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An innovative method of roller path design in conventional spinning: Online intelligent optimization

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Abstract

The optimization design of roller path is critical in conventional spinning as the roller path greatly influences the spinning status and forming quality. However, the roller path is characterized by high flexibility and diversity, which make the spinning status very complex, changing with time and inheritance during the conventional spinning process. All of these lead to the classical off-line process optimization for steady-state forming to be inefficient, and currently the heuristic and know-how based method has to be employed for roller path design. To address this bottlenecked issue, an innovative online intelligent optimization method was developed in this research, which combines the real-time prediction of spinning status and online optimization of roller movement track. The method can capture the dynamic change of spinning status and greedily optimize the roller movement track progressively to achieve the design of whole roller path. In tandem with these, an online intelligent optimization system for roller path design was developed with the support of intelligent sensing, learning, optimization and execution. It enables multi-functional of spinning condition monitoring, real-time prediction of spinning status, online dynamic processing optimization, and autonomous execution of optimal processing. Through system implementation and verification by case studies, the results show that the intelligent processing optimization and self-adaptive control of spinning process can be efficiently realized. The optimal roller path and matching spinning parameters (mandrel speed, feed ratio) can be efficiently obtained by only one simulation of the spinning process and no more trial-and-error is needed. Moreover, the optimized process can compromise the multi-objectives, including forming qualities (wall thickness reduction and flange fluctuation) and forming efficiency. The developed methodology can be generalized to handle other incremental forming processes.

Keywords: Conventional spinning; roller path; real-time prediction; online optimization; artificial intelligence

1. Introduction

Sheet metal spinning, with the advantages of low forming load, simple tooling and near-net shape, has been widely used to produce axisymmetric parts and structures in aviation and automotive industries (Xia et al., 2014; Kong et al., 2017; Chen et al., 2019). In spinning process, a sheet metal blank is rotated with mandrel and formed to the desired shape by roller gradually loading against the blank with the prescribed path. Based on the deformation characteristics, the spinning can be classified into shear spinning and conventional spinning, as shown in Fig. 1. In shear spinning (Fig. 1(a)), the mandrel has the consistent profile of the part to be spun. The part is formed by moving roller along the mandrel profile in a single pass. In conventional spinning (Fig. 1(b)), a simple cylindrical mandrel is usually applied for general purpose. Many parts with different shapes can be formed by adjusting the roller path in one or more passes (Wong et al., 2003; Music et al., 2010). Since the conventional spinning presents simpler tooling and better process flexibility, it is getting more and more attentions. Meanwhile, the roller path design is actually a critical issue as the roller path really plays a crucial role in the shape forming of part in conventional spinning.

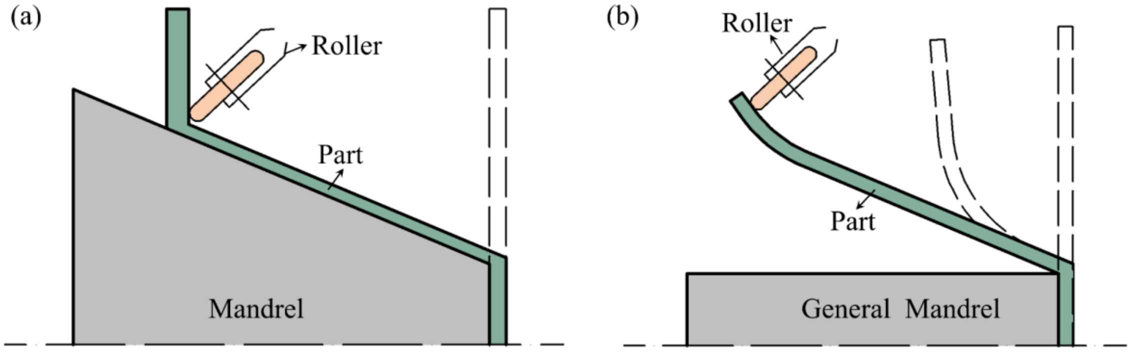

Fig. 1. Schematics of shear spinning (a) and conventional spinning (b).

Theoretically, roller path in conventional spinning can be any kind of curves with high flexibility and diversity. It is thus difficult to characterize the roller path by single or several variabilities, and there are enormous possible paths. On the other hand, the movement of roller is the primary external loading condition, which plays a great role in spinning status designated as deformation characteristics, wall thickness reduction, flange fluctuation and workpiece shape evolution during conventional spinning. Thus, the optimal design of roller path involves a multi-objective optimization. Meanwhile, the spinning is a typical incremental forming process by which the workpiece shape is gradually formed through the accumulation of local deformation. The changing of the workpiece shape results in the change of the stability of flange and the mechanical state in forming region, which would in turn affect the spinning status (Music et al., 2010; Liu et al., 2002; Kang et al., 1999). The combined effects of the flexible roller path and the changing workpiece shape would make the spinning condition and status to be very complex, changing with time and inheritance during the forming process. Therefore, it can be summarized that the optimization design of roller path in conventional spinning faces the following challenges: (1) roller path, as a design variable, is highly flexible and difficult-to-quantify; (2) assurance of multiple forming qualities is difficult; (3) spinning condition and status are changing with time and inheritance.

So far, only some qualitative understandings have been achieved on the effect of roller path on the conventional spinning performance, and the roller path design still relies on know-how and trial-and-error. Liu et al. (2002) found that the stress and strain in the workpiece spun by involute path are smaller and their distributions are more uniform than those spun by liner and quadratic paths in the first-pass conventional spinning. Wang and Long (2011) and Li et al. (2014) both recommended that the convex roller path produces the smallest tool force and wall thickness reduction among the convex, linear, concave and combined paths. Guo et al. (2017) investigated the dependence of the spinning results on four types of roller paths, and recommended two suggestions for roller path design, i.e., ‘similar geometry principle for restraining shape deviation’ and ‘small curvature principle for maintaining wall thickness’. Polyblank and Allwood (2015) parameterized the roller path by four parameters based on a quadratic Bezier curve, and studied their effects on the wall thickness reduction, flange fluctuation degree and spinning force. They further proposed a set of empirical rules for roller path design, such as ‘a more concave tool path is helpful to reduce wrinkling’, ‘forward passes should aim to maintain the tool force constant’, and so on. Similarly, Chen et al. (2008) proposed a method of roller path design based on an involute curve, in which the parameters of the involute curve are empirically determined according to the geometry sizes of mandrel and blank. Gan et al. (2018) came out with some empirical suggestions for the design of backward roller path based on quadratic Bezier curve, which is helpful to improve the uniformity of wall thickness.

The above empirical suggestions, however, are all obtained under several specific profiles, which are not universal due to the high flexibility and diversity of the roller path profile. An iterative adjustment by skilled workers is still needed in practice, which is not only costly and trial-and-error, but also difficult to obtain the optimal result. To overcome this problem, Russo et al. (2021) developed a haptic spinning system to capture and parameterize the know-hows of spinning artisans, and then created a database of roller path for many spinning cases. By analyzing the database, seven principles for tool path design were formulated, parameterized and applied in the design of roller path, which can improve design efficiency. However, this is still essentially an empirical and trial-and-error method based on the know-hows of the experienced workers. On the other hand, the classical off-line process optimization method for the steady-state forming process optimizes the processing parameters based on the black-box model between initial processing parameters and final forming results (Li et al., 2021; Shi et al., 2019). It is thus inefficient to design the high-flexible roller path since it could not consider the change with time and inheritance of spinning condition and status. Therefore, it is essential to develop an optimization method for roller path design that is scientific- and quantitative-based and considering the dynamic nature of the spinning status.

By leveraging the rapid advances in artificial intelligence (AI) technologies, the development of intelligent manufacturing is greatly revitalized. It is characterized by autonomous monitoring and sensing, autonomous learning and modelling, autonomous optimization and decision-making, autonomous control and execution for complex forming processes (Cuartas et al., 2021; Ismail et al., 2021; Park et al., 2021; Zhang et al., 2019). Considering these advantages of intelligent manufacturing, it provides an efficient and feasible method to handle the dynamic nature of spinning forming and optimize the roller path.

In this research, an innovative method of roller path design based on online intelligent optimization was proposed and the corresponding intelligent optimization system was developed. It presents the multi-functions of spinning condition monitoring, real-time prediction of spinning status, online dynamic optimization of processing, and autonomous execution of optimal parameters, thus can get the optimal roller path and the matching spinning parameters for conventional spinning easily. The proposed intelligent method for roller path design shifts the paradigm of the traditional heuristic and trial-and-error roller path design.

2. Methodology and architecture of online intelligent optimization system

The conventional spinning is a typical incremental forming process by which the workpiece is gradually formed via accumulating local deformation. During the spinning process, the spinning condition and status are very complex and dynamically change under the combined effect of flexible roller path and shape changing of workpiece. According to these characteristics, the optimization problem of roller path can be represented in the following form:

$$\begin{aligned} &\min_{\mathbf{u}\in\Omega} && z = g(\mathbf{y}(\mathbf{x},t_f)-\mathbf{y}(\mathbf{x})) + \int_{t_0}^{t_f} h(\mathbf{x},\mathbf{u}(t),t)dt \\ &\text{subject to} && \mathbf{y}(\mathbf{x},t_f) = \mathbf{y}(\mathbf{x},t_0) + \int_{t_0}^{t_f} \mathbf{f}(\mathbf{y}(\mathbf{x},t),\mathbf{u}(t))dt \end{aligned} \tag{1}$$

where t is the forming time; t_0 and t_f are the starting time and ending time of spinning process, respectively; $\mathbf{x}$ represents the space location of workpiece; $\mathbf{y}(\mathbf{x},t)$ refers to the workpiece state (wall thickness, defects, etc.); $\mathbf{u}(t)$ denotes the roller path, i.e., the design variable, which should meet the physical limits of spinning process ($\mathbf{u}(t)\in\Omega$); $\mathbf{f}(\mathbf{y}(\mathbf{x},t),\mathbf{u}(t))$ describes the evolution of workpiece state, i.e., the spinning status at t, which is a function of current workpiece state and roller path, the so-called spinning conditions. The objective function consists of two parts: g describes the deviation between the final workpiece state and the target state $\mathbf{y}(\mathbf{x})$; while $\int_{t_0}^{t_f} h(\mathbf{x},\mathbf{u}(t),t)dt$ denotes some constraints, which should be considered in the design of roller path. In this research, the forming quality (wall thickness reduction, flange fluctuation) and forming efficiency are considered in the objective function at the same time.

Considering the dynamic change of spinning status $\mathbf{f}(\mathbf{y}(\mathbf{x},t),\mathbf{u}(t))$, the online intelligent optimization method was proposed, which combines the ideas of real-time prediction of spinning status and online dynamic optimization of roller movement track. The real-time prediction of spinning status intends to capture the evolution of status function $\mathbf{f}(\mathbf{y}(\mathbf{x},t),\mathbf{u}(t))$, aiming at processing optimization. It is realized by combining the real-time monitoring of spinning condition and status and machine learning modelling. The online dynamic optimization of roller movement track is based on a greedy idea, which discretizes and optimizes the roller movement track progressively to achieve the optimization of the whole roller path. Then, the optimization of the whole unsteady process (Eq. (1)) is changed to the optimization of many discrete near-steady processes, as represented by:

$$\begin{aligned} &\min_{\mathbf{u}\in\Omega} && z = g(\Delta\mathbf{y}(\mathbf{x},t)-\Delta\mathbf{y}(\mathbf{x})) + h(\mathbf{x},\mathbf{u}(t)) \\ &\text{subject to} && \Delta\mathbf{y}(\mathbf{x},t) = \mathbf{f}(\mathbf{y}(\mathbf{x},t),\mathbf{u}(t)) \end{aligned} \tag{2}$$

where $\Delta\mathbf{y}(\mathbf{x},t)$ is the increment of workpiece state determined by the spinning status at t; $\Delta\mathbf{y}(\mathbf{x})$ represents target increment of workpiece state.

Fig. 2 gives the specific implementation process of online intelligent optimization method for roller path design. It is implemented based on a virtual simulation process of spinning. During the forming process, the spinning condition and status are monitored with a small interval. Based on the quantities of the monitoring data, the spinning status is predicted real-time. The roller path segment in the next moment is optimized and executed based on the spinning status prediction model. The above processes of monitoring, predicting, optimizing and executing are carried out repeatedly until the spinning process is finished. At last, the optimal whole roller path can be obtained by smoothening the optimized path segment.

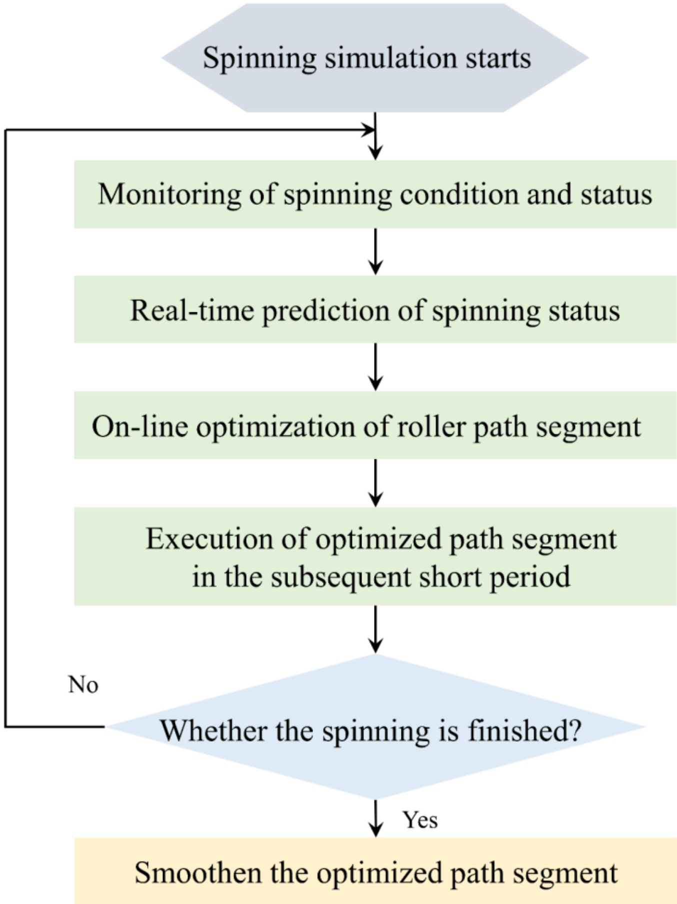

Fig. 2. Flow chart of the online intelligent optimization method for roller path design

To implement the above methodology, an online intelligent optimization system was developed with architecture shown in Fig. 3. It includes four functional modules described in the following:

(1) Module 1 is a FE model of conventional spinning. It simulates the spinning process and thus acts as a basis platform for intelligent optimization. To capture the dynamic change of the spinning condition and status, the whole spinning process is discretized into many short processes in the subsequent monitoring, learning and optimizing.

(2) Module 2 monitors and identifies the spinning characteristics. The spinning conditions (workpiece shape, roller path, roller feed ratio and mandrel speed) and corresponding spinning status (wall thickness reduction and flange fluctuation degree) in different discrete processes are identified, extracted and quantified. The continuously extracted data will be used to

support the modelling of dynamic changing of spinning status.

(3) Module 3 develops the prediction model of spinning status and thus captures the relationship between spinning condition and spinning status. It is developed using deep neural network (DNN), which mainly includes data acquisition, data preprocessing, DNN training and verification.

(4) Module 4 conducts the on-line optimization of roller path using the particle swarm optimization method (PSO) based on the developed DNN model of spinning status and real-time condition monitoring. It mainly consists of the definition of fitness function and determination of PSO parameters.

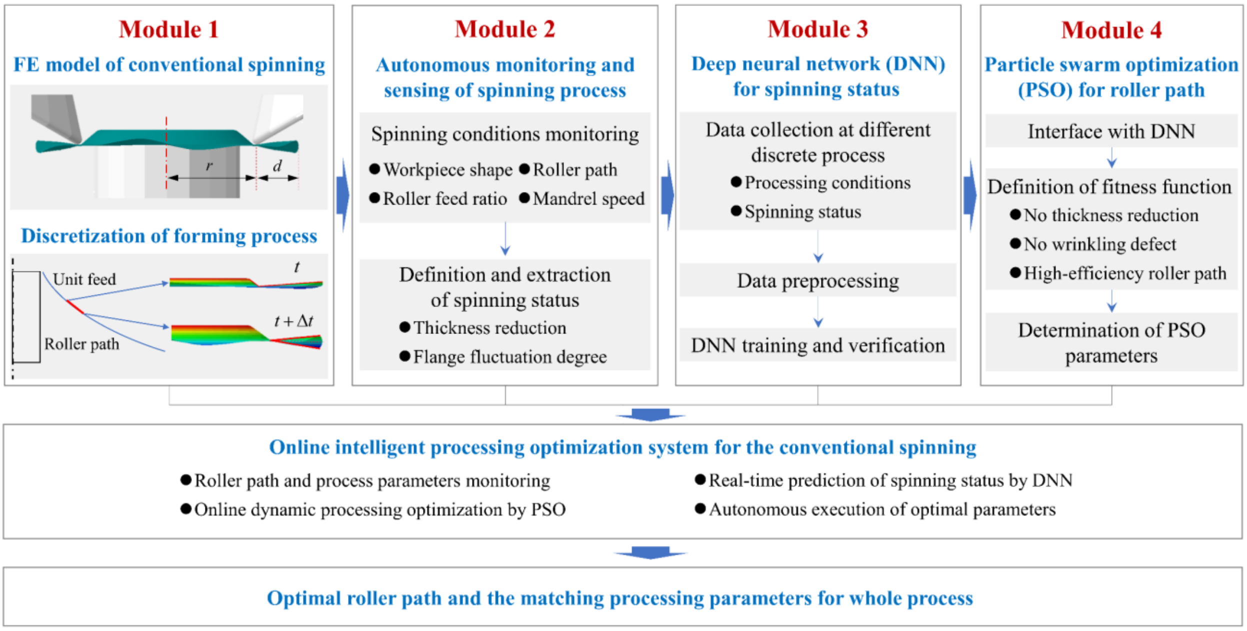

Fig. 3. Architecture of online intelligent optimization system

By integrating Modules 2, 3 and 4 into the FE model in Module 1, the online intelligent optimization system for roller path design is established. It presents the multi-functions of roller path and process parameters monitoring, real-time prediction of spinning status by DNN, online dynamic processing optimization by PSO, and autonomous execution of optimal parameters. Using the online intelligent optimization system, the optimal roller path and the matching spinning parameters for the whole forming process can be achieved easily. The development of each module in online intelligent optimization system will be described in Section 3 in detail.

3. Development of online intelligent optimization system

3.1 FE model of conventional spinning

By decades, FE simulation has become a crucial technology to support metal forming part design, process design and forming quality control in metal forming industries. It helps reveal many process related variables such as the distribution of thickness and instantaneous change of workpiece shape during forming process, which are generally not possible to be obtained by the traditional experimental approaches (Fu et al., 2006; Chan et al., 2009). Thus, FE simulation can be employed as a basis platform for the intelligent processing optimization.

In this work, the FE model of conventional spinning was developed using ABAQUS/Explicit, as shown in Fig. 4(a). It is composed of a general cylinder mandrel, two rollers and a circular blank. The blank is 1060 aluminum alloy plate with the thickness of 1 mm. Its elastic module and yield stress are 71.7 GPa and 30.85 MPa, respectively. Its plastic deformation behavior is represented by Hollomon-type equation:

$$\sigma=93.940\varepsilon^{0.179} \tag{3}$$

In FE modelling, the blank was set as a deformable body and meshed by the four-node quadrilateral shell elements (S4R). While both the mandrel and roller were treated as rigid bodies. The blank was tied with the mandrel by tie constraint and rotation movement was given to the mandrel. So that, the blank rotated with mandrel during spinning. Meanwhile, the roller moved along a specific path against the blank to form the part. The friction behavior between rollers and blank was described by Coulomb's friction model with the friction coefficient of 0.05.

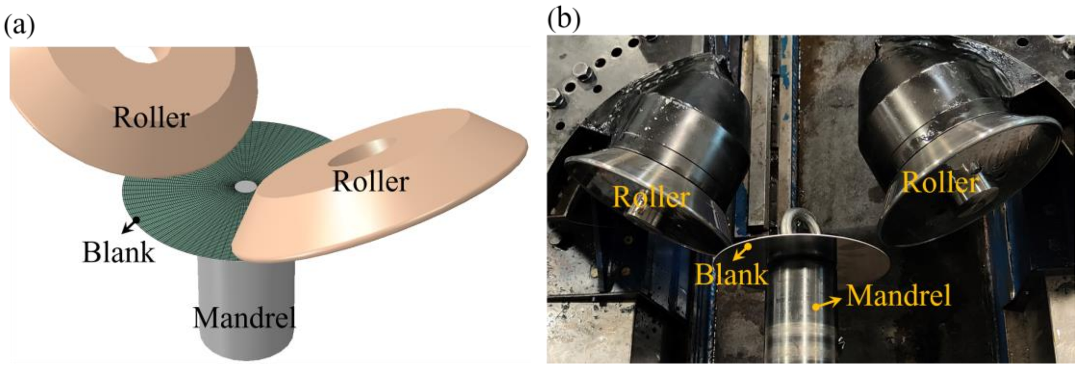

Fig. 4. Schematics of the FE model (a) and experimental setup (b) of the conventional spinning.

To validate the FE model, a spinning experiment was carried out on a CZ900/2CNC spinning equipment, as shown in Fig. 4(b). The geometries of tools and processing parameters in experiment are shown in Table 1. The roller path is a linear path with the half cone angle of 50 °, and the processing parameters keep unchanged during the forming process in the verification experiment. Meanwhile, FE simulation was conducted at the same conditions as the experiment. The simulated and experimental spun results are compared in Fig. 5. It is found from Fig. 5(a) that the simulated workpiece presents the shape very close to the experimental one. Especially for the slight flange fluctuation occurring in the forming process, it was also well captured by FE simulation. Furthermore, the wall thickness distribution along the generatrix of the simulated and experimental workpiece were also compared, as shown in Fig. 5(b). It reveals that the wall thickness distribution is non-uniform along generatrix. The thickness reduction is larger at the early forming stage, then decreases gradually to about zero with the forming process. The average and maximum relative errors of the simulated wall thickness are 1.87% and 4.58%, respectively. These results suggest that the FE model can accurately simulate the conventional spinning and is reliable to serve as the basis platform for the intelligent processing optimization.

Table 1. Processing parameters in the FE simulation and experiment.

Parameters	Values
Roller nose radius ρ (mm)	4
Roller diameter D_R (mm)	250
Mandrel diameter (mm)	90
Blank diameter D_0 (mm)	220
Half cone angle of roller path α (º)	50
Roller oblique angle β (º)	30
Mandrel speed n_M (rpm)	60
Roller feed ratio f (mm/r)	1

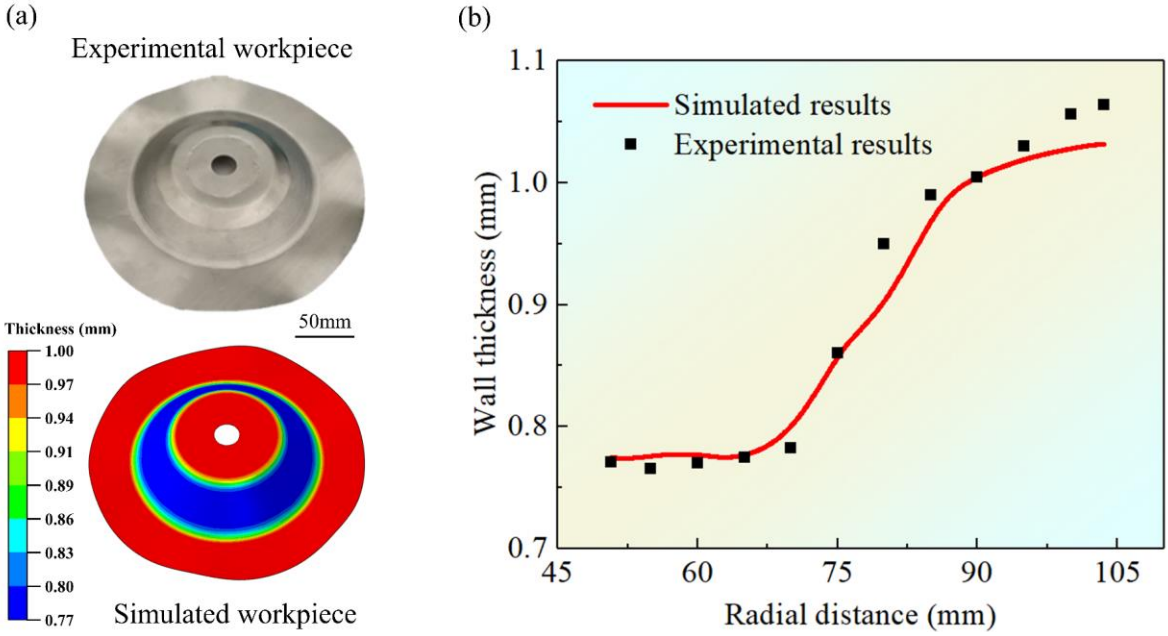

Fig. 5. Comparisons of the experimental and simulated results: (a) spun workpieces; (b) wall thickness distribution.

3.2 Monitoring of spinning process

As mentioned above, the spinning status greatly depends on the spinning condition, including the instant workpiece shape and loading condition of roller. Moreover, they change dynamically in forming process. Thus, identifying and quantifying the spinning condition and status are very critical for process monitoring and forming rules learning. In this section, their varying characteristics during the spinning process are analyzed and quantitatively characterized.

Fig. 6 (a) shows the typical variation of the workpiece shape in conventional spinning. At a certain time, the workpiece is divided into four regions, viz., the clamped, the formed, the forming, and the flange regions. It is generally recognized that the clamped and formed regions do not deform and do not significantly affect the deformation in forming and flange regions. However, the deformation is mainly determined by the loading location of roller, i.e., the inner radius of flange and the size of flange. Thus, the inner radius (r) and the width (d) of flange are used to quantitatively represent the feature of workpiece shape. As for the loading condition, it has been reported that roller path, roller feed ratio (f) and mandrel rotation (n_M) all greatly affect the spinning status in spinning process (Wang et al., 2011; Wang & Long, 2013; Zhan et al., 2007;

Sugar et al., 2016). The latter two factors (f and n_M) are the quantitative indexes and are easy to represent. The former roller path, however, is flexible and complex curve, which is difficult to quantitatively represented as a whole curve. To overcome this problem, it is treated as a series of discrete short liner segments, as shown in Fig. 6 (b). Each discrete liner segment is represented by two parameters, viz., the start location (represented by the inner radius of flange r) and half cone angle (α^i). On the other hand, it is well known that the flange wrinkling and distribution of wall thickness are two most important quality indexes. Thus, the instantaneous spinning status is represented by the thickness reduction ratio (φ_t) in forming region and the flange fluctuation degree (D_f). Furthermore, D_f is evaluated by the maximum height difference at outer edge of flange, as shown in Fig. 6(a).

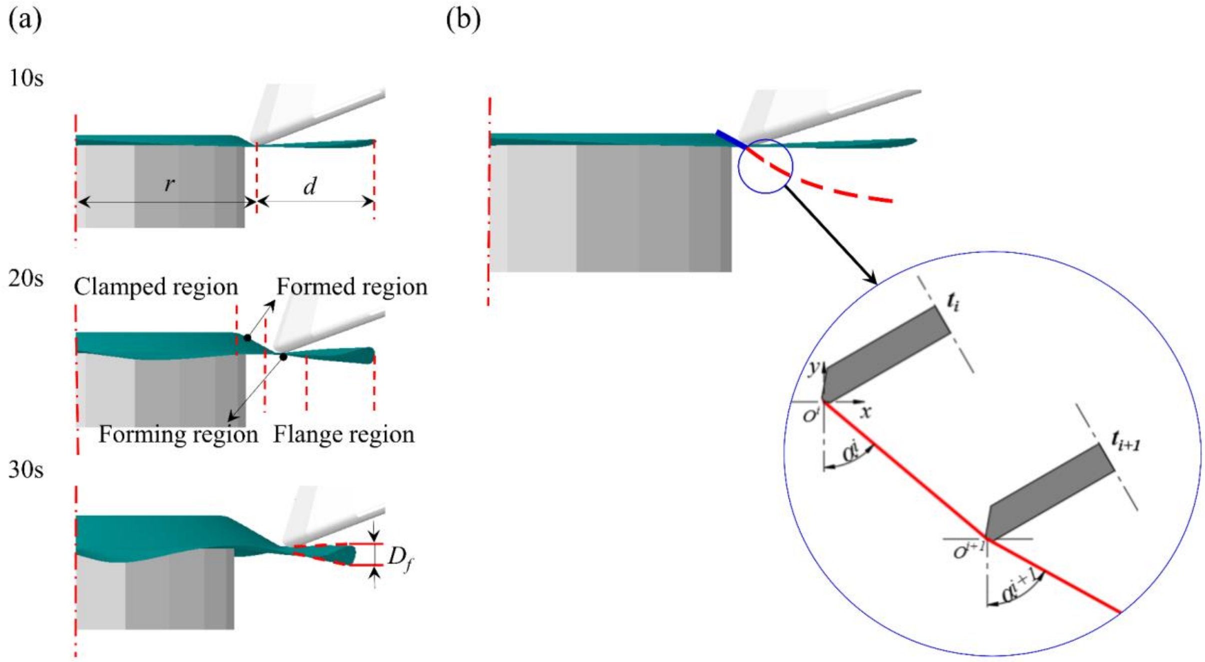

Fig. 6. Schematics diagram for the quantitative representation of workpiece shape (a) and roller path (b).

According to the above feature definition, the change of the workpiece shape, loading condition and spinning status can be quantitatively represented. To realize the autonomous monitoring of these features, an appropriative subroutine based on ABAQUS was developed to continuously extract the related data with a very small interval to be set as the time of mandrel rotating one round. This thus provides a basis for the subsequent modelling of spinning status and optimization of roller path.

3.3 Deep neural network for spinning status

To optimize the spinning result, an accurate model between the spinning status (response) and spinning condition (input) must be developed. This corresponds to the design of knowledge through autonomous learning and modeling in intelligent manufacturing. At present, the machine learning, such as multiple linear regression, support vector machines and deep neural network (DNN), are popular methods to modeling complex problem (Zhang et al., 2019; Wu et al., 2020; Wang et al., 2018). In this research, DNN was used to correlate the spinning status and spinning condition, due to its better performance in modelling the big data and complex relationship.

3.3.1 Framework of DNN

The DNN is structured by an input layer, several hidden layers and an output layer, as shown in Fig. 7. Each layer consists of a set of neurons, which are fully interconnected between neighboring layers. The first input layer has five neurons corresponding to five parameters of spinning condition, viz., the inner radius of flange (r), width of flange (d), half cone angle of roller path (α), roller feed ratio (f) and mandrel speed (n_M). As for the number of hidden layers and the number of neurons in each hidden layer, they are usually determined by the complexity of the problem. More hidden layers and neurons are helpful to get better model accuracy, but the model structure will be more complex. After many trail tests, the numbers of hidden layers and neurons in each hidden layer are determined as 8 and 15, respectively. The output layer has two neurons corresponding to two features of spinning status, i.e., the thickness reduction (φ_t) and the flange fluctuation degree (D_f). As for the activation function, Relu function is used for its higher calculation efficiency and wide application as follow:

$$\sigma_{\mathrm{Relu}}=\max(0,x) \tag{4}$$

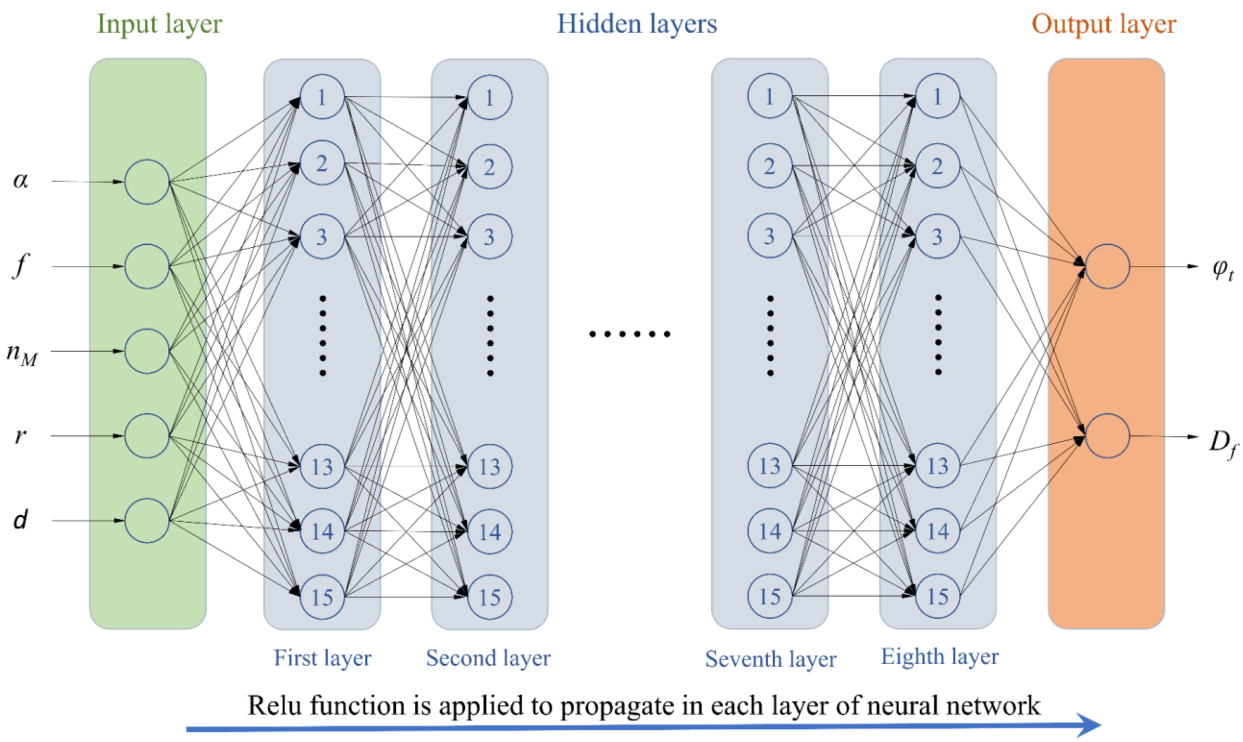

Fig. 7. Structure of the deep neural network.

3.3.2 Data preparation

Acquiring the evenly spread sampling data in the whole design space is very critical in developing an accurate DNN model. To this end, the space-filling Maximin Latin hypercube designs (maximin LHDs) was carried out to design the spinning experiment scheme. This method was proposed by Grosso et al. (2009), which can make the sampling points evenly spread within the whole design space. So that a global exploration could be made in the whole design space using as less samples as possible. Tables 2 and 3 show the design space of each processing condition and the detail spinning experiment schemes designed by maximin LHDs.

Table 2. Design space of each processing conditions.

Parameter	Value
Half cone angle α (°)	7.5-75
Roller feed ratio f (mm/r)	0.4-2.65
Mandrel speed n_M (rpm)	40-120
Initial blank radius R_0 (mm)	75-225

Table 3. Detailed spinning experiment scheme designed by the maximin LHDs.

No.	α (°)	f (mm/r)	n_M (rpm)	R_0 (mm)	*No.*	α (°)	f (mm/r)	n_M (rpm)	R_0 (mm)
1	75	1.15	76	130	17	39	2.575	70	155
2	72.75	2.2	88	185	18	36.75	1.825	94	225
3	70.5	2.425	85	100	19	34.5	0.4	73	150
4	68.25	1.3	124	115	20	32.25	1.375	40	140
5	66	1.075	82	215	21	30	1	61	220
6	63.75	1.975	46	135	22	27.75	0.775	109	205
7	61.5	0.85	43	175	23	25.5	1.525	106	80
8	59.25	0.475	112	170	24	23.25	1.675	130	165
9	57	1.6	127	190	25	21	0.625	118	125
10	54.75	0.7	49	95	26	18.75	0.925	64	85
11	52.5	1.9	52	210	27	16.5	2.5	103	120
12	50.25	0.55	97	90	28	14.25	2.05	55	200
13	48	2.275	121	105	29	12	2.125	58	110
14	45.75	1.75	67	75	30	9.75	1.225	79	160
15	43.5	1.45	91	145	31	7.5	2.35	100	195
16	41.25	2.65	115	180					

Then, all the samples were simulated with the liner roller path and initial conditions listed in Table 3. It should be noted that the spinning condition and corresponding spinning status change with forming process. Thus, their values in each discrete interval were extracted based on the method articulated in Section 3.2. After that, 2629 sets of data were obtained for model training and verification. To ensure the equal importance of various input variables, the data set of each variable was standardized by:

$$X^{(j)} = \frac{x^{(j)} - \min(x^{(j)})}{\max(x^{(j)}) - \min(x^{(j)})} \tag{5}$$

where, $\min(x^{(j)})$ and $\max(x^{(j)})$ are the minimum and maximum values in the data set of each variable. The data set of any variable was then mapped to a close interval [0,1], which is helpful to improve the training process and model stability.

3.3.3 Training and verification of DNN

To train the DNN model, the Huber index was employed to evaluate the difference between the measured and predicted output results. The formulation of the Huber index is:

$$\text{Huber}=\begin{cases}\frac{1}{2}\sum_{1}^{n}(y_i-y_i^{'})^2 & |y_i-y_i^{'}|\le\delta \\ \delta|y_i-y_i^{'}|-\frac{1}{2}\delta^2 & |y_i-y_i^{'}|>\delta\end{cases} \tag{6}$$

where n is the number of input training samples. y_i and $y_i^{'}$ are the predicted and measured output results, respectively. δ is set as 1. In addition, the optimization algorithm was set as an adaptive moment estimation (Adam). A part of the collected data (2237 sets) were used to train the DNN. Upon the training, the DNN model was validated by the rest data (392 sets). Fig. 8 shows the comparisons of the measured and the predicted results. Form Fig. 8 (a), it can be found that the average and the maximum relative errors of the predicted thickness reduction are 0.18% and 1.31%, respectively. Meanwhile, the average and maximum relative errors of the flange fluctuation degree are 1.05% and 11.22%, respectively, as shown in Fig.8 (b). These suggest that the developed DNN model is reliable and applicable in the real-time prediction of spinning status.

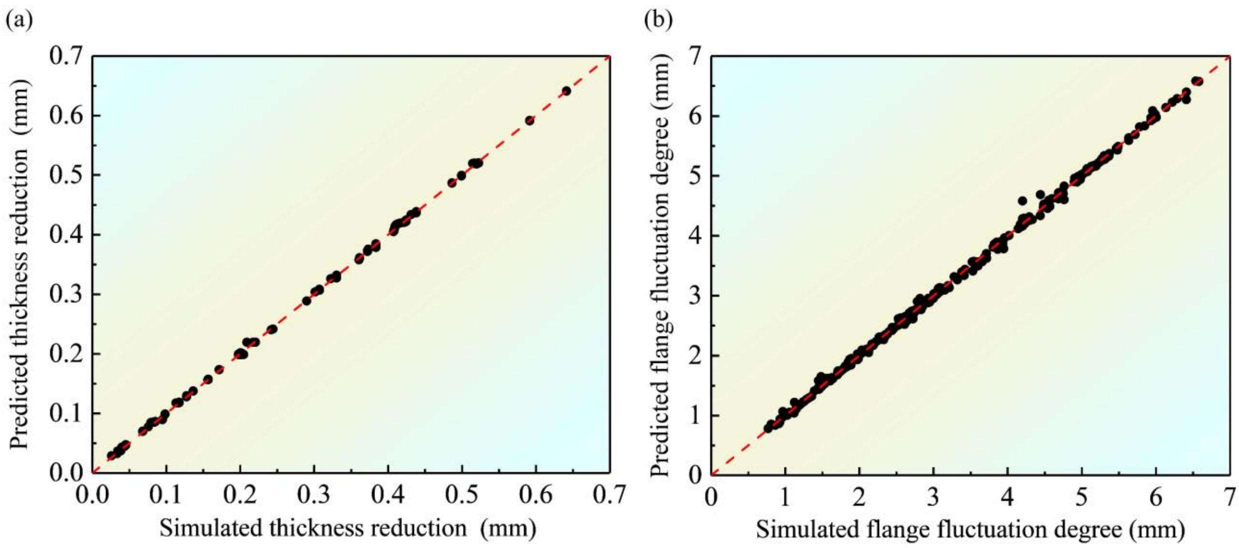

Fig. 8. Comparison of the predicted and the measured spinning status: (a) thickness reduction; (b) flange fluctuation degree.

3.4 Particle swarm optimization of roller path

Autonomous optimization is another key part for the intelligent processing design and manufacturing, whose result will be executed and then used to determine the forming results. It is usually a multi-objective optimization problem realized by some algorithms, such as genetic algorithm (GA) and particle swamp optimization (PSO). In contrast to GA, the PSO does not need a complex process of selection, crossover and mutation. Moreover, it presents the advantages of strong convergence and robustness, and high efficiency in finding global optimal solution (Xue et al., 2020). Thus, the PSO was used to optimize the roller path based on the DNN model.

The PSO algorithm, proposed by Eberhart and Kennedy (1995), is a random search optimization technology based on group collaboration. The particle swarm is randomly initialized with a population of candidate solutions. Each candidate solution is called as a particle. In optimization process, the particles move according to certain rules to find the optimal solution which meets some performance. The velocity and position of particles are updated based on its own historical experience and group experience. The detail updating rules for a particle *i* in the D-dimensional search space are represented by Eq. (7) and (8) (Xue et al., 2020; Song et al., 2020):

$$V_i^{k+1} = wV_i^k + c_1 r_1 (P_{bi}^k - X_i^k) + c_2 r_2 (P_g^k - X_g^k) \tag{7}$$

$$X_i^{k+1} = X_i^k + V_i^{k+1} \tag{8}$$

where V_i and X_i are the velocity and the position of particle i (i=1,2 , …, N); N is the number of particles in the swarm; k and k+1 represent the current iteration and next iteration, respectively; w is the inertia weight coefficient; c_1 and c_2 are the acceleration constant; r_1 and r_2 are two random number uniformly distributed in the range of [0, 1]; P_{bi} is the position of the best solution for the present visiting particle i; P_g is the position of the best known solution. As a result, the movement of a particle depends on three components: the inertia component, the cognitive component and the social component, as shown in Fig. 9 (Jallal et al., 2020).

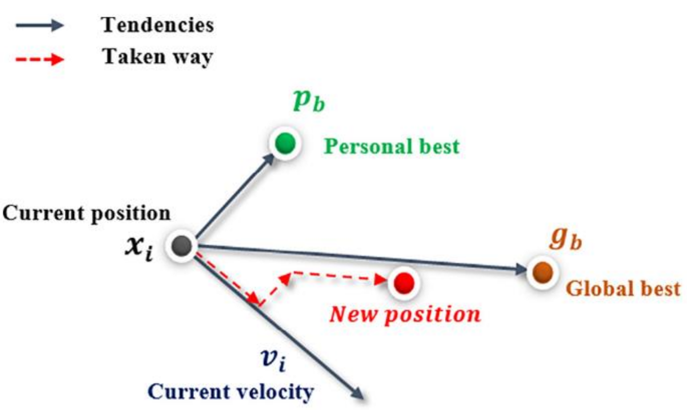

Fig. 9. Schematics of movement of a particle in PSO algorithm (Jallal et al., 2020).

When using PSO algorithm, the optimal objective must be determined. A fitness function should be defined to describe the optimality degree of each candidate solution. For conventional spinning, no obvious wall thickness thinning and no severe wrinkling are the main goals to achieve. Thus, two indexes of spinning status, viz., thickness reduction ratio (φ_t) and flange fluctuation degree (D_f), should be minimized in optimization process. Considering the deformation mechanism in conventional spinning, the roller path with a larger half cone angle is usually helpful to suppress the thickness reduction and flange fluctuation (Wang & Long 2011; Li et al., 2014). However, this may lead to a very low forming efficiency, even no deformation occurs with the half cone angle of 90 °. To overcome this obstacle, the forming efficiency, represented by the half cone angle of roller path (α), was also taken into account in optimization. Under the premise of forming quality, α should be as small as possible. Thus, a multi-objectives combined fitness function was defined via considering both the forming qualities and forming efficiency in the following:

$$F = \omega_1 \left|\varphi_t - \varphi_{td}\right| + \omega_2 \left|D_f - D_{fd}\right| + \omega_3 \alpha \tag{9}$$

where φ_{td} and D_{fd} are the desired thickness reduction ratio and flange fluctuation degree, respectively, which are both set as zero in this work; $\omega_1, \omega_2, \omega_3$ are weighting coefficients aimed to compromise the competition among three optimization objectives. The effects of the weighting coefficients on the optimized results will be analyzed later.

After that, the optimization of spinning process turns to be a minimization problem by PSO based on the DNN model for spinning status. In this research, the parameters of PSO were determined as follows: N is 30; c_1 and c_2 are both 2.05; w is 0.729; and the maximum iteration number is 3000. The optimized processing parameters are immediately input to the virtual spinning platform as the processing condition in the subsequent interval. This was implemented by the ABAQUS subroutine and the autonomous control and execution were finally realized.

To sum up, by integrating the function modules of monitoring of spinning condition, DNN model for spinning status, PSO of roller path and autonomous execution of optimized roller path into the virtual spinning platform, the online intelligent optimization system for conventional spinning was developed. On this basis, the instant optimal roller path and matching spinning parameters can autonomously be obtained online. It does not need any pre-set processing condition and can realize the intelligent self-adaptive control of spinning process to minimize the wall thickness reduction and flange fluctuation degree.

4. Application of the online intelligent optimization method

The proposed method of roller path design was applied and validated by a typical spinning case. The geometry sizes of billet, roller and mandrel in application case are all the same as those of the verification experiment (Table 1).

As described in section 3.4, the weighting coefficients of different optimization objectives in fitness function (Eq. (9)) should be prescribed to optimize the roller path, which would influence the competition among different objectives. In this research, there are two kinds of objectives in fitness function: (1) forming qualities including wall thickness reduction ratio and flange fluctuation degree, whose weights are adjusted by ω_1 and ω_2, respectively; (2) forming efficiency represented by half cone angle of roller path, whose weighting coefficient is ω_3. Firstly, the effect of ω_3 on the competition between forming efficiency and forming quality was investigated. ω_3 is set with the range from 0.05-0.65, while ω_1 and ω_2 are the same and equal to $(1-\omega_3)/2$. Fig. 10 (a) and (b) show the optimized roller path and the forming results under various ω_3, respectively. It can be seen from Fig. 10(a) that the optimized roller path gradually moves to bottom left with the increase of ω_3 and its average half cone angle of roller path is decreased, as shown in Fig. 10(b). This means that the forming efficiency can be improved by increasing ω_3. The higher ω_3, however, would lead to a large wall thickness reduction ratio (Fig. 10(b)), which is not expected for the quality of conventional spinning, viz., no obvious wall thickness thinning. In this work, taking the thickness reduction ratio smaller than 10% and higher forming efficiency as a benchmarking target, ω_3 is thus determined as 0.25.

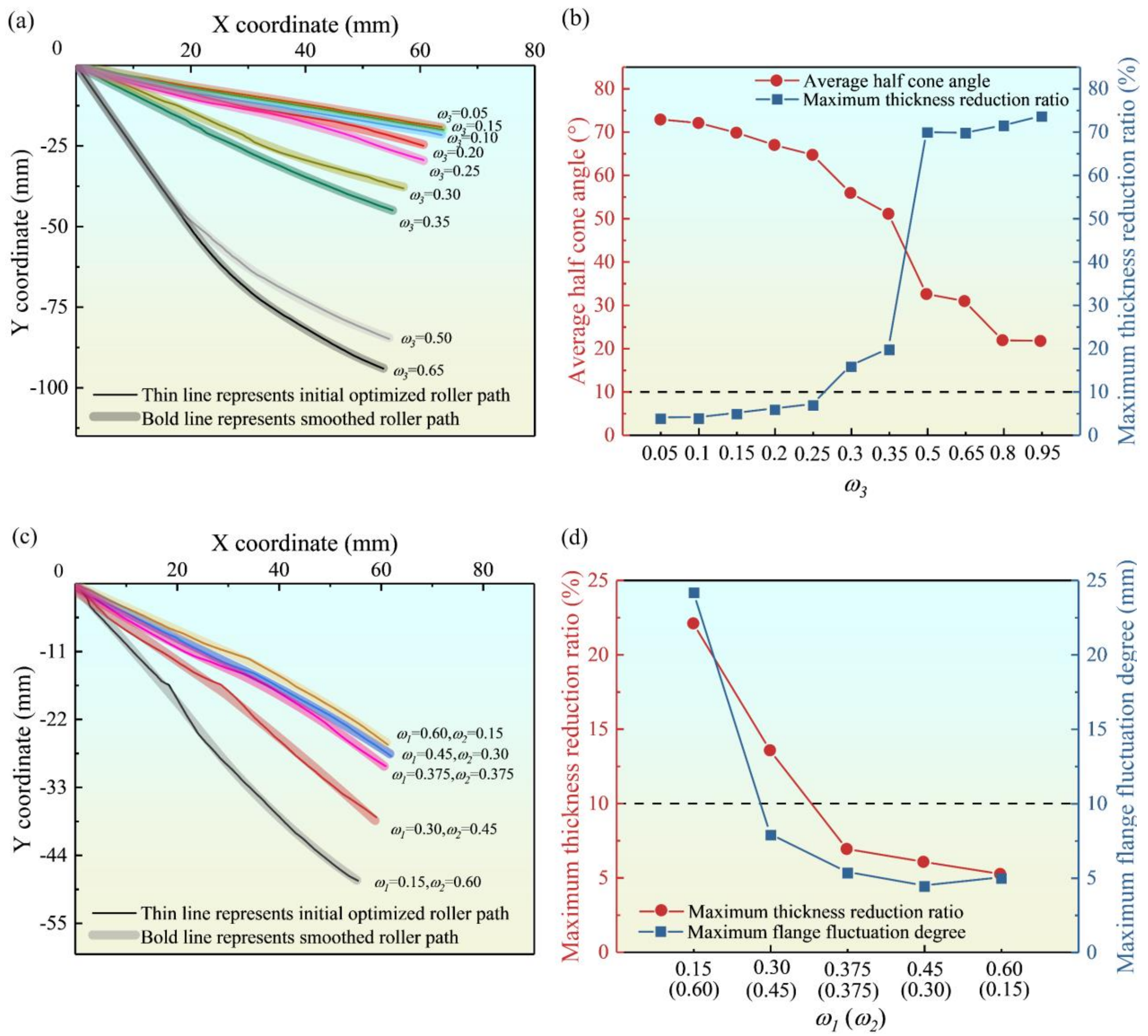

Fig. 10. Variations of the optimized roller path (a, c) and the forming results (b, d) with the weighting coefficients: (a, b) ω_3; (c, d) ω_1 and ω_2.

With ω_3 of 0.25, the effects of ω_1 and ω_2 on the competition between the two objectives of the forming quality (φ_t and D_f) were also investigated. ω_1 is set to have the value from 0.15 to 0.6, while ω_2 is set as 1-ω_1-ω_3. The variations of the optimized roller path and the forming results with ω_1 and ω_2 are given in Fig. 10 (c) and (d), respectively. It is found from Fig. 10(c) that the optimized roller path moves to bottom left with the decrease of ω_1, presenting a higher forming efficiency. The smaller ω_1, however, leads to an excessive wall thickness reduction and the flange fluctuation degree, as shown in Fig.10 (d). By the trade-off between the forming quality and forming efficiency, ω_1 and ω_2 are both determined as 0.375. Under this condition, the wall thickness reduction ratio is smaller than 7% and the maximum flange fluctuation degree is small with the value of about 5mm to satisfy the general requirements of conventional spinning.

Using the compromised weighting coefficients (ω_1 =0. 25, ω_2 =0.375, ω_3 =0.375), the optimal roller path (Fig. 11(a)) and the matching spinning parameters (Fig. 11(b)) can be obtained. It is found that the optimized roller path is not a simple linear path, and both the mandrel speed and feed ratio change with forming process. These suggest the proposed method is able to accommodate the change of spinning condition during forming process. On the other hand, it is seen that the optimized parameters all fluctuate to a certain extent in forming process, which may make the spinning unstable and the high risk of defect. To this end, the optimized roller path was smoothened and the spinning parameters were linearly fitted as the final optimal process, as shown in Fig. 11.

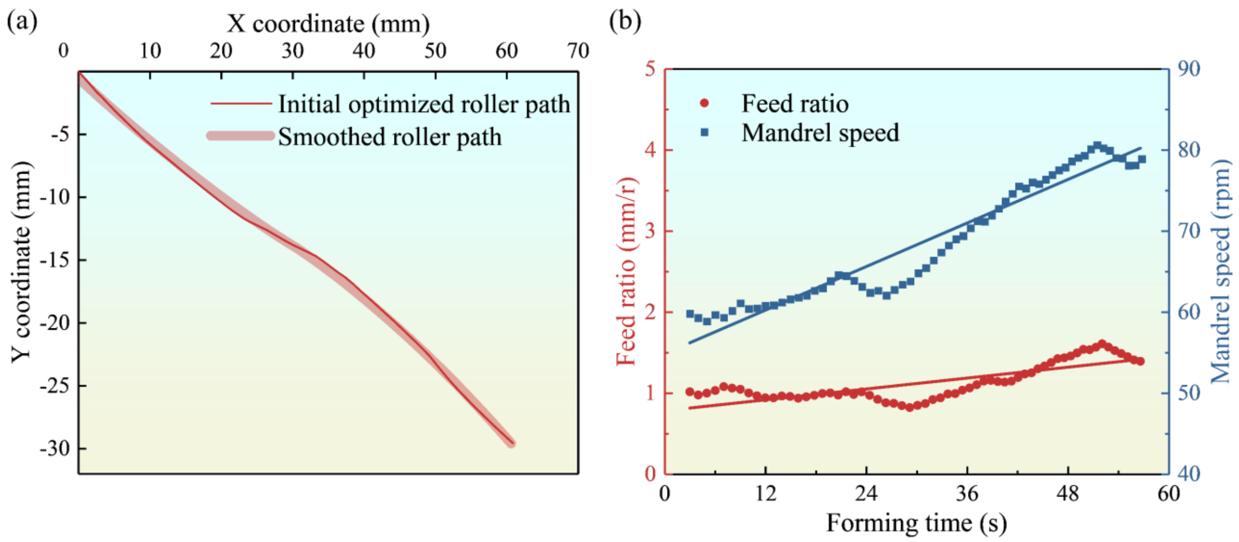

Fig. 11. The optimized processing parameters: (a) roller path; (b) mandrel speed and feed ratio.

The smoothened roller path and spinning parameters were implemented and validated by comparing with the non-optimized forming result (verification experiment in Section 3.1). Fig. 12 (a) shows the comparison of the typical circumferential stress distribution during forming process under the non-optimized and the optimized processing conditions. It can be seen that the circumferential stress in the flange region of the optimized workpiece is much more uniform and its maximum value is much smaller than that of the non-optimized workpiece. This thus decreases the risk of flange fluctuation and wrinkling defect (Chen et al., 2019). As shown in Fig. 12(b), the fluctuation degree under the non-optimized processing condition is quickly increased to a large degree (14 mm) and produce wrinkling defect (Fig.12(a)). While the fluctuation degree under the optimized processing condition is very small (≤5 mm) in the whole process. Fig. 12(c) shows the experimental workpiece formed under the optimized processing condition, whose shape is very close to the simulated result. The fluctuation degree of experimental workpiece is very small (3.81 mm), which satisfies the general requirements of conventional spinning. These suggest that the optimized process can effectively suppress the flange fluctuation degree, thus improve the forming stability and quality.

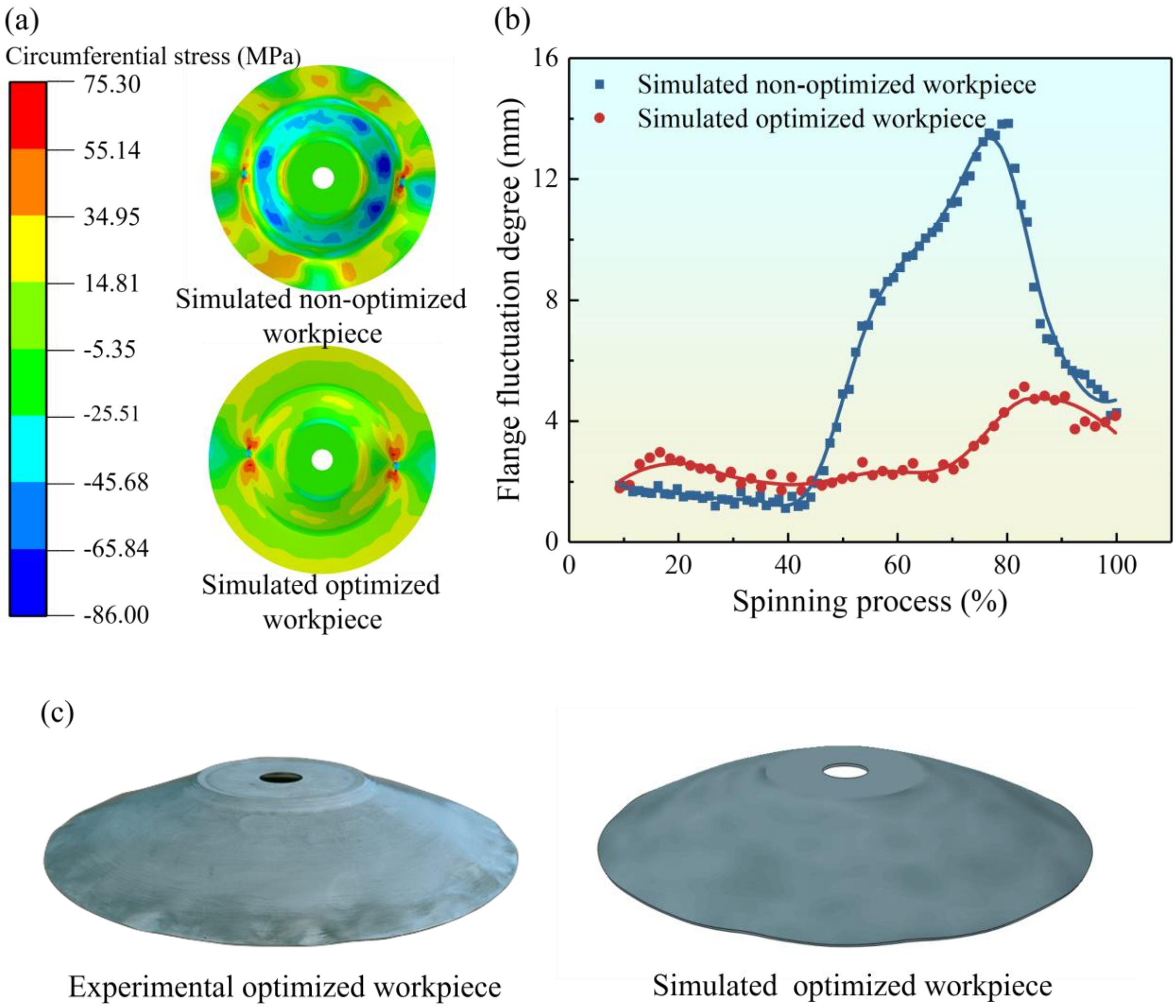

Fig. 12. Schematics of the circumferential stress distribution (a), flange fluctuation degree (b) and formed workpieces (c) under the optimized and non-optimized processing conditions.

Fig. 13(a) shows the comparison of the thickness distribution of the workpiece under the optimized and the non-optimized processing conditions. It can be seen that the optimized workpiece has much more uniform distribution and the larger thickness than the non-optimized workpiece. The variations of the thickness reduction ratio along generatrix under different conditions are shown in Fig. 13(b). It is found that the thickness reduction ratio of non-optimized sample reaches 23% at early forming stage, which obeys the sine-law thinning (φ_t =1-sinα) of shear spinning rather than the non-thinning of conventional spinning. In addition, the thickness reduction of non-optimized workpiece presents a significant non-uniformity. On the contrary, both of the simulated and experimental workpieces under the optimized processing condition present the maximum thickness reduction ratio smaller than 7%, which approaches the ideal conventional spinning without thickness reduction. Thus, the optimized parameters can effectively suppress the thickness reduction and improve the thickness uniformity.

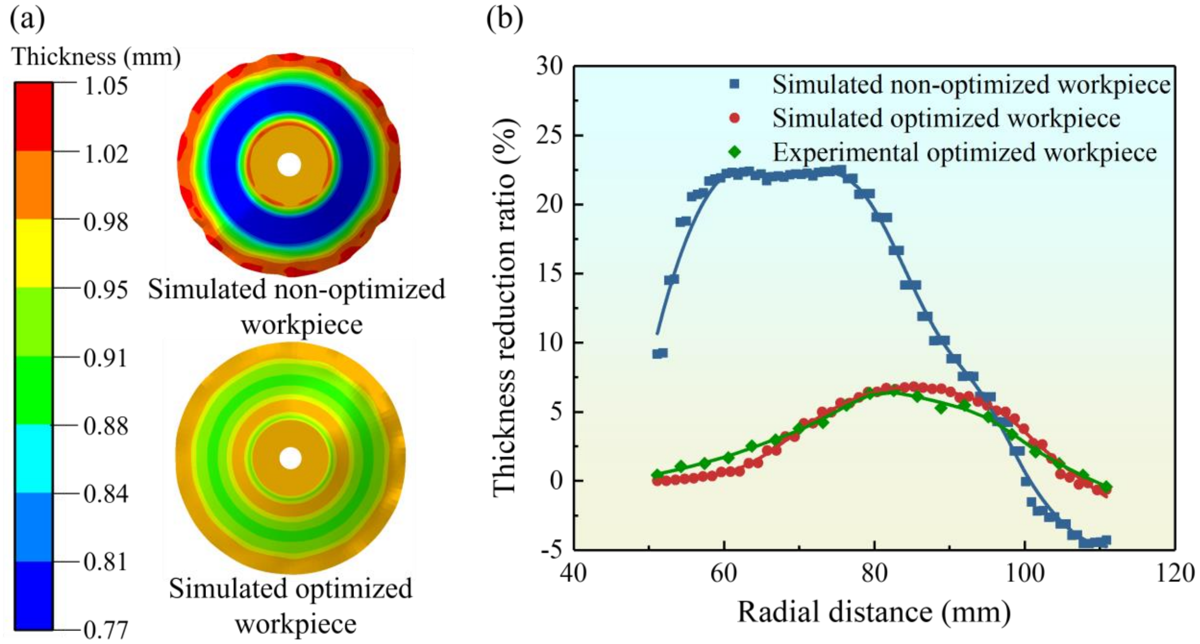

Fig. 13. Comparison of the wall thickness distribution (a) and wall thickness reduction ratio along generatrix (b) between workpieces under the optimized and non-optimized processing conditions.

5. Analysis and discussion

The above well application results validates that the proposed online intelligent optimization method and system are efficient in the design of roller path and matching spinning parameters. Compared to the traditional empirical design method, the new method has the following advantages, as summarized in Table 4:

- By combining the real-time prediction of spinning status and the online optimization of roller movement track, the new method considers the change with time and inheritance of spinning condition and status in optimization of conventional spinning process. This idea successfully solves the difficulty that the classical off-line process optimization method for steady-state forming is inefficient to design the high-flexible process path in incremental forming.
- It is an intelligent and quantitative design method instead of the traditional empirical method. The new method employs the AI technologies, including the virtual reality, status sensing, data analytics, deep learning and optimization algorithms. The optimal roller path can be autonomously obtained, implemented and updated online without any pre-set processing parameters. Therefore, the new method can realize the intelligent process optimization and self-adaptive control of the spinning process without relying on the know-how and experience of technicians. Moreover, it can provide the real optimal roller path rather than relatively feasible roller path by the traditional empirical method.
- Multiple objectives, including forming qualities (wall thickness reduction ratio and flange fluctuation degree) and forming efficiency (half cone angle of roller path), are taken into account in the new method. Moreover, the competition among three optimization objectives can be compromised by adjusting their weighting coefficients in the objective function.
- It is an efficient and economic design method instead of the traditional trial-and-error one. The traditional empirical method greatly depends on the know-how of the workshop personnel, thus, which is usually a costly, time-consuming and error-prone task. On the contrary, the new method can obtain both the optimal roller path and the matching spinning parameters (mandrel speed, feed ratio) with only one intelligent simulation process of spinning.
- It is a feasible and general method for the flexible process design in incremental forming process. With the rapid development of sensing technology of forming equipment, the

proposed online intelligent optimization method can be directly applied in practical forming process instead of virtual simulation process and thus realizing the intelligent spinning. Furthermore, since the new method considers the dynamic change of forming status and there is no need much prior engineering experience, it can be generalized to be the flexible process design in other incremental forming processes, such as rolling, single point incremental forming.

Table 4. Comparison between the traditional empirical design method and the new online intelligent optimization method

Traditional empirical design method	**New online intelligent optimization method**
Off-line design	Change with time and inheritance of spinning process are considered
Based on heuristic and know-how	Based on artificial intelligence technologies
Just roller path is designed	Both of roller path and matching processing parameters are optimized simultaneously
Feasible roller path	Optimal roller path
Only forming quality is considered	Multi-objectives of forming qualities and forming efficiency are considered and balanced
Costly and trial-and-error	Only one intelligent simulation of spinning process is needed
Poor universality	Well universality for other incremental forming, such as rolling, single point incremental forming, etc.
Poor practicality	Great potential to develop to intelligent spinning process with the development of sensor technology of forming equipment

6. Conclusions

In this paper, an innovative online intelligent optimization method of roller path design in conventional spinning was developed. The following conclusions can be drawn:

(1) The developed online intelligent optimization method combines the real-time prediction of spinning status and online optimization of roller movement track. The real-time prediction is intended to capture the dynamic change of spinning status, while the online optimization is based on greedy idea, which discretizes and optimizes the roller movement track progressively to

achieve the optimization of the whole roller path. In optimization, multiple objectives, including forming qualities (wall thickness reduction ratio and flange fluctuation degree) and forming efficiency (half cone angle of roller path), are taken into account and compromised.

(2) To implement the new method, an online intelligent optimization system was developed. It mainly includes four function modules: Module 1 is a FE model of conventional spinning, which acts as the virtual forming platform. Module 2 is developed to monitor the spinning condition and spinning status. Module 3 is developed for real-time prediction of spinning status through deep neural network. Module 4 optimizes the roller path by particle swarm optimization. By integrating the above four modules, the online intelligent optimization system has the multi-functions of spinning condition monitoring, real-time prediction of spinning status, online dynamic processing optimization, and autonomous execution of optimal processing.

(3) The new method and system was validated by a successful case application. It can realize the intelligent processing optimization and self-adaptive control of spinning process without relying on the know-how and experience of technicians. Both the optimal roller path and matching spinning parameters (mandrel speed, feed ratio) can be simultaneously obtained by only one intelligent simulation process of spinning. The optimized process can effectively control the flange fluctuation degree and wall thickness reduction, thus improve the forming stability and accuracy in conventional spinning.

(4) Compared with the traditional empirical design method based on experience and trial-and-error, the new method is scientific, intelligent, efficient and economical. Moreover, it can be generalized to be a flexible process design methodology in other incremental forming processes, such as rolling, single point incremental forming, etc.

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References

Chan, W.L., Fu, M.W., Lu, J., & Chan, L.C. (2009). Simulation-enabled study of folding defect formation and avoidance in axisymmetrical flanged components. *Journal of Materials Processing Technology, 209*(11), 5077-5086. https://doi.org/10.1016/j.jmatprotec.2009.02.005

Chen, J., Wan, M., Li, W.D., Xu, C.X., Xu, X.D., & Huang, Z.B. (2008). Design of the involute trace of multi-pass conventional spinning and application in numerical simulation. *Journal of Plasticity Engineering, 15*(6), 53-57.

Chen, S.W., Gao, P.F., Zhan, M., Ma, F., Zhang, H.R., & Xu, R.Q. (2019). Determination of formability considering wrinkling defect in first-pass conventional spinning with linear roller path. *Journal of Materials Processing Technology, 265*, 44-55. https://doi.org/10.1016/j.jmatprotec.2018.10.003

Cuartas, M., Ruiz, E., Ferreno, D., Setien, J., Arroyo, V., & Gutirroyo-Solana, V. (2021). Machine learning algorithms for the prediction of non-metallic inclusions in steel wires for tire reinforcement. *Journal of Intelligent Manufacturing, 32*(6), 1739 – 1751. https://doi.org/10.1007/s10845-020-01623-9

Eberhart, R., & Kennedy, J. (1995). A new optimizer using particle swarm theory. In *MHS'95 Proceedings of the Sixth International Symposium on Micro Machine and Human Science* (pp. 39-43). IEEE. https://doi.org/10.1109/MHS.1995.494215

Fu, M.W., Yong, M.S., Tong, K.K., & Muramatsu, T. (2006). A methodology for evaluation of metal forming system design and performance via CAE simulation. *International Journal of Production Research, 44(*6), 1075-1092. https://doi.org/10.1080/00207540500337643

Gan, T., Yu, Z.Q., Zhao, Y.X., Evsyukov, S.A., & Lai, X.M. (2018). Effects of backward path parameters on formability in conventional spinning of aluminum hemispherical parts. *Transactions of Nonferrous Metals Society of China, 28*, 328-339. https://doi.org/10.1016/S1003-6326(18)64666-7

Grosso, A., Jamali, A.R.M.J.U., & Locatelli, M. (2009). Finding maximin latin hypercube designs by Iterated Local Search heuristics. *European Journal of Operational Research, 197*(2), 541-547. https://doi.org/10.1016/j.ejor.2008.07.028

Guo, H., Wang, J., Lu, G., Sang, Z.H., & Wang, Q.H. (2017). A study of multi-pass scheduling methods for die-less spinning. *Journal of Zhejiang University SCIENCE A, 18*(6), 413-429. https://doi.org/10.1631/jzus.a1600403

Ismail, M., Mostafa, N.A., & EI-Assal, A. (2021). Quality monitoring in multistage manufacturing systems by using machine learning techniques. *Journal of Intelligent Manufacturing*, https://doi.org/10.1007/s10845-021-01792-1

Jallal, M.A., Chabaa, S., & Zeroual, A. (2020). A novel deep neural network based on randomly occurring distributed delayed PSO algorithm for monitoring the energy produced by four dual-axis solar trackers. *Renewable Energy, 149*, 1182-1196. https://doi.org/10.1016/j.renene.2019.10.117

Kang, D.C., Gao, X.C., Meng, X.F., & Wang, Z.H. (1999). Study on the deformation mode of conventional spinning of plates. *Journal of Materials Processing Technology, 94*, 226-230. https://doi.org/10.1016/S0924-0136(98)00447-6

Kong, Q.S., Yu, Z.Q., Zhao, Y.X., Wang, H., & Lin, Z.Q. (2017). Theoretical prediction of flange wrinkling in first-pass conventional spinning of hemispherical part. *Journal of Materials Processing Technology, 246*, 56-68. https://doi.org/10.1016/j.jmatprotec.2016.07.031

Li, H., Yang, J.C., Chen, G.Y., Liu, X., Zhang, Z., Li, G.J., & Liu, W.H. (2021). Towards intelligent design optimization: Progress and challenge of design optimization theories and technologies for plastic forming. *Chinese Journal of Aeronautics, 34*(2), 104-123. https://doi.org/10.1016/j.cja.2020.09.002

Li, Y., Wang, J., Lu, G.D., & Pan, G.J. (2014). A numerical study of the effects of roller paths on dimensional precision in die-less spinning of sheet metal. *Journal of Zhejiang University SCIENCE A, 15*(6), 432-446. https://doi.org/10.1631/jzus.a1300405

Liu, J.H., Yang, H., & Li, Y.Q. (2002). A study of the stress and strain distributions of first-pass conventional spinning under different roller-traces. *Journal of Materials Processing Technology, 129*, 326-329. https://doi.org/10.1016/S0924-0136(02)00682-9

Music, O., Allwood, J.M., & Kawai, K. (2010). A review of the mechanics of metal spinning. *Journal of Materials Processing Technology, 210*(1), 3-23. https://doi.org/10.1016/j.jmatprotec.2009.08.021

Park, H., Ko, H., Lee, Y.-S.T., Feng, S., Witherell, P., & Cho, H. (2021). Collaborative knowledge management to identify data analytics opportunities in additive manufacturing. *Journal of Intelligent Manufacturing,* https://doi.org/10.1007/s10845-021-01811-1

Polyblank, J.A., & Allwood, J.M. (2015). Parametric toolpath design in metal spinning. *CIRP Annals, 64*(1), 301-304. https://doi.org/10.1016/j.cirp.2015.04.077

Russo, I.M., Cleaver, C.J., & Allwood, J.M. (2021). Seven principles of toolpath design in conventional metal spinning. *Journal of Materials Processing Technology, 294*, 117131. https://doi.org/10.1016/j.jmatprotec.2021.117131

Shi, J., Song, J.C., Song, B., & Lu, W.F. (2019). Multi-objective optimization design through machine learning for drop-on-demand bioprinting. *Engineering, 5*, 586–593. https://doi.org/10.1016/j.eng.2018.12.009

Song, Y.N., Zhang, F.R., & Liu, C.C. (2020). The risk of block chain financial market based on particle swarm optimization. *Journal of Computational and Applied Mathematics, 370*, 112667. https://doi.org/10.1016/j.cam.2019.112667

Sugar, P., Sugarova, J., & Petrovic, J. (2016). Analysis of the Effect of Process Parameters on Part Wall Thickness Variation in Conventional Metal Spinning of Cr-Mn Austenitic Stainless Steels. *Journal of Mechanical Engineering, 62*(3), 171-178. https://doi.org/10.5545/sv-jme.2015.2901

Wang, J.J., Ma, Y.L., Zhang, L.B., Gao, R.X., & Wu, D.Z. (2018). Deep learning for smart manufacturing: methods and applications. *Journal of Manufacturing Systems, 48*, 144-156. https://doi.org/10.1016/j.jmsy.2018.01.003

Wang, L., & Long, H. (2011). A study of effects of roller path profiles on tool forces and part wall thickness variation in conventional metal spinning. *Journal of Materials Processing Technology, 211*(12), 2140-2151. https://doi.org/10.1016/j.jmatprotec.2011.07.013

Wang, L., & Long, H. (2013). Roller path design by tool compensation in multi-pass conventional spinning. *Materials & Design, 46*, 645-653. https://doi.org/10.1016/j.matdes.2012.10.048

Wang, L., Long, H., Ashley, D., Roberts, M., & White, P. (2011). Effects of the roller feed ratio on wrinkling failure in conventional spinning of a cylindrical cup. *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture, 225*(11), 1991-2006. https://doi.org/10.1177/0954405410396024

Wong, C.C., Dean, T.A., & Lin, J. (2003). A review of spinning, shear forming and flow forming processes. *International Journal of Machine Tools and Manufacture, 43*(14), 1419-1435. https://doi.org/10.1016/S0890-6955(03)00172-X

Wu, X., Huang, Z.T., & Ji, Y.F. (2020). Deep neural network method for channel estimation in visible light communication. *Optics Communications, 462*, 125272. https://doi.org/10.1016/j.optcom.2020.125272

Xia, Q.X., Xiao, G.F., Long, H., Cheng, X.Q., & Sheng, X.F. (2014). A review of process advancement of novel metal spinning. *International Journal of Machine Tools and Manufacture, 85*, 100-121. https://doi.org/10.1016/j.ijmachtools.2014.05.005

Xue, Y.G., Bai, C.H., Qiu, D.H., Kong, F.M., & Li, Z.Q. (2020). Predicting rockburst with database using particle swarm optimization and extreme learning machine. *Tunnelling and Underground Space Technology, 98*, 103287. https://doi.org/10.1016/j.tust.2020.103287

Zhan, M., Yang, H., Zhang, J.H., Xu, Y.L., & Ma, F. (2007). 3D FEM analysis of influence of roller feed rate on forming force and quality of cone spinning. *Journal of Materials Processing Technology, 187-188*, 486-491. https://doi.org/10.1016/j.jmatprotec.2006.11.114

Zhang, Y.X., You, D.Y., Gao, X.D., & Katayama, S.J. (2019). Online monitoring of welding status based on a DBN model during laser welding. *Engineering, 5*(4), 671-678. https://doi.org/10.1016/j.eng.2019.01.016