AN APPLICATION OF ANN-GA HYBRID APPROACH ON MODELING AND OPTIMIZING ROLL FORMING OF ALUMINUM CAR DOORBELT

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Abstract: In this paper, an Artificial Neural Network – Genetic Algorithm (ANN-GA) hybrid model has been employed to model and optimize the Roll Forming (RF) process of an aluminum car doorbelt. In this approach, an artificail neural network (ANN) is built, and the Genetic Algorithm (GA) is used to optimize the network weights and biases for obtaining the reliable prediction results for the mechanical behavior of the aluminum sheet. The maximum longitudinal strain (MLS) and the spring back angle of the doorbelt at the final step are modeled at the network outputs, since they are two major factors affecting the quality of aluminum car doorbelt. The parametric study is performed by employing this ANN-GA hybrid model to investigate the effects of process parameters on the product quality. Subsequently, the optimization of parameters is carried out to obtain the optimal process configuration resulting in the flawless and high quality aluminum car doorbelt. The confirmation experiment is done to confirm the reliability of the optimization results. The results in this paper prove the applicability and high-efficiency of the ANN-GA approach in modeling and optimizing the RF process of aluminum car doorbelt

Key words: ANN-GA hybrid model, Roll Forming, Aluminum, Car doorbelt.

1. INTRODUCTION

A car doorbelt is used to protect against the penetration of dust, water, or other things from the outside into the car. It also improves the softness in operating glass of the door. A car doorbelt consists of two parts: metallic and coating parts. The metallic part is the most important one since it keeps the doorbelt firmly coupled with the car door. Normally, this part is manufactured by the Roll Forming (RF) process.

The RF processes of aluminum car doorbelts are complicated. Since the profiles of the car doorbelts are usually complicated and unsymmetrical, these RF processes are usually long process having many roll stands. Each roll stand can consist of upper, lower, and side rolls. It results in the complicated deformation behavior of the metal sheet, since there are many bending angles and contact surfaces between the rolls and sheet.

Many studies have been done to investigate the characteristics of RF processes using the steel materials. In 2002, Farzin *et al.* investigated the buckling limit of the strain in the RF process and concluded that the value of the buckling limit is independent of bending angle (Farzin *et al.*, 2002). The defect occurs when the maximal value of longitudinal strain was larger than the buckling limit, and the flower diagram of a flawless process could be obtained by this limit. Study by Tehrani *et al.* in 2006 on the localized edge buckling in RF process of symmetrical section has shown that the forming angle should be kept below a particular limit. Otherwise the local edge buckling may occur (Tehrani *et al.*, 2006). In 2008, an analysis of RF process was implemented in the numerical simulation by Bui and Ponthot and the characteristics and defects in forming process were analyzed clearly (Bui and Ponthot, 2008). The parametric study had also been done for the material properties, the inter stand distance, the roll sheet friction, and the rotation velocity of roll. This study strongly confirmed the potential of the Finite Element approach in analyzing RF process. The optimizations of RF process also had been carried out by many previous studies. In 2008, Zeng *et al.* studied on the optimization design of RF based on Response Surface Method (Zeng *et al.*, 2008). In this research, the design factors were the forming angle increment and the lower roll radius. The optimization objective was minimizing the spring back angle while keeping the longitudinal strain less than the buckling limit. One year later, 2009, Paralikas *et al.* optimized the process parameters by a semi-empirical approach (Paralikas *et al.*, 2009). The factors selected in this research were the roll forming line velocity, the inter distance between roll stations, the roll gap and the diameters of the rolls. The goal of optimization was minimizing the elastic longitudinal strains and the shear strains at the sheet edge for each roll station. The optimal configuration of process parameter results in a low cost solution and the minimization of the redundant deformation.

These previous studies mainly concerned on the RF processes having simple product profiles and the investigated materials were steels. In the past, the materials for producing the car doorbelts mainly were steels. However, along with nowadays trends, these materials are gradually changed from steels to aluminums to reduce the weight of products. This change of material may result in many unexpected defects since the mechanical properties of aluminum are different to those of steel. Besides, a RF process of an aluminum car doorbelt is a long process having complicated product profiles and consisting of many defects. The mechanical behaviors of the aluminum sheet during this forming process are high nonlinear functions. Modeling such high nonlinear problems has been reported is impossible if the conventional methods such as Response Surface Method are employed. These features make the RF of an aluminum car doorbelt become a challenging process in analyzing and optimizing. Previously, the investigation of the mechanical behaviors of the aluminum sheet in this process was mainly carried out by performing experiments. It is not an economic way since the cost for producing prototypes is relatively high. Therefore, it is required to find a new efficient approach for modeling the mechanical behaviors of the aluminum sheet in the RF of a car doorbelt. On the other hand, since the mechanical properties of aluminums are different to steels, the effects of the process parameters on the quality of aluminum car doorbelt also are different to those of steel ones. Therefore, along with the increase in producing aluminum car doorbelt, investigating the effects of process parameters in forming and optimizing these parameters are necessary for obtaining the highest quality aluminum car doorbelt.

In this paper, an application of the ANN-GA approach for efficiently solving these requirements is presented. The rest of this paper is organized as follows. Section 2 introduces an experiment and discusses the characteristics of the RF process of an aluminum car doorbelts. The Finite Element Analysis (FEA) of this RF process also is introduced. Section 3 presents the description of the ANN-GA hybrid approach for applying to the RF process of an aluminum car doorbelt. In section 4, the implementation of the modeling and optimization of the RF process of aluminum car doorbelt by ANN-GA hybrid approach is presented. The parametric study also is discussed in this section. Section 5 presents the results of the confirmation experiment. Finally, section 6 summarizes the findings of this paper.

2. THE ROLL FORMING PROCESS OF ALUMINUM CAR DOORBELT

2.1 Experiment set-up

The experiment in this paper is carried out at Roll Eng Company, Korea. The profile and flower diagram of our car doorbelt is shown in Figure 1.

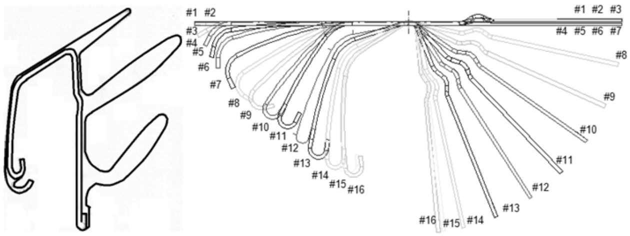

Fig. 1. The profile and flower diagram of the car doorbelt in experiment

Previously, the material used for manufacturing this product was the stainless steel SUS 430. However, this material has been changed from the stainless steel SUS 430 to the aluminum 05P 5052 for reducing the weight of the car doorbelt. The material mechanical behavior is assumed to follow the Swift's isotropic strain hardening law:

$$\sigma_v = K.(\varepsilon_0 + \varepsilon_p)^n$$

Here σ_v - the flow stress; ε_0 – the initial strain (0.0483); ε_p - plastic strain; K – the strength coefficient (398 MPa); n – the strain hardening exponent (0.25).

The RF process of this car doorbelt includes 16 steps. Initially, an aluminum sheet having 49.6 mm of width and 0.4 mm of thickness is fed into the forming line. It is moved by the friction forced caused by the contacts between rolls and the sheet. During its movement, the aluminum sheet is gradually bent by the rolls and formed the desired shape at the final roll stand.

All rolls are placed in a sequence called the forming line. In our experiment, each roll stand has the same distance to its consecutive one. This distance is called the inner distance between roll stands d. Its value can be adjusted by translating the roll stands. However, this value should be kept within an appropriate range. The reason is that too small value of the inner distance between roll stands will result in the occurrence of buckling and redundant deformation while too large one will require more shop-floor and therefore, increase the cost for manufacturing a car doorbelt (Halmos, 2005). The appropriate range of the inner distance in our process is determined in the factory as: $150 \le d \le 200$ (mm).

Each roll is rotated around its axis to cause the movement of the sheet. Approximately, all rolls have the same rotation velocites, and this value is denoted by ω. Similar to the inner distance, the rotation velocities of rolls should be kept in an allowable range. The reason is that, too small value of the rotation velocity will lower the manufacturing productivity while too large one will result in the occurrence of buckling and defects (Halmos, 2005). In our experiment, the range of the rotation velocity is determined as: $1 \le \omega \le 5$ (rad/s).

The friction forces occurring in the contact surfaces between the rolls and sheet play an important role in the success of RF, since it causes the movement of the aluminum sheet. Its value is determined by the value of the friction coefficient *f*. The friction coefficient should be kept in an appropriate range to confine the value of friction forces. Too small value of the friction coefficient may result in insufficient friction forces for letting the sheet move, while too large one can lead to the fracture of the aluminum sheet (Halmos, 2005). The value of the friction coefficient in forming process can be adjusted by the lubrication of the rolls and aluminum sheet. Empirically, the range of the friction coefficient in our realistic manufacturing is: $0.1 \leq f \leq 0.5$.

Besides varying the friction coefficient *f*, the variation of the ratio of the roll gap to sheet thickness *r* can also vary the value of the friction forces. This ratio can significantly affect the success of forming process. Too large value of this ratio may result in insufficient friction forces while too small one can cause the fracture in the aluminum sheet since the pressed force is so high (Halmos, 2005). The appropriate range of the ratio between the roll gap and sheet thickness in our experiment is determined by the realistic manufacturing as: $1 \leq r \leq 1.15$.

2.2 Characteristics of the RF process of aluminum car doorbelt

The RF processes of aluminum car doorbelt are the challenge forming process and have many difficulties. Normally, the profile of a car doorbelt is complicated with many bending angles. Therefore, its forming process consists of many steps and has a long forming line. In some cases, this process requires not only the upper and lower rolls but also the side rolls; and its complexity increases. Because of its complexity, there are many defects can occur during forming such as the waviness, wrinkle, or buckling. In the past, the materials of the car doorbelts were mainly steels. However, nowadays, they are gradually replaced by aluminums to reduce the weight of products. These changes of the materials bring more obstacles such as the occurrence of unexpected defects to the RF process of a car doorbelt since the mechanical properties of aluminums are different to those of steels.

In a RF process, the longitudinal strain plays an important role on determining the product quality. It is the major factor causing the occurrence of defects in RF process. In 2002, Farzin *et al.* investigated the buckling limit of the strain in RF and concluded that the defect occured when the maximal value of longitudinal strain was larger than this buckling limit (Farzin *et al.*, 2002). In the RF process of a car doorbelt, the defects such as the waviness or wrinkle frequently occur after changing the materials from steels to aluminums (Figure 2). The reason is that the longitudinal strain in the RF process using aluminum materials usually larger than that in the RF process using steel materials and easily become greater than the buckling limit. Therefore, in order to produce the high quality aluminum car doorbelt, it is required to model the variation of the longitudinal strain during forming process and develop an optimization strategy for keeping the longitudinal strain less than the buckling limit.

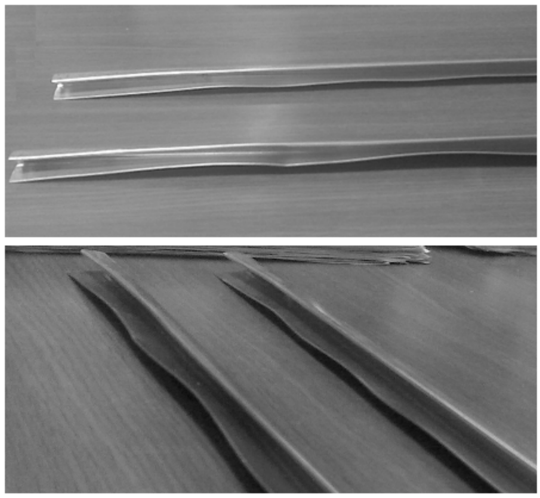

Fig. 2. The occurrence of defects such as the waviness in car doorbelts after changing the materials from steels to aluminums

The other requirement that must be considered in the RF process of aluminum car doorbelt is minimizing the spring back angle at the final pass. Spring back is a popular phenomenon occurring in different forming processes. The value of spring back angle varies with respect to the change of material used in manufacturing (Panthi *et al.*, 2010). In the RF process of a car doorbelt, the occurrence of the spring back changes the profile of aluminum sheet after forming. Therefore, the aluminum sheet must be overbent at the final pass to obtain the desired shape. After overbending, the aluminum sheet will spring back to form the correct product profile. Normally, the overbending angle is set equal to the spring back angle (Halmos, 2005). However, the spring back angles before and after overbending are different since the geometries of the sheet before and after overbending are different. This difference causes the error of the final formed profile. If the value of the spring back angle before overbending is large, this difference is large and significantly reduces the product quality. However, if the value of the spring back angle before overbending is minimized, this difference is minimized and the product quality is increased. On the other hand, if the spring back angle is large, it is required to overbend a large angle at the final forming pass. Therefore, the total bending angle at this pass consisting of the initial bending angle and overbending angle can become excessive. In 2007, Lindgren concluded that the value of longitudinal strain increases with the increase in the bending angle

(Lindgren, 2007). Therefore, the excessive total bending angle at the final forming pass can results in the excessive longitudinal strain that is larger than the buckling limit, and the defects can occur. Finally, to obtain the high quality car doorbelt, the spring back must be minimized. Therefore, it is required to predict the spring back angle and develop a method for minimizing the spring back angle in the RF process of an aluminum car doorbelt.

2.3 Finite Element Analysis (FEA) of the RF process of aluminum car doorbelt

In this paper, the FEA of the RF process of aluminum car doorbelt is carried out by employing the ABAQUS program. In the simulation of ABAQUS, the rolls are modeled by using the analytical rigid elements. The surface to surface contacts algorithm is used to model the contact relationship between the rolls and the aluminum sheet. The rolls are modeled to rotate around their axis. The sheet is modeled as having an initial velocity for simulating the process of feeding the aluminum sheet into the forming line. After that, the sheet is moved by the friction forces occurring in contact surfaces between the roll and the sheet. The length of the aluminum sheet in simulation must not be less than two times of the inner distance between roll stands to ensure the sheet always be kept horizontal by contacting to at least two lower rolls.

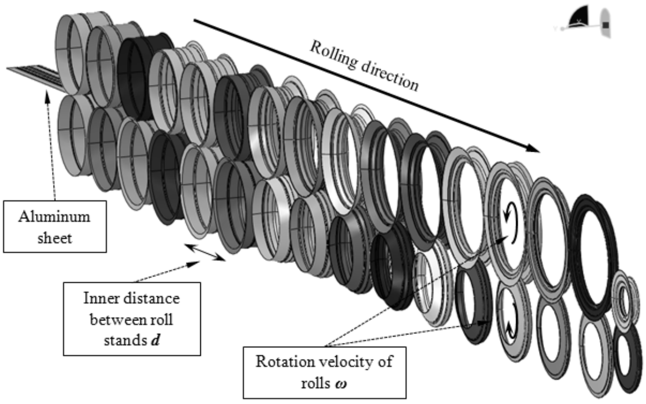

Fig. 3. The simulation of the RF process of the car doorbelt of our experiment

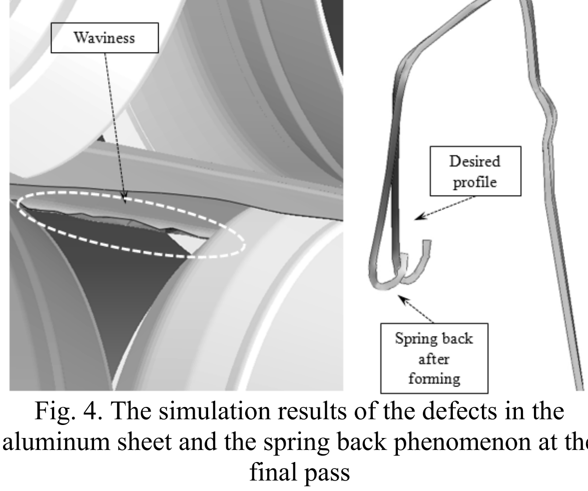

Fig. 4. The simulation results of the defects in the aluminum sheet and the spring back phenomenon at the final pass

Figure 3 shows the simulation of our RF process of a car doorbelt. There are 16 roll stands and the aluminum sheet is bent gradually at each rolls stands to form the car doorbelt. From the simulation results of FEA, the variation of the longitudinal strain, the defects in the aluminum sheet and the spring back angle at the final pass can be obtained (Figure 4).

3. ANN-GA HYBRID APPROACH FOR THE RF PROCESS OF ALUMINUM CAR DOORBELT

In general, the RF process is a process having many forming steps, many contact surfaces, and long manufacturing time. Particularly, the RF process of aluminum car doorbelt contains more difficulties than other RF processes, since its product profiles are relatively complicated. Because of its complexity, the deformation and the distribution of stress/strain in the aluminum sheet are the high nonlinear functions. Modeling such high nonlinear problems is impossible if the conventional approximation methods such as the RSM are employed. Nowadays, some new modeling and optimization tools such as the ANN and GA have been emerged and show certain capabilities to efficiently solving these challenging problems (Shahani et. al, 2009; Wang et. al., 2003). To fully exploit the advantages of these newly emerged methods, they are employed in this paper for modeling and optimizing the RF process of aluminum car doorbelt.

3.1 Artificial Neural Network (ANN) and Genetic Algorithm (GA)

An ANN is a mathematical model using for modeling and prediction. The network has an input layer, hidden layers, and an output layer. The input layer consists of all the input factors. Data from the input layer are processed at each hidden layers and the output vector is computed in the output layer. The data set for developing an ANN model is divided into two sets, one is used for training the network, and the remaining is used to verify the reliability of the network (Pal *et al.*, 2008). Input and output pairs are fed to the network and weights and biases are adjusted to minimize the error between the network outputs and actual values (Brezak *et al.*, 2010; Ozerdem and Kolukisa, 2008).
The GA is an optimization tool that can work equally well in either continuous or discrete search space (Ledoux *et al.*, 2010). It comprises of selection, cross over, mutation processes. The evolution starts with a population of randomly generated individuals in the first generation. In each generation, the fitness of every individual in the population is calculated, compared with the best value and modified to form a new population. The new population is then used in

the next iteration of the algorithm. The algorithm terminates when either a maximal number of generations has been produced or a satisfactory fitness level have been reached for the population (Dey *et al.*, 2009).

3.2 ANN-GA hybrid approach for the RF process of aluminum car doorbelt

The ANN-GA hybrid model is a combination of two methods mentioned above. The ANN is a powerful tool in modeling, while the GA is an efficient tool in optimization. Therefore, a combination exploiting their advantages together is expected to become a more powerful method and can overcome the drawbacks of each individual one (Wang et al., 2003; Sun et. al., 2010).

In ANN-GA hybrid approach for the RF of aluminum car doorbelt, initially a neural network is built to model the variation of the major factors in the process. Two major factors must be considered in this process are the maximum longitudinal strain MLS and the spring back angle α. They are modeled by the outputs of the neural network. Therefore, the network has two output neurons representing for MLS and α. On the other hand, the major process parameters in a RF process which were discussed in the previous section are the inputs of the network. They are: the inner distance between roll stands d, the rotation velocity of rolls ω, the friction coefficient f, and the ratio of the roll gap to the sheet thickness r. Therefore, the network has four input neurons representing for d, ω, f, r. The schematic description of the network is shown in figure 5. In this paper, the operation of the ANN-GA hybrid network is programmed using the MATLAB software.

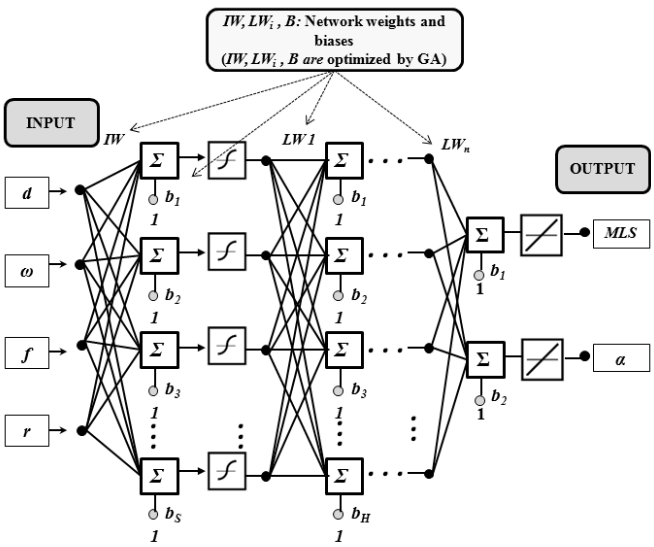

Fig. 5. The schematic description of the ANN-GA hybrid network for modelling the RF process of aluminium car doorbelt

Initially, the values of process parameters are fed into the input neurons of the network. These data are processed at each hidden layer by using the network weights, network biases, and the transfer functions. After passing all hidden layers, the outputs representing the predicted results are obtained at the output layer. The relationship between the outputs and the inputs in the network is expressed as:

$$\text{Outputs} = f_n(LW_{n-1}.\ f_{n-1}(\ \dots\ .f_2(LW_1.f_1(IW.p+b_1)+b_2)\ \dots\ +b_{n-1})+b_n)$$

Where, p is the input vector; IW is the input weights; LW_i and b_i are the weights and bias of the hidden layers i; f_i is the transfer function of the layer i.

At the beginning, the values of the network weights and biases are arbitrarily set. Therefore, the error between the results predicted by the network and the actual values are relatively large. It indicates the network does not correctly model the relationships between the MLS, α, and the process parameters. In order to improve the network performance, the network weights and biases are optimized to minimize the error between the predicted results and the actual values. This optimization is called the training process. It requires a set of the input values and their actual output results. This set is called the training data and is obtained from the experiments or simulations. The factor used for evaluating the performance of the training process is the mean square error MSE:

$$MSE = [(\ MLS_{predicted} - MLS_{actual})^2 + (\ \alpha_{predicted} - \alpha_{actual})^2]^{(1/2)}$$

In this paper, each process parameter is divided into five levels and a series of simulations following the L_{25} orthogonal array is carried out. The MLS and α in each simulation are extracted from the simulation results. After carried out all required simulations, the necessary data are obtained and are listed in Table 1. These data are divided into two parts, one for training the network (21 simulations), and one for validating the reliability of the network (four simulations).

The training process in the ANN-GA hybrid model is carried out by the GA. In GA, the network weights and biases are coded as the chromosomes while the fitness function is the MSE between the predicted and actual results. Initially, a population is generated, and it is evolved after each generation to produce the better fitness value. This training process is terminated when the MSE obtained is less than 0.01. At this moment, the network successfully learnt the relationship between the MLS, α, and the process parameters.

The optimal structure of a neural network, such as the optimal number of the hidden layers or the number of hidden neurons, is still a problem without solution. To obtain the optimal structure of our network for the RF of our car doorbelt, various selections having different numbers of the hidden layers and hidden neurons are built. They will be trained with the training data to identify which one produces the minimum error between the predicted results and the actual values. After comparing their performances, the optimal structure of the network for modeling the RF process of aluminum car doorbelt is determined as: two hidden layers having six and five hidden neurons in each layer, respectively.

Table 1. Simulation results from L_{25} orthogonal array

Exp.	*d* *(mm)*	*ω* *(rad/s)*	*f*	*r*	*α*	*MLS* *(e-3)*
1	150	1	0.1	1	3.177	9.12
2	150	2	0.2	1.0375	1.089	7.92
3	150	3	0.3	1.075	3.057	8.106
4	150	4	0.4	1.1125	2.433	6.888
5	150	5	0.5	1.15	3.641	9.008
6	162.5	1	0.2	1.075	1.268	7.976
7	162.5	2	0.3	1.1125	3.691	8.144
8	162.5	3	0.4	1.15	4.066	7.192
9	162.5	4	0.5	1	5.227	11.72
10	162.5	5	0.1	1.0375	2.077	8.296
11	175	1	0.3	1.15	2.874	8.203
12	175	2	0.4	1	2.688	11.072
13	175	3	0.5	1.0375	3.720	11.904
14	175	4	0.1	1.075	2.016	7
15	175	5	0.2	1.1125	1.244	7.088
16	187.5	1	0.4	1.0375	2.774	8.680
17	187.5	2	0.5	1.075	1.819	10.296
18	187.5	3	0.1	1.1125	1.448	7.560
19	187.5	4	0.2	1.15	2.101	8.368
20	187.5	5	0.3	1	4.583	9.512
21	200	1	0.5	1.1125	4.968	9.328
22	200	2	0.1	1.15	1.512	7.59
23	200	3	0.2	1	3.249	8.584
24	200	4	0.3	1.0375	2.036	9.642
25	200	5	0.4	1.075	1.267	9.784

4. MODELING AND OPTIMIZATION OF THE ROLL FORMING PROCESS OF THE ALUMINUM CAR DOORBELT

The training process of the optimal network is shown in figure 6. It can be observed that the initial error between the predicted results and the actual values is relatively large.

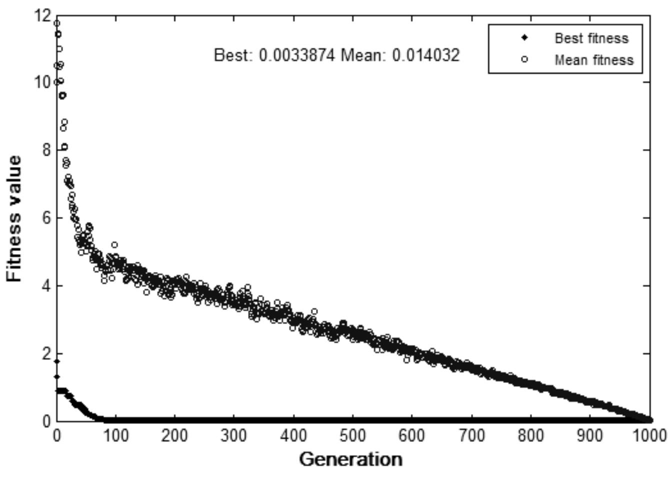

Fig. 6. The training process of the ANN-GA hybrid network

However, during the training process, or the optimization of network weights and biases, this error is gradually reduced. Finally, the error that reached the value of 0.003 indicates that the network successfully learnt the relationship between the MLS, α, and the process parameters. The training process is terminated.

The validation process is performed to validate the reliability of the ANN-GA hybrid network. The error between the predicted results and the actual values in this process lies within 1-8% (Figure 7). Therefore, it can be concluded that the prediction ability of the network is reliable and this network can be employed to correctly model the RF process of the aluminum car doorbelt.

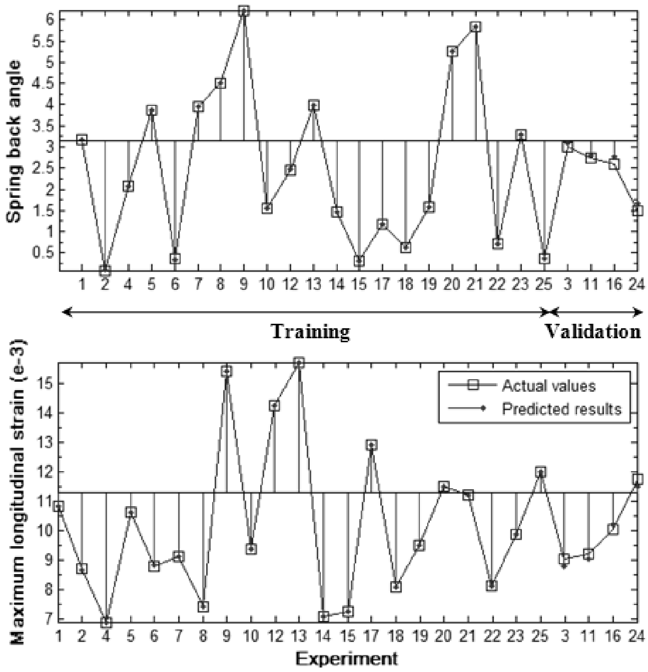

Fig. 7. The comparison of the predicted results and actual values

The parametric study is performed to investigate the effects of process parameters on the quality of aluminum car doorbelt. Four major process parameters considered in this paper are the inner distance between roll stands d, the rotation velocity of rolls *ω*, the friction coefficient f, and the ratio of the roll gap to the sheet thickness r. Two important factors determining the quality of the roll-formed aluminum car doorbelt are the maximum longitudinal strain MLS and the spring back angle α.

The effect of the inner distance between roll stands *d* on the variation of the maximum longitudinal strain is shown in figure 8. From this figure, it can be observed that the increase in the inner distance between roll stands *d* results in the reduction of the MLS. When the inner distance *d* has the smallest value, the MLS is maximum and the defects occur; while when inner distance is maximized, the MLS has the minimum value. On the other hand, the effect of the inner distance on the variation of the spring back angle is shown in figure 9. It can also be observed that the spring back angle decreases with the increase in the inner distance. It leads to the reduction of the over bending angle at the final pass, and the process is safer. Finally, from these remarks, it can be concluded that the increase in the inner distance results in the rise of product quality since it causes the reduction in both MLS and spring back angle.

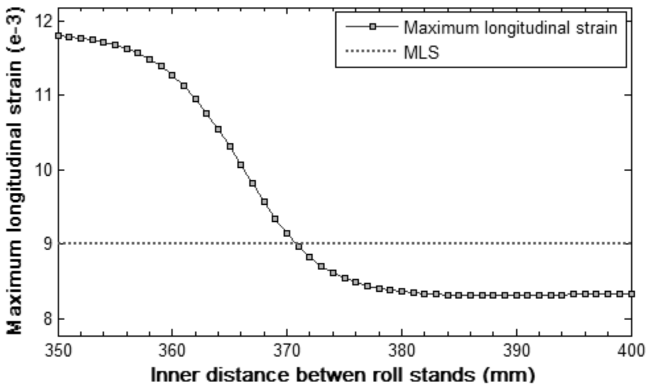

Fig. 8. The effect of the inner distance between roll stands on the variation of the maximum longitudinal strain

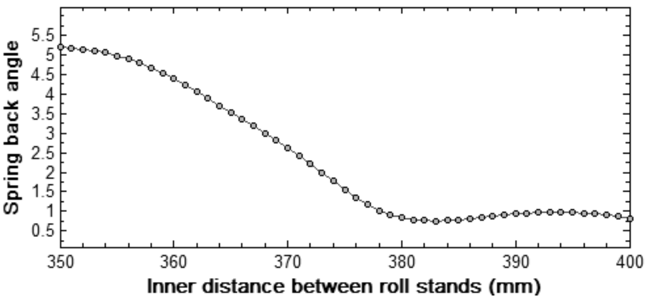

Fig. 9. The effect of the inner distance on the variation of the spring back angle

The effect of the rotation velocity of rolls on the variation of the maximum longitudinal strain is shown in figure 10. Initially, the rotation velocity is low and the MLS is less than the buckling limit. The rotation velocity is gradually increased, and the process still is safe when the rotation velocity is small enough. However, if the rotation velocity is increased up to a particular value, the value of MLS significantly increases and the defects occur. Therefore, in order to avoid the excessive large MLS, the rotation velocity should be kept less than a particular limit. On the other hand, the effect of the rotation velocity on the variation of the spring back angle is shown in figure 11. When the rotation velocity is low, the spring back angle is relatively high. However, the spring back angle gradually decreases with the increase in the rotation velocity. When the rotation velocity is large enough, the increase in it has a negligible effect on the variation of the spring back angle. Therefore, the rotation velocity of rolls should be larger than a particular limit to obtain the small value of spring back angle. Besides, it should be less than another limit to avoid the excessive large MLS and keep the process safe.

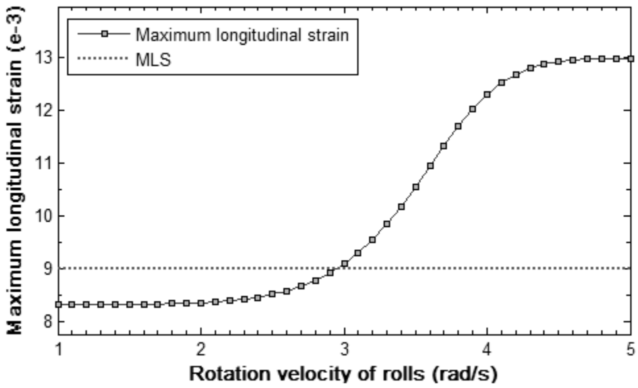

Fig. 10. The effect of the rotation velocity of rolls on the variation of the maximum longitudinal strain

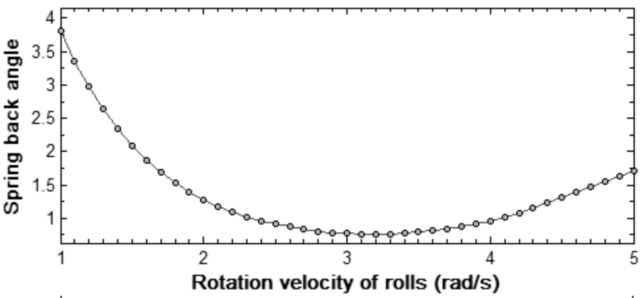

Fig. 11. The effect of the rotation velocity on the variation of the spring back angle

The effect of the friction coefficient *f* on the variation of the maximum longitudinal strain is shown in figure 12. This figure indicates that the MLS still is less than the buckling limit when the value of the friction coefficient still is small enough. When the friction coefficient is greater than a particular limit, the value of the MLS quickly rises and become excessive. Therefore, in order to avoid the occurrence of defects, the friction coefficient in forming process should be kept less than its particular limit. On the other hand, the effect of the friction coefficient on the variation of the spring back angle is shown in figure 13. It can be seen that the friction coefficient has a significant effect on the change in spring back angle. However, there is no simple rule for this effect is observed. Therefore, the optimization of process parameters should be performed to obtain the optimal value of the friction coefficient resulting in the allowable values of MLS and spring back angle.

The effect of the ratio of the roll gap to sheet thickness *r* on the variation of the maximum longitudinal strain is shown in figure 14. This figure indicates that the increase in this ratio results in the reduction of the MLS, or a safer process. This conclusion is in agreement with the experiments where the increase in the ratio of the roll gap to sheet thickness *r* reduces the friction forces and therefore, reduces the MLS. On the other hand, the figure 15 shows the effect of the ratio *r* on the variation of the spring back angle. It can be clearly seen that the ratio *r* has a significant effect, but there is no simple rule for predicting the variation of spring back angle with respect the variation of the ratio r can be observed. Therefore, an optimization of the process parameters should be performed to obtain the optimal value of the ratio of the roll gap to sheet thickness r.

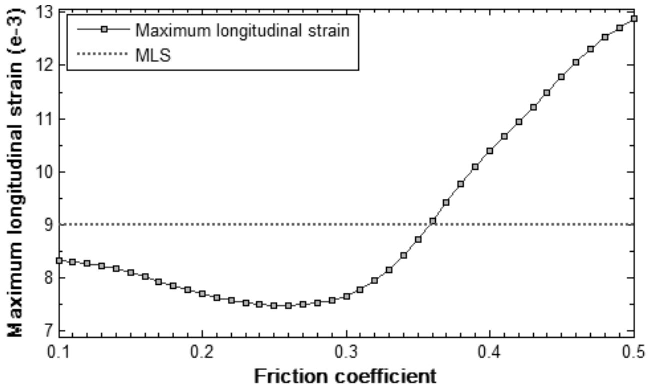

Fig. 12. The effect of the friction coefficient on the variation of the maximum longitudinal strain

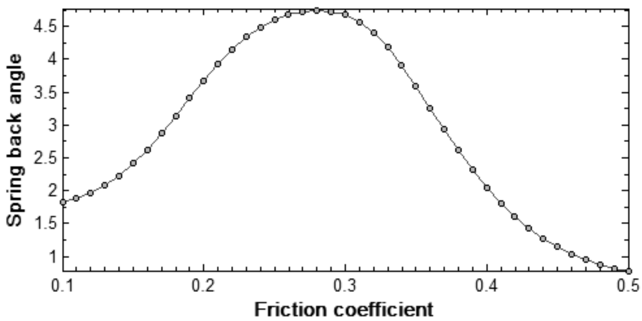

Fig. 13. The effect of the friction coefficient on the variation of the spring back angle

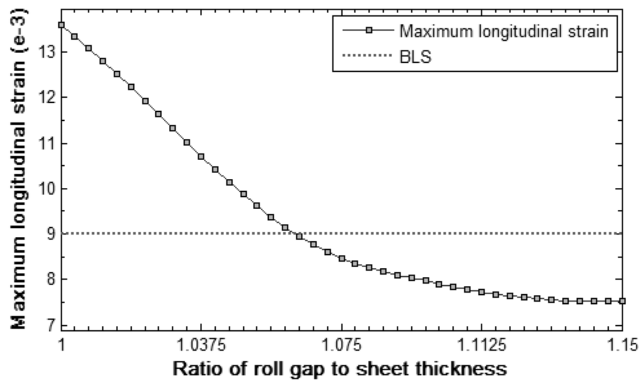

Fig. 14. The effect of the ratio of the roll gap to sheet thickness on the variation of the maximum longitudinal strain

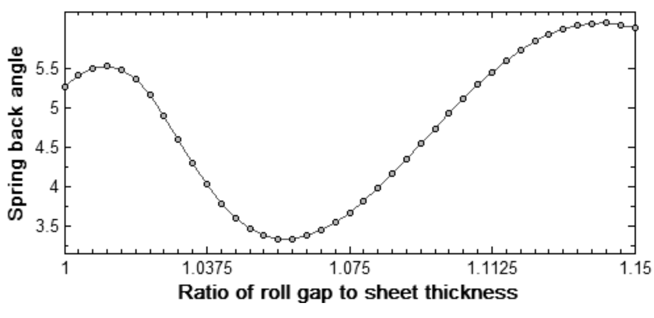

Fig. 15. The effect of the ratio of the roll gap to sheet thickness on the variation of the spring back angle

The results of the parametric study above can be used to predict the variation of the major mechanical factors in the forming process with respect to the variation of process parameters. It also indicates the significance of the effect of each process parameter on the product quality. However, in order to obtain the optimal values of process parameters that resulting in the highest quality aluminum car doorbelt, the optimization of process parameters must be performed.

As mentioned in the section 2, two major factors affecting the quality of an aluminum car doorbelt are the maximum longitudinal strain and the spring back angle. It was concluded that the changes in process parameters such as the inner distance, rotation velocity of the rolls, friction coefficient, and the ratio of the roll gap to sheet thickness, can result in the changes of the product's stress, strain as well as its spring back angle. Therefore, the optimization of these process parameters can improve the quality of aluminum car doorbelt by minimizing the spring back angle and keeping the maximum longitudinal strain less than the buckling limit to avoid the occurrence of defects. From the parametric study, it can be concluded that all major process parameters have the significant effect on the product quality. Therefore, all of them must be considered in the optimization.

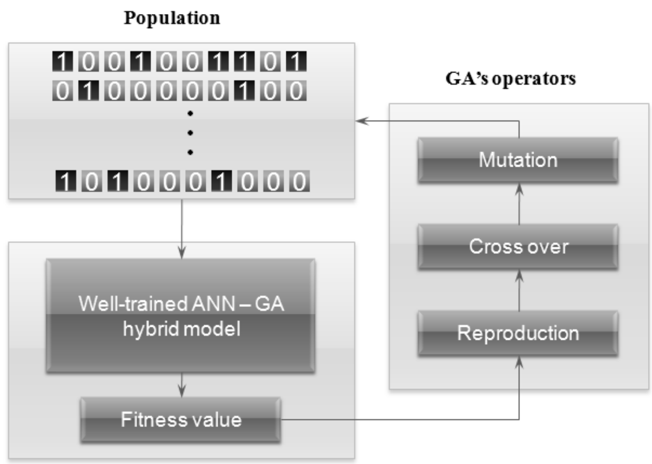

Fig. 16. The description of the ANN-GA hybrid approach for optimizing the RF process of aluminum car doorbelt

In this paper, the optimization of the process parameters in the RF of the aluminum car doorbelt is carried out by employing the ANN-GA hybrid approach. The optimization objective is minimizing the spring back angle while the optimization constraints are the buckling limit set on the maximum longitudinal strain and the manufacturing conditions set on the process parameters. Four major process parameters optimized are: the inner distance d, the rotation velocity of rolls ω, the friction coefficient f, and the ratio of the roll gap to sheet thickness r. These parameters are coded as the chromosomes while the spring back angle is set as the fitness function in the GA. To carry out this task, the well-trained ANN-GA hybrid model that can correctly model the mechanical behaviors of our RF process is embedded into the GA. It is used to calculate the values of maximum longitudinal strain and spring back angle with respect to different configurations of process parameters. Initially, a population is generated in GA. After that, it is evolved in each generation to produce the better fitness values. The optimization is terminated when the maximum number of generations is reached or the optimization results cannot be improved during a large number of generations. The description of the ANN-GA hybrid approach for optimizing the RF process of a car doorbelt is shown in figure 16.

In optimization, the most important constraint is the buckling limit set on the maximum longitudinal strain to prevent the occurrence of defects. In order to obtain the buckling limit in our process, a bending angle increment is increased until the defects such as the waviness or wrinkle occurs in the experiment or simulation. The maximum longitudinal strain at this time is equal to the buckling limit. This value in our RF process is obtained as 9.10-3. Therefore, the constraint set on maximum longitudinal strain during our optimization is: MLS ≤ 9.10-3.

Besides the above constraint, the manufacturing conditions are other constraints in our optimization. As mentioned in the previous section, the ranges of the process parameters should be carefully determined since the excessive values of the parameters can significantly decrease the quality of the car doorbelt. In our process, these ranges are determined by realistic manufacturing conditions in the factory as: $150 \le d \le 200$ (mm), $1 \le \omega \le 5$ (rad/s), $0.1 \le f \le 0.5$, $0.1 \le r \le 0.15$. These ranges are the constraints on the process parameters during the optimization.

The population having 100 individuals is generated in GA. This population is evolved after each generation to produce the better fitness value. The optimization is stopped after 120 generations since the value of the fitness function has converged to the minimum one. The minimum spring back angle obtained by the optimization is 1.157^0. The maximum longitudinal strain in the optimization results is 5.50 .10-3. This value is less than the buckling limit. Therefore, the defects do not occur, and the forming process is safe. The optimal process parameters obtained by the optimization are: the inner distance between roll stands: $d = 163.8$ (mm); the rotation velocity of rolls: $\omega = 3.45$ (rad/s); the friction coefficient: $f = 0.37$; the ratio of the roll gap to the sheet thickness: $r = 1.15$.

5. EXPERIMENTAL VERIFICATION

To confirm the reliability of the optimization results, the confirmation experiment is performed (Figure 17). The cross section of the aluminum car doorbelt in this experiment is shown in figure 18. The aluminum car doorbelt after the RF process having good quality and no existence of defects is shown in figure 19. The spring back angle in the experiment is around 1^0 and is in agreement with the predicted result of the hybrid model. After the forming, the coating process is done, and the commercial aluminum car doorbelt is obtained (Figure 19).

From the experiment results, it can be concluded that our optimization strategy is efficient and can be applied to the realistic manufacturing.

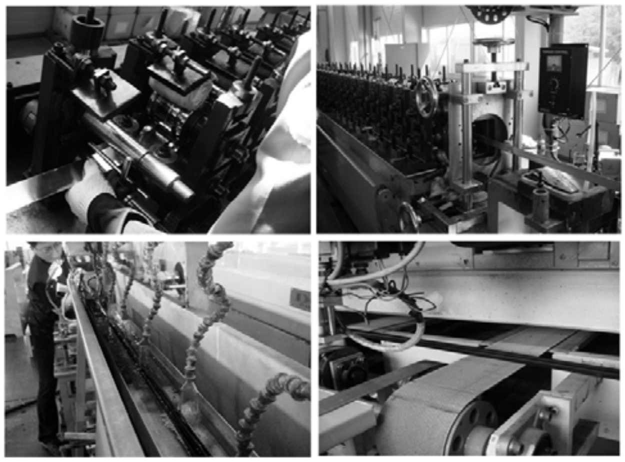

Fig. 17. The confirmation experiment to confirm the reliability of the optimization results

Fig. 18. The cross section of the aluminum car doorbelt in the confirmation experiment

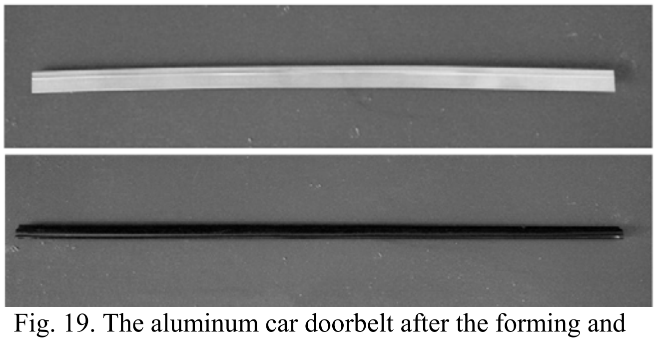

Fig. 19. The aluminum car doorbelt after the forming and coating processes

6. CONCLUSIONS

This paper presented an application of the ANN-GA hybrid approach for modeling and optimizing the RF process of an aluminum car doorbelt. The maximum longitudinal strain and the spring back angle were modeled at the outputs of the hybrid network, while the inner distance between roll stands *d*, rotation velocity of rolls *ω*, friction coefficient *f*, and ratio of the roll gap to the sheet thickness *r* were the inputs of the network. After the training process carried out by the GA, the error between the predicted results and the actual values in the validation process lied within 1 – 8%. This result proved the capability and efficiency of the ANN-GA hybrid model in modeling the RF process of an aluminum car doorbelt. The parametric study performed by employing this hybrid model indicated that all major process parameters *d, ω, f,* and *r* have the significant effects on the product quality. Moreover, it can be concluded that in the RF process of aluminum car doorbelt, the maximum longitudinal strain decreases with the increase in *d* and *r*, or the decrease in *ω* and *f,* while the spring back angle decreases with the increase in *d* and *ω*. The optimization of the process parameters using the ANN-GA hybrid approach was performed to obtain the optimal process configuration resulting in the highest quality aluminum car doorbelt. The optimization objective was minimizing the spring back angle while the optimization constraints were the buckling limit set on the maximum longitudinal strain and the manufacturing conditions set on the process parameters. The flawless aluminum car doorbelt having the minimum spring back angle obtained in the confirmation experiment proved the reliability of the optimization results. It can be concluded that the ANN-GA hybrid approach is an efficient and powerful method for modeling and optimizing the RF process of a car doorbelt.

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