t) + \boldsymbol{V}_i(t) \tag{3}$$

where $\boldsymbol{X}_i(t)$ denotes the position of the i-th seagull at the t-th iteration; and $\boldsymbol{V}_i(t)$ denotes its velocity. The update of the velocity is then influenced by the current best position and random factors to ensure diversity in the global search.

(2) **Predation phase:** after searching for potential food sources, the gull colony starts to concentrate their flights to these locations in order to capture the optimal solution. In this phase, the gulls update their positions as follow:

$$\boldsymbol{X}_i(t+1) = \boldsymbol{X}_i(t) + \alpha\big(\boldsymbol{X}_{\text{best}}(t) - \boldsymbol{X}_i(t)\big) + \beta\,\boldsymbol{R} \tag{4}$$

where $\boldsymbol{X}_{\text{best}}(t)$ denotes the current optimal position; α and β are adjustment factors; $\boldsymbol{R}$ is a random vector. In this way, the seagull is able to perform a fine search in the local region and improve the probability of finding the global optimal solution.

The advantage of SOA lies in its ability to achieve a good balance between global search and local optimisation. By mimicking the natural behaviour of seagulls, SOA can effectively avoid the defect that traditional optimization algorithms are prone to fall into local optimal solutions [26], thus improving the stability and efficiency of the optimization process.

3.2. **Principles of Twin Neural Networks.** The TNN architecture is a specialized structure designed to handle classification tasks, especially in scenarios involving imbalanced datasets. The TNN is inspired by the Twin Support Vector Machine (TWSVM), which addresses class imbalance by constructing two non-parallel hyperplanes. Each hyperplane is optimized to be as close as possible to the data points of one class while maintaining a certain margin from the data points of the other class. This approach is advantageous for neural networks as it allows for better generalization and scalability for large datasets. The structure of TNN is shown in Figure 3.

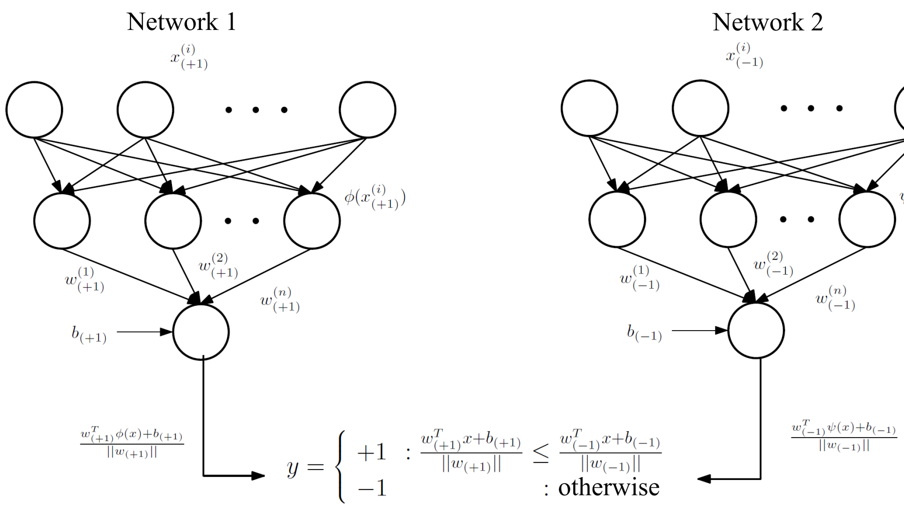

Figure 3. The structure of TNN

A twin neural network consists of two parallel neural networks, each responsible for learning a distinct class-specific hyperplane. The basic architecture includes three layers: an input layer, a hidden layer, and an output layer [27]. The neurons in the hidden layer map the input features into a higher-dimensional space, denoted by $\phi(\cdot)$, where linear separability can be achieved more efficiently. The final output layer generates the classification decision based on the distance from the learned hyperplanes.

The error functions for the two networks, $E^{(+1)}$ and $E^{(-1)}$, are shown as follows.

$$E^{(+1)} = \frac{1}{2N_B}\sum_{i=1}^{N_B}(t_i - y_i)^2 + \frac{C^{(+1)}}{2N_A}\sum_{i=1}^{N_A}\big((w^{(+1)})^\top \phi(x_i^{(+1)}) + b^{(+1)}\big)^2 \tag{5}$$

where N_A and N_B are the number of samples in classes +1 and −1 respectively, t_i is the target output, y_i is the predicted output, and $C^{(+1)}$ and $C^{(-1)}$ are regularisation parameters.

To optimise the twin neural network, the derivatives of the error functions with respect to the weights w and biases b are computed and used to update these parameters iteratively.

$$\frac{\partial E^{(+1)}}{\partial w^{(+1)}} = \frac{1}{N_B}\sum_{i=1}^{N_B}(t_i - y_i)(1-y_i^2)\,\phi(x_i^{(+1)}) + \frac{C^{(+1)}}{N_A}\sum_{i=1}^{N_A}\left((w^{(+1)})^\top \phi(x_i^{(+1)}) + b^{(+1)}\right)\phi(x_i^{(+1)}) \tag{6}$$

$$\frac{\partial E^{(-1)}}{\partial w^{(-1)}} = \frac{1}{N_A}\sum_{i=1}^{N_A}(t_i - y_i)(1-y_i^2)\,\phi(x_i^{(-1)}) + \frac{C^{(-1)}}{N_B}\sum_{i=1}^{N_B}\left((w^{(-1)})^\top \phi(x_i^{(-1)}) + b^{(-1)}\right)\phi(x_i^{(-1)}) \tag{7}$$

Similarly, the derivatives with respect to the biases are.

$$\frac{\partial E^{(+1)}}{\partial b^{(+1)}} = \frac{1}{N_B}\sum_{i=1}^{N_B}(t_i - y_i)(1-y_i^2) + \frac{C^{(+1)}}{N_A}\sum_{i=1}^{N_A}\left((w^{(+1)})^\top \phi(x_i^{(+1)}) + b^{(+1)}\right) \tag{8}$$

$$\frac{\partial E^{(-1)}}{\partial b^{(-1)}} = \frac{1}{N_A}\sum_{i=1}^{N_A}(t_i - y_i)(1-y_i^2) + \frac{C^{(-1)}}{N_B}\sum_{i=1}^{N_B}\left((w^{(-1)})^\top \phi(x_i^{(-1)}) + b^{(-1)}\right) \tag{9}$$

These equations ensure that the twin neural network parameters are updated to minimise the classification error iteratively. The prediction for a test sample x is based on its distance from the two hyperplanes. The decision rule is given by.

$$y = \begin{cases} +1 & \text{if } \frac{w^{(+1)^T}\phi(x)+b^{(+1)}}{\left\|w^{(+1)}\right\|} \leqslant \frac{w^{(-1)^T}\phi(x)+b^{(-1)}}{\left\|w^{(-1)}\right\|} \\ -1 & \text{otherwise} \end{cases} \tag{10}$$

This rule assigns the class label based on which hyperplane is closer to the sample, thereby ensuring a robust classification even in the presence of imbalanced data.

By employing twin neural networks, we leverage the advantages of twin support vector machines within a neural network framework, achieving better scalability and generalisation performance, particularly for large and imbalanced datasets.

4. **SOA-WTNN.** In order to optimise the injection moulding process parameters, this paper proposes a model based on SOA Weighted Optimisation Twin Network (SOA-WTNN). The model combines the global search capability of SOA and the efficient feature extraction capability of the twin network, aiming to achieve accurate optimisation of injection moulding process parameters.

The SOA-WTNN model consists of two main components: the TNN and the SOA optimiser. The TNN is used to extract the feature representations of the process parameters and compute the similarity of different parameter combinations, while the SOA optimiser searches the feature space to find the optimal combinations of the process parameters. The TNN consists of two sub-networks that share the same weights, each of which receives a combination of the process parameters as an input that is mapped to the high-dimensional feature space through a hidden layer. The design of the SOA-WTNN model consists of the following main steps: initialisation, training of the twin network, SOA optimisation and iterative updating.

In the initialisation phase, the range of process parameters is first set, including the six main process parameters mentioned above (A, B, C, D, E, F). The setting of the initial values of each process parameter can be obtained from empirical values. The twin network is trained using the initialised process parameters to construct a model of the relationship between the parameters and the quality of the injection moulded part (the amount of warping deformation). The training process of the twin network, as described earlier, includes steps such as the construction of positive and negative sample pairs, feature extraction and loss function calculation.

For the optimisation of injection moulding process parameters, the loss function is defined as follows:

$$E^{(i)} = \frac{1}{2N} \sum_{i=1}^{N} (y_i - f(x_i; w, b))^2 + \lambda \sum_{j=1}^{M} \|w_j\|^2 \tag{11}$$

where y_i is the target output (warping deformation), $f(x_i; w, b)$ is the predicted output of the twin network, λ is the regularisation parameter, N is the number of samples, and M is the number of process parameters.

The SOA optimises the weights and biases of the WTNN to minimise the loss function by simulating the seagull foraging behaviour. The specific steps are as follows:
(1) *Initialise the gull population:* randomly initialise the position and velocity of the gull population, with each gull representing a combination of process parameters.
(2) *Evaluate fitness:* calculate the fitness of each gull under the current combination of process parameters $\text{Fitness}\left(\vec{X}_i\right) = E^{(i)}$, i.e., the amount of warping deformation predicted by WTNN.
(3) *Update position and speed:* update position and speed according to the rules of foraging behaviour of the gull colony, as in (3) and (4).
(4) *Update the optimal position:* according to the fitness value of the current iteration, update the individual optimal position and the group optimal position.

$$\vec{P}_i = \arg\min_{\vec{X}_i} \text{Fitness}\left(\vec{X}_i\right) \tag{12}$$

In each iteration, new combinations of process parameters are obtained through SOA optimisation, the inputs to the TNN are updated and the TNN is retrained to further improve the prediction accuracy. The iterative process continues until the loss function converges or the preset number of iterations is reached. Through the above steps, the SOA-WTNN model can effectively optimize the injection moulding process parameters, reduce warping deformation, and improve the quality and productivity of the parts.

4.1. **Example of process optimisation for injection moulded parts.** In order to verify the effectiveness of the SOA-WTNN model, we selected traditional optimization models, including GA-BPNN [23], PSO-BPNN [24] and TNN, and conducted a comparative analysis of the performance of these models in the same injection moulding process parameter optimization task. The research object of this paper is the front bumper injection moulding part of a car, and the optimization objective is to minimize the warping deformation. The process parameter objects are six main process parameters (A, B, C, D, E, F).

The specific settings of the experimental parameters of SOA-WTNN are shown in Table 6.

In order to fairly compare the optimisation effect of each model, we use the same initial parameter settings and evaluation indexes. The evaluation indexes are warping deformation amount (W_z), calculation time (T_c) and convergence speed (V_c). The experimental results are shown in Table 7, demonstrating the performance of different optimisation models in the optimisation of injection moulding process parameters.

Table 6. Experimental parameter settings

Parameters	Numerical Value
Group size	50
α	0.5
β	0.7
Maximum number of iterations	100
Input layer	7 nodes (corresponding to 7 process parameters)
Hidden layer	Two hidden layers with 50 nodes each
Output layer	1 node (corresponding to the amount of warping deformation)
Activation function	ReLU
Loss function	Mean Square Error (MSE)
TNN optimisation algorithm	Adam
Learning rate	0.001
λ	0.01
Batch size	32
Epoch	100

Table 7. Experimental results for different optimisation models

Modelling	W_z	T_c	V_c
GA-BPNN	0.215	150s	50 iterations
PSO-BPNN	0.198	130s	45 iterations
TNN	0.185	120s	40 iterations
SOA-WTNN	0.172	100s	30 iterations

It can be seen that the SOA-WTNN model outperforms the other optimisation models in terms of optimal warping deformation, computation time and convergence speed. The optimal warping deformation of the SOA-WTNN model is 0.172, which is significantly lower than that of the GA-BPNN, PSO-BPNN and TNN models. This indicates that the SOA-WTNN model can find the optimal process parameter combinations more efficiently, thus reducing the warping deformation. The computation time of the SOA-WTNN model is 100 s, which is significantly shorter than the other models. This is due to the efficient global search capability of SOA and the fast feature extraction capability of the twin network, which makes the optimisation process more efficient. The SOA-WTNN model converges within 30 iterations, which is faster than the other models. This indicates that the SOA-WTNN model has higher efficiency in the process of finding the optimal solution and can reach the convergence state quickly.

In order to show the optimisation effect of different models more intuitively, we plotted the convergence curves of each model during the optimisation process, as shown in Figure 4. It can be seen that the SOA-WTNN model has the fastest decreasing speed in the initial stage and reaches the optimal warping deformation amount in less iterations, which proves its high efficiency and superiority in the optimisation of process parameters. Through the above comparative analysis, the SOA-WTNN model performs significantly better than the traditional optimisation model in the optimisation of injection moulding process parameters, with higher optimisation effect and efficiency.

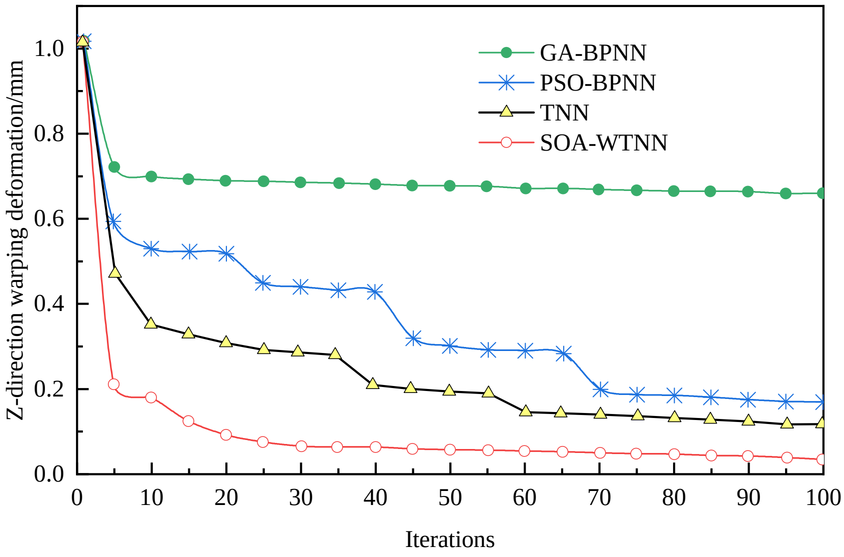

Figure 4. Variation of warping deformation during iteration for different optimisation models

5. **Conclusion.** In this paper, an optimization method of injection moulding process parameters based on SOA-WTNN is proposed, which effectively solves the limitations of traditional optimization methods in dealing with complex nonlinear relationships and multivariate interactions. Through detailed analysis of the injection moulding mechanism and process parameters, the key factors affecting warping deformation are modelled in this paper and optimised using the SOA-WTNN model. The experimental results for the front bumper of a car show that the SOA-WTNN model performs well in optimising the process parameters, significantly reduces the warping deformation, and improves the quality of the parts and production efficiency. The specific conclusions are as follows:

(1) Holding time (C), mould temperature (D) and melt temperature (A) have a significant effect on the warping deformation of the injection moulded parts, while holding pressure (B), injection time (F) and cooling time (E) have a weak effect on the warping deformation of the injection moulded parts.

(2) Through SOA optimisation, the model is able to efficiently perform a global search to find the best combination of process parameters, thus reducing the warping deformation to 0.172. Compared to the conventional method, the computation time of the SOA-WTNN model is significantly reduced to only 100 seconds, demonstrating its high efficiency.

The experimental data in this paper are mainly from specific injection moulding process datasets, and the singularity of the dataset may limit the generalisation ability of the model. Future work should consider introducing more different types of injection moulding process datasets to validate the effectiveness of the model in a wider range of application scenarios and to further improve the adaptability and robustness of the model.

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