An Improved Teaching-Learning Based Optimization for Optimization of Flatness of a Strip During a Coiling Process

Sujin Bureerat[1], Nantiwat Pholdee[1(✉)], Won-Woong Park[2], and Dong-Kyu Kim[3]

[1] Department of Mechanical Engineering, Faculty of Engineering, Sustainable and Infrastructure Research and Development Centre, Khon Kaen University, 123 Moo 16, Mittraphap Road, Tambon Muang, Khon Kaen, Thailand
nantiwat@kku.ac.th

[2] National Research Laboratory for Computer Aided Materials Processing, Department of Mechanical Engineering, KAIST, 291 Daehak-ro, Yuseong-gu, Daejeon, South Korea

[3] Neutron Science Division, Korea Atomic Energy Research Institute, 111 Daeduk-daero 989 beon-gil, Yuseong-gu, Daejeon, South Korea

Abstract. Performance enhancement of a teaching-learning basedz optimizer (TLBO) for strip flatness optimization during a coiling process is proposed. The method is termed improved teaching-learning based optimization (ITLBO). The new algorithm is achieved by modifying the teaching phase of the original TLBO. The design problem is set to find spool geometry and coiling tension in order to minimize flatness defects during the coiling process. Having implemented the new optimizer with flatness optimization for strip coiling, the results reveal that the proposed method gives a better optimum solution compared to the present state-of-the-art methods.

Keywords: Evolutionary algorithm · Flatness defect · Optimization · Strip coiling · Teaching-learning based optimization

1 Introduction

There are several processing stages during the manufacturing of a coil strip, e.g. roughing, rolling, cooling, and coiling. Based on the previous investigation by Jung and Im [1, 2], the final strip shape had non-uniform thickness profiles consisting of $\cap$, $\cup$, M, and W shapes. Generally, it is difficult to predict the final shape of the strip due to various related processing parameters in production facilities. The strip crown, while being coiled, may include imperfections that were initiated during the rolling process resulting in flatness imperfection taking place on the coil strip [3, 4].

As a result, the strip is normally welded, cut, and recoiled in the recoiling line so as to satisfy customer strip flatness requirements. However, although adding the recoiling line to the process, flatness problems sometimes cannot be avoided especially for the high-strength coil strip. In order to understand the flatness defect formation mechanism

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during the coiling process, Sims and Place [5] proposed a stress model of the coil assuming that the coil was an axial-symmetry hollow cylinder. Miller and Thornton [6] and Sarban [7] introduced a finite element method and a semi-analytical model to calculate the three-dimensional stress distribution within the coil. Nevertheless, in those models, they did not consider the physical clearance between each coiled wrap due to the strip crown as a cause of the axial inhomogeneity. Yanagi et al. [8] proposed an analytical model by wrapping the thick cylinder (the coil) with the thin-walled cylinders (the new coiling strips) to deal with inhomogeneous deformation of the cold-rolled thin-strip in the axial direction caused by the clearance and the strip crown. Moreover, Park et al. [9] studied the effect of processing parameters including a strip crown, a spool geometry, and coiling tension on the stress distribution on the strip during the coiling process where the analytical elastic model was used. In this study, it was found that enhancement of strip flatness of the cold-rolled thin-strip could be accomplished by suppressing the strip crown and lowering the coiling tension intensity compared to the measured circumferential strain distribution.

To alleviate the undesirable formation of flatness defects, manufacturing the strip coil without the strip crown is suggested as the best solution for fulfilling the strip flatness requirement. Nevertheless, suppressing the strip crown during the rolling process, as illustrated in Fig. 1, is somewhat difficult or even impossible to carry out due to many processing parameters involved. Therefore, use of optimization to find the optimum solution for a spool geometry and coiling tension was conducted [10, 11] in order to improve the strip flatness during the strip coiling process.

Optimization is a special kind of mathematical problem assigned to search for a design solution optimizing a predefined objective or merit indicator within a given feasible region. A numerical optimizer is usually employed to find such a solution. It can be categorized as an optimization method either with and without using function derivatives. The former is based on hard computing while the latter is based on a stochastic process and soft computing. The most popular non-gradient optimizer is an evolutionary algorithm (EAs) or later known as a meta-heuristic (MH). It has been implemented on a wide range of engineering applications and has shown several advantages [12–21]. For metal strip manufacturing, optimization by means of meta-heuristics has been used most commonly in the rolling process so as to control the flatness problem, whereas their use in the strip coiling process has been rarely reported [22–27].

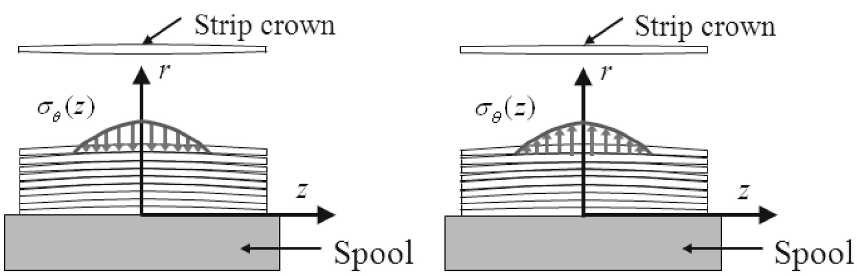
In this study, optimization of flatness of the strips has been enhanced by an improved teaching-learning based algorithm (ITLBO). This method is compared to several well established EAs, such as simulated annealing (SA) [16], differential evolution (DE) [28], artificial bee colony optimization (ABC) [29], real code ant colony optimization (ACOR) [30], original teaching-learning based optimization (TLBO) [31], league championship algorithm (LCA) [32], charged system search (ChSS) [33], Opposition-based Differential Evolution Algorithm (OPDE) [10] and Enhanced teaching-learning based optimization with differential evolution (ETLBO-DE) [11] to determine the spool geometry and coiling tension where the objective is to minimize the axial inhomogeneity of the stress to improve the flatness of the strip. For function evaluations, the analytical elastic model proposed by Park et al. [9] similar to the one suggested by Yanagi et al. [8] was employed.

2 Formulation of the Optimization Design Problem

It is known that wavy edges occur during the strip coiling process, when the circumferential stress at the middle zone of the strip is highly compressed, while two edges are under tension or slight compression. Also, if the middle strip zone is under high tension while the two edges are compressed or slightly stretched, center buckle can happen [8, 9]. Figures 1(a) and (b) display the circumferential stress (σ_θ) distribution along the z direction within the thin strip, which respectively caused the wavy edge and center buckle.

Generally, it is impossible to obtain a flat strip after finishing a rolling process. The strip always has a crown shape. When the strips are being coiled, tension loads need to be applied, the middle zone (z = 0) of the strip at the inner coil will be considerably compressed in comparison with the two edges because of the coiling tension and the strip crown. In such a situation, the center buckle defect at the inner coil will not appear but the wavy edge defect can possibly occur. As such, the wavy edge defect at the inner coil is the major problem during the coiling process. Figure 2 depicts the circumferential stress (σ_θ) distribution in the z direction at the radius (r) of the coil (computed by the Love's elastic solution proposed by Park et al. [9]) contributing to wavy edge defect formation during the strip coiling process. It is possible to reduce the wavy edge defect by decreasing the axial inhomogeneity of the stress distribution and the maximum compressive stress at the compressive zone [10].

In this paper, optimization using the ITLBO and other well-known and newly developed EAs will be used to find the optimum solution for the processing parameters including coiling tension (σ_T) and spool geometry, as illustrated in Fig. 3.



(a) the wavy edge (b) center buckle

Fig. 1. Circumferential stress distributions for (a) the wavy edge and (b) center buckle, respectively [8, 9]

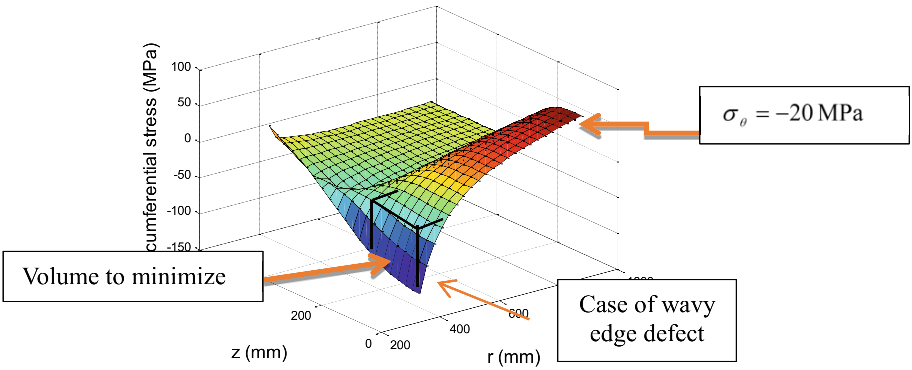


Fig. 2. Circumferential stress distribution (σ_θ) in the coil determined by Love's elastic solution [9]

To decrease the axial inhomogeneity of the stress distribution and the maximum compressive stress, minimization of the volume of the circumferential stress and maximum compressive stress (shown in Fig. 2) is defined as an objective function. In Fig. 2, the volume can only be computed for the coil, where compressive stresses were higher than 20 MPa, in order to minimize the zone that is likely to have the wavy edge defect. The objective function of the optimization problem can then be written as:

$$\text{Minimize} \qquad f(\alpha_b, \eta_b, \sigma_{T,i}) = \frac{V}{V_0} + \frac{\max(\sigma_{\theta c})}{\max(\sigma_{\theta c0})} \tag{1}$$

minimize

$$\begin{aligned} &0 \le \alpha_b \le 4, \\ &0 \le \eta_b \le 4, \\ &25 \le \sigma_{T,i} \le 50 \text{ MPa}; \qquad i = 1, \ldots n_{\max} \\ &\left|\sigma_{T,i} - \sigma_{T,i-1}\right| \le 2 \text{ MPa}, \end{aligned}$$

where $\sigma_{\theta c}$ and V are respectively the compressive circumferential stress higher than 20 MPa (refer to Fig. 2) and the approximate volume of the circumferential stress. $\sigma_{\theta c0}$ and V_0 are the respective values for the original design of the process. The $\sigma_{T,i}$ is the coiling tension at coil number i. The coiling tension is normally set to be constant for all coils [34]. The variable $n_{\max}$ is the maximum number of coils, which has been assigned to be 220 in this paper. η_b and α_b in Eq. (2) are spool crown exponent and the spool crown height, which were used for defining the spool geometry, as described in Fig. 3:

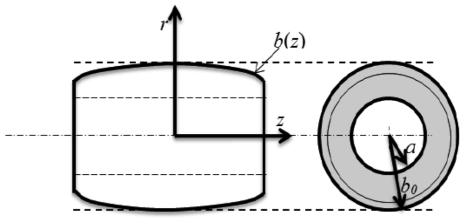


Fig. 3. Spool Geometry used in the present investigation

$$b(z) = b_0 - \alpha_b \left(\frac{|z|}{z_{\max}} \right)^{\eta_b} \tag{2}$$

where b_0 (z = 330 mm) and $b(z)$ are the initial value of the outer radius of the spool and the outer radius of the spool along the z direction, respectively. $z_{\max}$ = 525 mm is the width of the spool. The inner radius of the spool (a) in Fig. 3 has been assigned to be 300 mm. The total number of design variables, therefore, is 222 (220 for coiling tensions and 2 for the spool geometry).

3 Improved Teaching-Learning Based Optimization

From the previous section, the optimization problem can be considered being large-scale. It has been found [10, 11], that TLBO is suitable for this type of design problem. The teaching-learning based optimization (TLBO) algorithm is an evolutionary algorithm, or an optimizer without using function derivatives, proposed by Rao et al. [31]. The concept of TLBO searching mechanism is based on mimicking a teacher on the output of learners in a classroom. Basically, the learners can improve their intellectual and knowledge by two stages i.e. learning directly from the teacher and learning among themselves. During the teacher stage, a teacher may teach the learners, however, only some learners can acquire all things presented by the teacher. Those who can accept what the teacher taught will improve their knowledge. For the second stage, which is called the learning phase, the learners can improve their knowledge during discussion with other learners. Based on the different levels of the learners' knowledge, the better learners may transfer knowledge to the inferior learners.

From the view point of optimization, the algorithm starts with a randomly created initial population, which is a group of design solutions. Learners are identical to design solutions whereas the best one is considered a teacher. The objective function is analogous to the knowledge which needs to be improved towards the optimum solution. Having identified a teacher and other learners for the current iteration, the population will be updated by two stages including "Teacher Phase" and "Learner Phase". In the "Teacher Phase", an individual ($\mathbf{x}_i$) will be updated based on the best individual ($\mathbf{x}_{\text{teacher}}$) and the mean values of all populations ($\mathbf{x}_{\text{mean}}$) as follows:

$$\mathbf{x}_{\text{new},i} = \mathbf{x}_{\text{old},i} + r\{\mathbf{x}_{\text{teacher}} - (T_F \cdot \mathbf{x}_{\text{mean}})\} \tag{3}$$

Where T_F is a teaching factor, which can be either 1 or 2 and $r \in [0,1]$ is a uniform random number.

For the "Learner Phase", the members in the current population will be modified by exchanging information between themselves. Two individuals $\mathbf{x}_i$ and $\mathbf{x}_j$ will be chosen at random, where $i \neq j$. The update of the solutions can then be calculated as:

$$\mathbf{x}_{\text{new},i} = \begin{cases} \mathbf{x}_{\text{old},i} + r\left(\mathbf{x}_i - \mathbf{x}_j\right) & \text{if } f(\mathbf{x}_i) < f\left(\mathbf{x}_j\right) \\ \mathbf{x}_{\text{old},i} + r\left(\mathbf{x}_j - \mathbf{x}_i\right) & \text{if } f\left(\mathbf{x}_j\right) < f(\mathbf{x}_i) \end{cases} \tag{4}$$

At both teacher and learner phases, the new solution ($\mathbf{x}_{\text{new}}$) will replace its parent if it has better knowledge or produces better objective function value, otherwise, it will be rejected. The two phases are sequentially operated until the termination criterion is fulfilled.

For the improved teaching-learning based optimization (ITLBO), an opposition-based approach, binary crossover, and the probability of operating the learning phase are added to the original TLBO to improve the balance of search exploration and exploitation. Four random numbers including, $rand_1$, $rand_2$, $rand_3$, and $rand_4$, have been used for performing opposition-based approach, binary crossover, and the learning phase. The main search procedure starts by generating an initial population, updating the population at the teaching phase and learning phase similarly to the original TLBO. However, at the teaching phase, the updating can be done by the following equation;

$$\mathbf{x}_{\text{new},i} = \mathbf{x}_{\text{old},i} + (-1)^{rand_1} r\{\mathbf{x}_{\text{teacher}} - (T_F \cdot \mathbf{x}_{\text{mean}})\} \tag{5}$$

where $rand_1$ is a random value with either 0 or 1. Then, the binary crossover is applied if a uniform random number having an interval of 0 and 1 ($rand_2$) is lower than the crossover probability (P_r). For a new individual $\mathbf{x}_{\text{new}}^T = [x_{\text{new},1}, \ldots, x_{\text{new},D}]$ and an old individual $\mathbf{x}_{\text{old}}^T = [x_{\text{old},1}, \ldots, x_{\text{old},D}]$, the binary crossover step can be expressed as follow;

$$x_{new,j} \begin{cases} x_{old,j} & \text{if } rand_3 < CR_1 \quad j = 1, \ldots, D \\ x_{teacher,j} & \text{if } CR_1 \leq rand_3 < CR_2 \quad j = 1, \ldots, D \end{cases} \tag{6}$$

where the $rand_3$ is a uniform random number generated from 0 to 1. The CR_1 and CR_2 are the predefined crossover rates, while D is the number of design variables, respectively. Thereafter, the learning phase is conducted if a uniform random number generated from 0 to 1 ($rand_4$) is lower than the probability value (L_p), otherwise, the learning phase will be skipped. The search process will be repeated until the termination criterion is satisfied. The computational steps of the proposed algorithm are shown in Algorithm 1.

Algorithm 1 An improved TLBO

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Input: Maximum iteration number (maxiter), population
size (nP), Crossover probability Crossover rate (CR1 and
CR2), learning phase probability (Lp).
Output: xbest, fbest
Initialization
1.Generate an initial population randomly.
2.Evaluate objective function values
Main algorithm
3.For i =1 to maxiter
   3.1 Identify the best solution (xteacher)
     (Teacher Phase)
       For j=1 to np
       3.2 Update the population using equation (5)
           If rand2 < Pr
               3.2.1 Applied binary crossover using equa-
               tion (6)
           End
           3.2.1 Evaluate the objective function value f
           (xnew,j)
           3.2.2 If f(xnew,j)<f(xold,j)
                   Replace xold,j by xnew,j
           End
       End

       If rand4 < Lp
       (Learner Phase)
       For j=1 to np
       3.3 Update the population using equation (4)
           3.3.1 Evaluate the objective function value
           f(xnew,j)
           3.2.2 If f(xnew,j)<f(xold,j)
                   Replace xold,j by xnew,j
           End
       End
End
```

4 Numerical Experiments

In order to examine the search performance of the proposed ITLBO, several EAs have been used to solve the optimum design problem of the strip flatness as described in the previous section. The EAs used in this study are as follows:

- DE [28]: The DE/best/2/bin strategy was used. DE scaling factor was random from 0.25 to 0.7 in each calculation and crossover probability was 0.7.
- SA [16]: An annealing temperature was reduced exponentially by 10 times from the value of 10 to 0.001 in the optimization searching process. On each loop 2n children were created by means of mutation to be compared with their parent. Here, n is the number of design variables.
- ABC [29]: The number of food sources was set to be $3n_p$. A trial counter to discard a food source was 100.
- ACOR [30]: The parameters used for computing the weighting factor and the standard deviation in the algorithm were set to be $\xi = 1.0$ and $q = 0.2$, respectively.
- TLBO [31]: Parameter settings are not required.
- LCA [32]: The default parameter settings provided by the authors were used.
- ChSS [33]: The number of solutions in the charge memory was $0.2n_p$. Here, n_p is the population size. The charged moving considering rate and the parameter PAR were set to be 0.75 and 0.5, respectively.
- OPDE [10]: The DE/best/2/bin strategy was used. DE scaling factor was random from 0.25 to 0.5 in each calculation and crossover probability used was 0.7.
- ETLBO-DE [11]: Used the DE parameter setting and Latin hypercube sampling (LHS) technique to generate an initial population.
- ITLBO (Algorithm 1): The P_r, CR_1, CR_2 and L_p were set to be 0.5, 0.33, 0.66 and 0.75, respectively.

Each optimizer was employed to solve the problem for 5 optimization runs. Both the maximum number of iterations and population size were set to be 100. For the optimizers using different population sizes, such as simulated annealing, their search processes were stopped with the total number of function evaluations as 100×100. The optimal results of the various optimizers from using this limited number of function evaluations were compared. The best optimizer was used to find the optimal processing parameters of the strip coiling process.

5 Results and Discussion

After applying each optimization algorithm to solve the problem for 5 runs, the results are given in Table 1. The mean values (Mean) are used to measure the convergence rate while the standard deviation (STD) determines search consistency. The lower the mean objective function value the better, and the lower the standard deviation the more consistent. In the table, max and min stand for the maximum and minimum values of the objective function, respectively.

For the measure of convergence speed based on the mean objective value, the best method is ITLBO while the second best and the third best performers are ETLBO-DE and OPDE, respectively. The worst results came from ABC. For the measure of search consistency based on STD, the best was also ITLBO while the worst was ABC, which was similar to the measure of the search convergence. The second best and the third best for consistency were ETLBO-DE and ACOR, respectively. The minimum objective function value was obtained by the ITLBO.

Based on the results obtained, it was clearly indicated that the proposed ITLBO by adding opposition based method, binary crossover, and learning phase probability can improve the search performance of the original TLBO for solving the optimization design problem of the strip coiling process.

The optimal spool crown exponent and height obtained are 1.0822 and 2.3645, respectively. The optimal distribution of coiling tensions as a function of coil numbers is shown in Fig. 4. The results reveal that the coiling tensions start with the highest value initially and then decrease when the number of coils increases. After a few series of coiling, the tension levels become almost constant, converging to the lower bound at the end of the process. Figure 5 shows the plot of the circumferential stress distributions along the z and r directions of the original and optimum design solutions in that order. The comparison of the maximum compressive stresses and the standard deviation of stresses at the inner strip between the original and optimal designs is given in Table 2. The results show that the optimal processing parameters obtained by the proposed ITLBO algorithm can reduce the maximum compressive stress and the axial inhomogeneity of the stress distribution at the inner strip, which might cause undesirable wavy edge defects during the strip coiling process.

Table 1. Objective function values calculated

Evolutionary algorithms	Mean	STD	Max.	Min.
DE	0.9700	0.0275	1.0096	0.9354
ABC	1.7637	0.0787	1.8800	1.6751
ACOR	1.0621	0.0070	1.0705	1.0546
ChSS	1.4026	0.0289	1.4448	1.3678
LCA	1.7116	0.0408	1.7580	1.6473
SA	1.5451	0.0645	1.6323	1.4841
TLBO	0.9915	0.0132	1.0066	0.9766
OPDE	0.9539	0.0179	0.9715	0.9297
ETLBO-DE	0.8850	0.0047	0.8897	0.8784
ITLBO	0.8740	0.0025	0.8783	0.8720

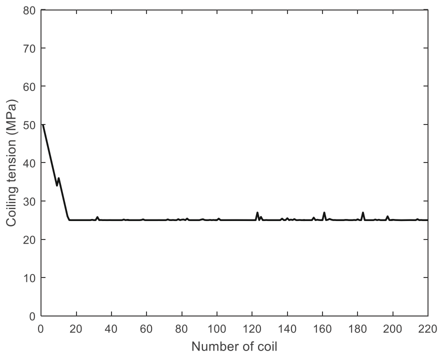
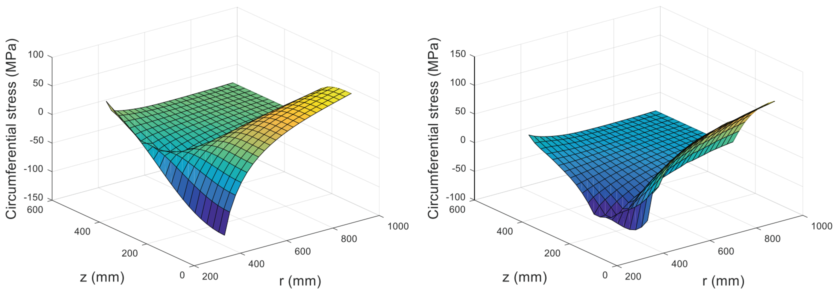


Fig. 4. Coiling tension levels as a function of number of coils



(a) Original design (b) Optimal design

Fig. 5. Comparison of circumferential stresses along the z and r directions for the original design and optimal design, respectively

Table 2. Maximum compressive stress and the standard deviation of stresses at the inner coil

	Original design	Optimal design
Maximum compressive stress [MPa]	111.546	68.0270
Standard deviation of stresses	48.375	29.3703

6 Conclusions

The new population-based optimization algorithm obtained by improving the original TLBO for solving the flatness optimization of the strip coiling process has been proposed. The search performance of the method was compared to various established evolutionary algorithms. The numerical results show that the new optimizer ITLBO is the best performer for both convergence rate and consistency. With this, the new parameters including the spool geometry and the coiling tension distribution have been obtained and can be used in the real strip coiling process. Further studies will be made to enhance the mathematical model of the strip coiling process. A self-adaptive version of ITLBO will be investigated for search performance enhancement.

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