Fuzzy modelling of surface scratching in contact sliding

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Abstract. This paper presents a fuzzy modelling technique for the prediction of surface scratching problems encountered in sheet metal forming processes involving contact sliding. To generalize the contact conditions with die-sheet interactions in such processes, ball-on-disk sliding investigations, including modelling and experiment, were carried out with various ball diameters to mimic the die-contact radii effect and a range of contact loads to simulate the effect of contact stress variation experienced in forming processes. Because die-contact radius, surface roughness and contact stress changes cannot be exactly defined in a practical production process, in the modelling of the ball-on-disk configuration, ball diameter, normal load, surface roughness, sliding cycles and extent of scratching depth in a metal sheet surface were treated as fuzzy variables for the prediction. Based on the comparison between predictions with the relevant experimental measurements, it can be seen that the fuzzy modelling technique developed in this paper can predict very well the surface scratching.

1. Introduction

In the deep drawing process, sliding between the metal sheet and die/mould surfaces undergoes high contact stresses. As a result, such contact sliding can cause severe surface wear and subsequent scratching damage of the counterparts. However, it has turned out to be difficult to predict the evolution process of surface scratching damage because of the complexities in deformation and wear mechanisms. Therefore, it is of great importance to develop a feasible and effective method to predict the extent and evolution of surface scratching in the contact sliding process.

To solve this problem, some researchers, e.g. Archard [1], Rhee [2] and Bayer [3], have carried out empirical investigations to study the surface wear in the sliding process and relate the wear volume with the normal load, sliding distance and surface hardness. In these empirical studies, the influence of real contact stress on surface wear was not taken into consideration. For the wear problem in deep drawing process, Ersoy-Nürnberg et al. [4] presented a modified Archard’s model, in which the wear coefficient was given as a function of accumulated wear work. Groche et al. [5] combined this method with finite element method and investigated the effects of sliding speed and contact stress.
these researches and findings, the evolution process of microscopic surface damage during the contact sliding process was not presented in the studies mentioned above.

To investigate the surface damage evolution and wear mechanisms properly, some experimental methods were proposed and utilized. In the research carried out by Gåård et al. [6], a slider-on-flat-surface tribological system was developed to figure out the wear process of sheet metal surfaces. The initiation and evolution process of surface galling was studied and presented. In addition, the acoustic emission technique was also used to identify the initiation and variation process of surface wear in the studies conducted by Skåre and Krantz [7] and Shanbhag et al. [8]. However, it is still challenging to obtain reliable acoustic emission signals during the sheet metal forming process.

In general, these aforementioned approaches are not capable of predicting the surface damage evolution in the contact sliding process. It is preferable to establish appropriate models which can make full use of the available knowledge and provide reliable prediction results about the surface scratching damage. The artificial intelligence techniques have proved to be appropriate choices for this purpose. For example, the fuzzy logic approach, proposed by Zadeh [9], has been identified with good representation capability. It was used by Ali and Zhang to predict the residual stresses [10], surface roughness [11] and surface burn [12] in surface grinding processes.

In this paper, fuzzy modelling technique was used to predict the surface scratching damage induced by contact sliding. The experimental results of ball-on-disk sliding tests were adopted to establish a fuzzy prediction model, in which the ball diameter, normal load, surface roughness of sheet metal, sliding cycles and surface scratching depth were incorporated as fuzzy variables. In addition, a modified quantum-behaved particle swarm optimisation (QPSO) algorithm was developed for further optimization of the fuzzy inference model. The prediction performance of the optimized fuzzy inference model was verified by the comparison between prediction results and experimental measurements.

2. Experimental setup
Ball-on-disk sliding experiments were carried out by using a CETR tribometer, as shown in Figure 1. The materials of sheet metals and balls were advanced high-strength steel QP980 and high carbon chromium bearing steel GCr15, respectively. In the sliding process, the ball slid against the sheet metal surface reciprocally and the instant friction coefficient was given by the CETR tribometer. The sheet metal surfaces had three different levels of surface roughness, including $R_a = 0.04 \, \mu m$, $0.06 \, \mu m$ and $0.08 \, \mu m$. After each sliding test, a Zygo microscope (NewView 700) was used to measure the sliding track in the sheet metal surface and calculate the maximum scratching depth ($h_{max}$). In this study, the value of $h_{max}$ was adopted as the output variable to characterise the extent of surface scratching damage. Contact pressure in the ball-on-disc sliding tests can be estimated by employing the Hertz contact theory [13] and its average values in different contact conditions as illustrated in Figure 2. The yield strength (Rp0.2) of the QP980 steel is around 700MPa [14]. Thus, the contact pressure in the current sliding tests is of the same order of magnitude as that in the sheet metal forming process, demonstrating the close correlation between laboratory and industrial conditions.
Figure 1. Experimental setup of ball-on-disk sliding test

Figure 2. Average contact pressure in ball-on-disc sliding conditions

3. Fuzzy modelling technique
In this study, a rule-based fuzzy inference model was developed by using the fuzzy logic approach. To further improve the feasibility and learning ability of the established fuzzy prediction model, a modified QPSO algorithm was proposed to refine its definition parameters and adjust the fuzzy inference relationships.

3.1. Fuzzy logic approach
The fuzzy logic approach has been widely used to deal with the continuous transition between different states. In fuzzy modelling, the input variables are transformed into their corresponding fuzzy linguistic terms by using membership functions. The general form of a membership function can be given in Figure 3. Its value $\mu$ can describe the continuous transitions from “zero-belonging ($\mu=0$)” to “total-belonging ($\mu=1$)” and its accuracy is of great importance to the modelling performance.
In general, a fuzzy modelling consists of three steps: (1) the fuzzification of input and output variables; (2) the establishment of fuzzy rule base and inference engine; (3) the defuzzification of prediction results. In this study, the Mamdani-type [15] fuzzy inference system was adopted, and the weighted-sections method was utilized to produce defuzzification results.

3.2. Development of fuzzy prediction model

In this section, four critical parameters were adopted as the input variables, including ball diameter, normal load, surface roughness of sheet metal and sliding cycles. Besides, the maximum scratching depth \( h_{\text{max}} \) was incorporated in the fuzzy model as the output variable. Simplified membership functions were adopted in this stage by taking \( b = c \), as presented in Figure 4. By taking the experimental results as the training database, a preliminary fuzzy prediction model was established. To test the prediction performance of the established fuzzy model, the parameter \( \varepsilon \), given by Eq. (1), was used to calculate the average prediction error between the predicted results and experimental measurements.

\[
\varepsilon = \frac{1}{M} \times \sum_{j=1}^{M} \frac{\text{abs}(R^* - R^j)}{R^j}
\]  

(1)

where \( R^* \) and \( R \) are the results of prediction and experimental measurements, respectively. For the preliminary fuzzy model, it can reproduce the original training database with the \( \varepsilon \) value of 6.85\%. Therefore, the fuzzy model needs further optimization to improve its prediction performance by adaptively tuning the membership functions.
3.3. Optimization of fuzzy prediction model

In this section, the optimization of the preliminary fuzzy prediction model can be achieved by refining the definition parameters of membership functions to minimise the value of $\varepsilon$. Thus, the fuzzy model optimization can be converted into an $N$-dimensional optimisation problem with the objective function of $\varepsilon$. In the preliminary fuzzy model, the total number of definition parameters of both input and output variables is 102, which means the value of $N$ will be 102 as well.

For the $N$-dimensional optimisation problems, particle swarm optimisation (PSO) algorithm [16] and quantum-behaved particle swarm optimisation (QPSO) algorithm [17] have been widely used. In these algorithms, the particle swarm refers to a population of possible solutions and each solution is defined as a particle. However, both optimization algorithms are unable to deal with high-dimensional optimisation processes. Therefore, the QPSO algorithm is further developed in this study by exerting an adaptive crossover operator. When the particle swarm is found to get trapped into a local minimum zone, all the $pbest$ particles, which refer to the personal best positions found by each particle, are sorted based on their function values and some lagging $pbest$ particles with worse function values will be selected. These selected lagging $pbest$ particles will be hybridized with their crossbreeding particles randomly generated in the search space. If a newly-generated particle manages to find a better solution, it will be adopted as the new $pbest$ particle. Such selection and crossover operations will be repeated until the termination criterion is reached.

It is found that the modified QPSO algorithm manages to achieve a good balance between convergence speed and search ability. By combining the fuzzy logic approach and the further developed QPSO algorithm, an efficient artificial intelligence method is proposed in this study, which is capable to learn from the training data and refine the definition parameters adaptively.

4. Results and discussions
4.1. Results of model optimization

In this section, the further developed QPSO algorithm was employed to train the preliminary fuzzy prediction model by refining its membership functions. For the model optimization, the average prediction error $\varepsilon$ was adopted as the objective function and the population size and maximum iteration times in the QPSO algorithm were set as 40 and 2000, respectively. The optimized membership functions of input and output variables are shown in Figure 5.

![Membership Functions](image)

Figure 5. Optimized membership functions of input and output variables

After model optimization, an optimal combination of all the definition parameters is determined. It can be found that the average prediction error in reproducing the original training database was significantly reduced, from 6.85% to 2.89%. In addition, the optimized membership functions in Figure 4 are obviously different from their original ones in Figure 3, which is determined by the inherent nonlinear characteristics of surface damage problem. Overall, the developed fuzzy inference model can learn from the training database and tune its definition parameters adaptively by coupling the advantages of the modified QPSO algorithm.

4.2. Results of model verification

To check the performance of the optimized fuzzy inference model, additional sliding experiments were carried out and the experimental results were adopted as the verification database. For comprehensive comparison and analysis, the combinations of input variables used in the verification
experiments were different from those used in the training database. From the comparison results in Figure 6, the average prediction error was 3.49% when the optimized fuzzy inference model was utilized to predict the value of maximum scratching depth $h_{\text{max}}$. However, the average prediction error of the preliminary fuzzy inference model was 8.15%. Clearly, the learning capacity of developed fuzzy inference model and the optimization ability of modified QPSO algorithm were demonstrated by the significant decrease in the average prediction error.

![Figure 6. Comparison between prediction and experimental results](image)

5. Conclusions
This paper has managed to develop and optimize a fuzzy inference model, which is capable to predict the extent of maximum scratching depth in the sheet metal surface with high prediction accuracy. Ball-on-disk sliding experiments were carried out to simulate the contact conditions in the sheet metal forming process and the experimental results were adopted as the database. The fuzzy inference model has the ability to learn from the experimental database and then further enhance its prediction performance with the application of the modified QPSO algorithm. The feasibility and reliability of the developed fuzzy prediction model have been demonstrated by the verification results. It can be expected that the fuzzy modelling approach will play an important role in the complex engineering problems where the traditional prediction methods are not applicable.

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