Fuzzy approach to shape control in cold rolling of steel strip

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Indexing term: Fuzzy control

Cross-sectional shape control in the cold rolling of thin steel strips has been simulated using a fuzzy controller and emulator developed using fuzzy theory and neural networks, respectively, based on production data. Irregular cross-sectional shapes of cold-rolled thin steel strips were classified into six types. For each irregular strip shape, fuzzy control rules were developed and applied continuously until the strip shape converged to the desired flat shape. The simulation results demonstrated that the developed fuzzy controller worked properly.

Introduction: The control of cross-sectional shape in rolling thin strips of steel at room temperature has become an important issue in the steel industry. The classical control scheme such as Kalman-filter control has its own limitation for process control for such cases because the process is highly nonlinear [1].

Fuzzy control research was initiated by Mamdani [2]. Many other researchers have investigated the possibilities of fuzzy control in various areas of application. In particular, Hasegawa and Taki [3] studied the shape control system for cold rolling based on fuzzy theory to improve the cross-sectional strip shape.

In the present study, a new approach to improve the productivity and quality of the thin and flat cold-rolled strips ranging in thickness between 0.3 and 0.5mm has been proposed based on fuzzy theory. This proposed controller was developed for the Taejon iron and steel compay.

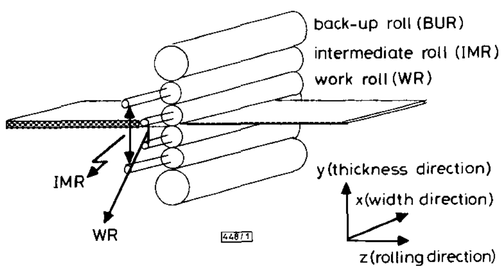

Fig. 1 *Schematic diagram of cold rolling system*

Control variables: A schematic illustration of the cold rolling system is depicted in Fig. 1. In general, the irregular cross-sectional shape can be approximated by power series as follows: $y = \lambda_1 x + \lambda_2 x^2 + \lambda_3 x^3 + \lambda_4 x^4$. Here, x represents the normalised width, and λ_i represent the shape parameters. From the formula, we obtained two important parameters Λ_2 and Λ_4, where $\Lambda_2 = y_1(\pm 1) = \lambda_2 + \lambda_4$ and $\Lambda_4 = y_1(\pm 1/\sqrt{2}) = (1/2)\lambda_2 = (1/4)\lambda_4$.

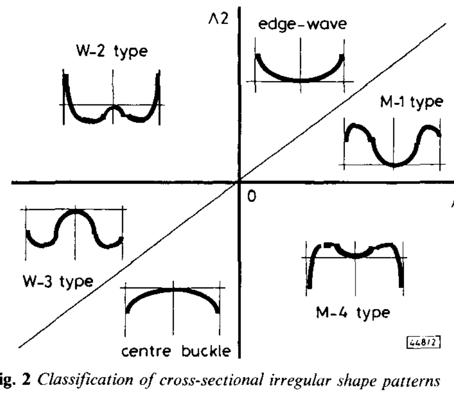

Fig. 2 *Classification of cross-sectional irregular shape patterns*

Analysis of the product data showed that a strong correlation existed between the changes of bending forces of work (ΔF_w) and intermediate rolls (ΔF_i) and shape deformation parameters (Λ_2 and Λ_4). Therefore the fuzzy controller uses Λ_2 and Λ_4 as the inputs and ΔF_w and ΔF_i as the outputs. The irregular shapes were geometrically classified into six types as shown in Fig. 2.

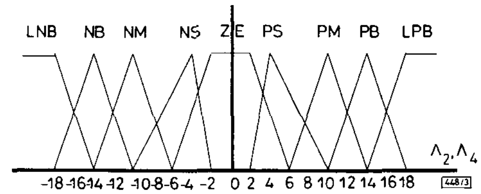

Fig. 3 *Fuzzy linguistic variables*

Fuzzy control system: Fuzzy control is characterised by a number of fuzzy control rules. A fuzzy control rule is expressed by a fuzzy implication in the form of 'if ... then ...', which includes fuzzy linguistic variables. The Mamdani operation was used as the fuzzy reasoning method [2]. The linguistic variables have triangular form as shown in Fig. 3. For each type of irregular shape, the fuzzy control rules were

If Λ_2 is PM and Λ_4 is PM, then ΔF_w is PM, ΔF_i is PM

If Λ_2 is PM and Λ_4 is PS, then ΔF_w is PM, ΔF_i is PS

To predict the controlled strip shape obtained from the fuzzy controller, an emulator was constructed based on the MLP (multilayer perceptron) neural network.

The number of learning data was 1303, and the number of test data was 6506. These data were collected from the continuous operation at the plant. The neural network of the emulator consists of eight input nodes (F_w, ΔF_w, F_i, ΔF_i, Λ_2, $\Delta\Lambda_2$, Λ_4, and $\Delta\Lambda_4$) and two output nodes (Λ_2 and Λ_4). The emulator used the back propagation algorithm and the accuracy of the emulator was tested to be valid.

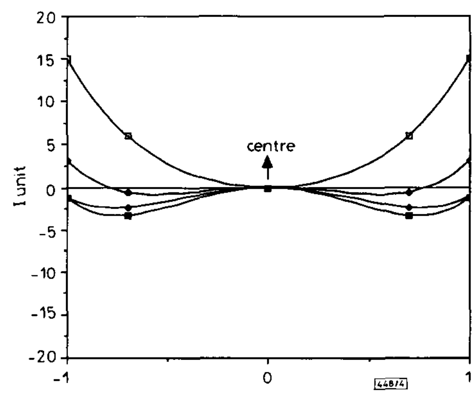

Fig. 4 *Simulation results of shape control for 'edge-wave type'*

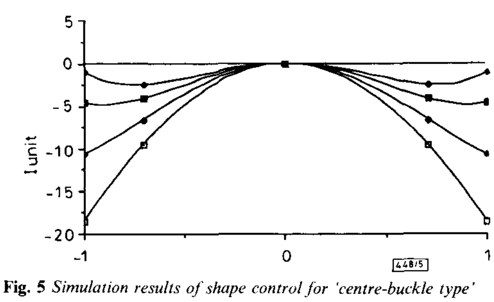

Fig. 5 *Simulation results of shape control for 'centre-buckle type'*

Simulation and discussion: In the simulations, the control was performed for each irregular strip shape until the values of the shape deformation parameters Λ_2 and Λ_4 were located within ±3 I-unit (control unit). We have simulated the controller more than five times for each type. Fig. 4 shows a simulation result for the edge-wave type. It is shown that the initial shape ($\Lambda_2 = 15.0$, $\Lambda_4 = 6.0$) converged to a flat shape after three iterations. Fig. 5 shows the result for the centre-buckle type. These simulations state that the proposed fuzzy controller can be effectively used in real cold rolling process.

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Improved algorithm for Widrow adaptive control scheme

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Indexing terms: Adaptive control, Model reference adaptive control system

A modified adaptive control algorithm is presented which improves the performance and efficiency of the well known scheme proposed by Widrow. Based on the instrumental variables estimation theory, the convergence of the new algorithm is proven. The results of a computer simulation result are also given to show the successful performance of the algorithm.

Introduction: In the field of adaptive systems, the approach of using an FIR (finite impulse response) filter and the LMS (least mean squares) adaptive algorithm as developed by Widrow for adaptive modelling and control is well known [1]. It has been shown that adaptive inverse-model control can be achieved by identifying a delayed inverse model of a stable but uncertain plant, and then the model is used as the adaptive controller for the plant.

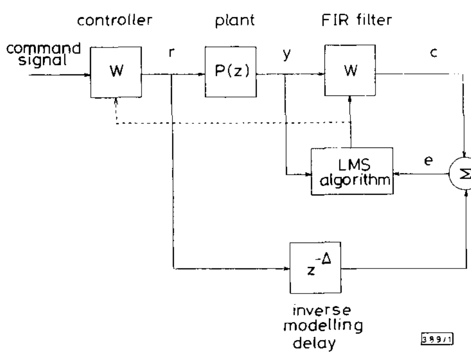

Fig. 1 *Adaptive inverse plant modelling and control (scheme 1)*

This design concept is illustrated in Fig. 1 (called scheme 1) in which the inverse plant model is represented by an FIR filter with weight w. The LMS algorithm for updating w is

$$w_{k+1} = w_k + 2\mu e_k x_k$$
$$x_x = [y_k, y_{k-1}, \cdots, y_{k-L}]^T \quad L : \text{length of FIR filter} \tag{1}$$

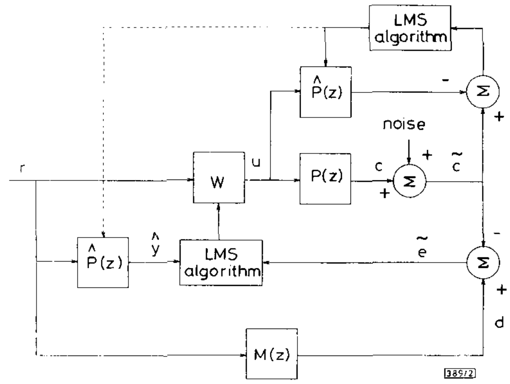

Fig. 2 *Model reference adaptive control (scheme 2)*

When the plant output is corrupted by random noise, w will be biased which would degrade its quality as an optimal controller. This difficulty can be overcome if the alternate control system configuration of Fig. 2 (called scheme 2) is used [1]. The tradeoff is the introduction of an additional modelling process for the forward plant FIR model $\hat{P}(z)$ with weights w_p, which is simultaneously identified along with the updating of w in the controller. The LMS algorithm for w in scheme 2 is

$$w_{k+1} = w_k + 2\mu\tilde{e}_k\hat{x}_k$$
$$\hat{x}_x = [\hat{y}_k, \hat{y}_{k-1}, \cdots, \hat{y}_{k-L}]^T \tag{2}$$

$\hat{x}$ is referred to as the 'filtered x' in [1]. We note that a reference model $M(z)$ is introduced in scheme 2 as a generalisation of the time delay in scheme 1.

Because the LMS algorithm is unbiased when the error e is noisy, both the forward plant model weights w_p and the controller weights w are unbiased in the presence of random noise n at the plant output, so the controller is not degraded as before. However, the transient behaviour of w in scheme 2 is not predictable because $\hat{x}$ is directly affected by the dynamics of the weights w_p in $\hat{P}(z)$. Simulations show that scheme 2 takes much longer to converge than scheme 1.

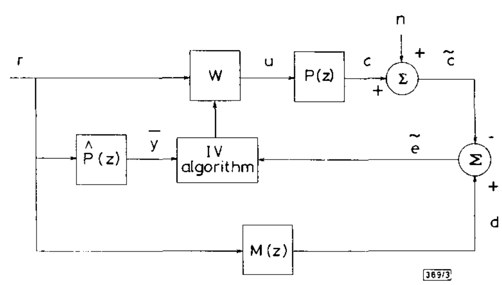

Fig. 3 *Modified model reference adaptive control (scheme 3)*

Improved algorithm: The purpose of this Letter is to introduce a new control configuration (scheme 3) shown in Fig. 3. The adaptive algorithm is

$$w_{k+1} = w_k + 2\mu\tilde{e}_k\bar{x}_k$$
$$x_x = [\bar{y}_k, \bar{y}_{k-1}, \cdots, \bar{y}_{k-L}]^T \tag{3}$$

The major departure from scheme 2 is that the task of estimating the forward plant model $\hat{P}(z)$ is avoided, and $\hat{P}(z)$ is replaced by the nominal plant model $\bar{P}(z)$. We assume that $\bar{P}(z)$ is always available in practice, and the actual plant $P(z)$ deviates from $\bar{P}(z)$ when uncertainties exist in the plant. In the following, we show that this simpler control configuration is asymptotically convergent and it performs as well as expected in simulations.

Because $\bar{P}(z)$ is strongly correlated with $P(z)$, we can define the following statistical properties between $\bar{x}_k$, x_k, and d_k:

$$E[\bar{x}_k x_k^T] = Q \qquad Q \text{ is nonsingular}$$
$$E[\bar{x}_k d_k] = g \qquad g \neq 0$$
$$E[\bar{x}_k n_k] = 0 \qquad x_k \text{ is uncorrelated with } n_k$$