Regression Approach to a Novel Lateral Flatness Leveling System for Smart Manufacturing

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Abstract: Sheet metal coils are widely used in the steel, automotive, and electronics industries. Many of these coils are processed through metal stamping or laser cutting to form different types of shapes. Sheet metal coil leveling is an essential procedure before any metal forming process. In practice, this leveling procedure is now executed by operators and primarily relies on their experience, resulting in many trials and errors before settling on the correct machine parameters. In smart manufacturing, it is required to digitize the machine’s parameters to achieve such a leveling process. Although smart manufacturing has been adopted in the manufacturing industry in recent years, it has not been implemented in steel leveling. In this paper, a novel leveling method for flatness leveling is proposed and validated with data collected by flatness sensors for measuring each roll adjustment position, which is later processed through the multi-regression method. The regression results and experienced machine operator results are compared. From this research, not only can the experience of the machine operators be digitized, but the results also indicate the feasibility of the proposed method to offer more efficient and accurate machine settings for metal leveling operations.

Keywords: coil leveling; roller leveling; sheet metal coil; regression; lateral leveling

1. Introduction

The metal forming industry is considered the main part of mass production in the automotive, electronics, telecommunication, and construction industries. In the metal forming industry, sheet metal coil has been widely used in either metal stamping or laser cutting. In each coil, there are always different common symptoms of unleveling problems, as shown in Figure 1 [1]. The five common symptoms are coil set, crossbow, twisted strip, center buckle, and a wavy edge of the coil. The most common symptom of an unleveled coil is coil set, which is caused by the way the sheet metal is stored and packaged with a surface-to-surface length differential [2]. Coil set can easily be leveled or flattened by a roller leveler with entrance and exit gap adjustment to the rolls. On the other hand, center buckle, wavy edge, and crossbow are lateral (width) lengthwise differences and require leveling in the lateral direction [3]. Due to the increase in sheet leveling quality demand in recent years, leveling in a lengthwise direction can no longer be sufficient for a much higher quality application. As a result, lateral leveling has become a crucial point for leveling quality to deliver high-quality products. In this paper, the research will be focused on the lateral leveling of coil sheet metal.

The leveling process is achieved through a leveling machine, with a sheet metal coil feedthrough on the leveler with the alternating bending process. In recent years, smart manufacturing has been widely discussed for industrial applications due to the initiation of Industry 4.0, and one of the definitions has been defined to better predict and maintain production processes [4]. However, smart manufacturing has not been widely applied within the steel coil leveling process. The leveling process depends on the coil’s thickness, width, tensile strength, yield strength, outer diameter, inner diameter, and the line speed of the production line. It is often through experienced machine operators with many years...
of experience together with trial-and-error techniques that the desired leveling quality is achieved through roll adjustments. During the leveling process, if the operator inputs unsuitable parameters, the whole leveling process of the strip will be required to reverse and restart, a process which is often around 5–10 m in length. Therefore, this manufacturing operation is considered time-consuming and may create much unusable waste sheet metal during the machine setup stage before becoming fully operational. The main advantage for this research is shortening this trial-and-error process. From the literature [5–7], most previous research has focused on investigation with the use of mechanical theories of the leveling mechanism of sheet metals. This method is commonly referred to as the model-driven approach. Apparently, there is limited research tackling the same issue through a data-driven approach based on machine learning techniques. However, with growing demands in smart manufacturing, it is desirable to integrate machine learning technologies into the steel coil processing industry to improve productivity and to offer reliable and repeatable results in leveling sheet metal coils.

![Common symptoms of sheet metal coils.](image)

Figure 1. Common symptoms of sheet metal coils.

Residual stress caused by the manufacturing process was reported in the literature to be the key factor affecting the leveling quality of the sheet metal coils. Many published results regarding the residual stress were based on the solid mechanics model. Yi et al. [8] investigated the evolution of the residual stress in multi-roll leveling, considering the curvature coupling between bendings of the sheet metal through the multi-roll. In their investigation, it was reported that multi-roll leveling could result in rolling residual stress while reducing the initial residual stress of the sheet. Although the larger plastic deformation caused by the intermeshing of the working rolls at the entry is beneficial for the complete elimination of the sheet metal coil’s initial residual stress, the rolling residual stress that is induced in the sheet metal during the multi-roll process can inevitably increase at the same time. Therefore, the total combined residual stress of the sheet metal after leveling depends on the appropriate leveling parameters. Gruber and Hirt [9] linked both the target values of sheet flatness and residual stress distribution and developed a numerical model of a seven-roll leveler that is used to determine the roll positions, resulting in a flat sheet and a defined residual stress distribution. Smith’s [10] simulated results presented here are for 3/8-inch-gauge material with a yield strength of 344 N/mm². The model predicts similar results for both different gauges and different yield strengths. Gruber and Hirt [11] further investigated the correlations between the incoming strip condition, the roll intermeshes, and the residual stresses, which are evaluated to achieve both a constant flatness as well as a distinct residual stress distribution after leveling. Lopez et al. [12] developed the application of the well-known laser ranging techniques in flatness inspection and construction and the testing of a flatness measurement and inspection system capable of acquiring the true shape of a steel strip in real-time, leading to calculating its flatness indexes so they can be used in the quality inspection of the steel products. Abvabi et al. [13] found an inverse technique that could be used to obtain the residual stress profile and material constants. This technique provided the best fit in a finite element analysis of bend-
ing with the experimentally derived moment curvature relation. Park [14] and Liu [15] developed a numerical algorithm for analyzing the effect of the leveling conditions on the residual stress. With the reported methods, one was able to implement the effect of plastic deformation in leveling, tension, work roll bending, and the initial state of the sheet (residual stress and curl distribution).

In recent years, machine learning for smart manufacturing has been a widely discussed topic in many different applications, such as image processing, medical application, energy management, and planning data-driven digital twins [16]. Here are several examples reported in the literature that the machine learning method can improve the model-based approach. Zhong et al. [17] identified that the machine learning method can be used for reliability analyses and decision support systems through the use of regression analysis to predict the interval generation framework. Makki and Mosly [18] applied logistic regression to predict construction site accidents, which can be reduced through proactive steps using prediction models. Wu et al. [19] used ordinal logistic regression to the automatic scoring system for the functional movement screen (FMS). Truong et al. [20] proposed machine learning approaches to develop an energy prediction algorithm for accurately forecasting the day-ahead hourly energy consumption profile of a residential building while considering the occupancy rate. Mitu et al. [21] identified that automated spectral analysis of surface wave inversion can be enhanced with the use of machine learning’s linear regression (LR) algorithms. Kim et al. [22] utilized multiple regression models to estimate the power generation of a solar power plant with changing weather conditions. Yang et al. [23] developed an automated optical inspection (AOI) system for O-ring inspections using regression analysis. Liang et al. [24] proposed a novel multi-objective particle swarm optimization (MOPSO) algorithm employing the Gaussian process regression (GPR)-based machine learning (ML) method for multi-variable, multi-level optimization problems with multiple constraints. Finally, Lee et al. [25] used multiple ordinal logistic regression analyses to explore the medical outcomes among respiratory patients.

In this paper, multiple regression algorithms are employed to predict the output values based on input features from the data set input into the leveling system. This paper is divided into experimental methods and a regression model. The experimental method that will be addressed in what follows will be carried out with simulations and experimental data to verify such measurements with supporting algorithms and measured data. It is found that greater improvement can be reached with the proposed method with regression analysis when compared with trial and error based on the experienced operator.

2. Machine Application Background

The schematic drawing of the model leveling machine can be seen in Figure 2. As illustrated in Figure 2a, the sheet metal coil is fed through between the top layer and bottom layer of the leveling machine. The leveling machine consists of work rolls, intermediate rolls, and backup rolls. The work rolls are in direct contact with the sheet metal. The intermediate rolls act as a pressure distribution buffer between the backup rolls and work rolls. As is shown in Figure 2b, five backup roll sets, which are placed evenly along the sheet’s lateral direction but with rolls in each set packed similar to the work rolls and intermediate rolls along the sheet’s traveling direction, are used to support the work roll through the intermediate roll. In addition, the five backup roll sets are used to prevent the deflection of the work rolls while leveling the coil sheet material. The other main purpose of the backup roll sets is shape correction, particularly for the coil sheet’s lateral leveling process. Therefore, backup roll adjustments were our primary focus for this paper.

In the neutral setting, the work rolls and backup rolls are straight and parallel. This setting is used for leveling coil set and crossbow symptoms as shown in Figure 1, as those two cases do not have uneven lateral coil problems. However, lateral (widthwise) leveling requires adjusting the height of each of the roll in the backup set; that is, it requires adjusting the force pointing down toward the work rolls through the intermediate rolls for each of the five backup sets as shown in Figures 2 and 3. For the leveling machine, it is
common to place the multi-roll along the sheet’s traveling direction (i.e., the lengthwise
direction), since the sheet inevitably exhibits a waveform in its shape from its initial coil set [26]. However, in such a design, an assumption is made of an ideal or perfect state along the sheet’s lateral direction and that no waviness is allowed to appear in the sheet’s widthwise portion. In reality, due to manufacturing imperfections and handling damages, this is not actually true. For example, for wider sheet metal coils, cross-width imperfections in the form of edge wave and center buckle can be easily observed. As such, the leveling or adjustment of the waviness of the sheet becomes important. In such cases, as illustrated in Figure 3, due to edge wave imperfection, the sheet has a longer length in its two edges than its center part, whereas for the center buckle case, it has a longer length in the center than at the two edges. Since the mentioned backup sets in present industry machines can only make adjustments to the so-called non-flat sheet span along its lateral direction (i.e., making the sheet thinner), this adjustment will need to adjust where the fibers are shorter to equalize the length and make the sheet flat.

Figure 2. Schematic drawing of the (a) front view and (b) side view of the industry leveling machine used in this study.

Figure 3. Leveling machine backup adjustment [27] for (a) leveling edge wave and (b) leveling center buckle.

In the case of leveling center buckle or the sheet retaining a long center along its lateral direction, such as in the case shown in Figure 3b, it is required to stretch the edges until they are the same length as the center [27]. In this scenario, the backup rollers are adjusted to be tight on the center and loose in the edges. On the other hand, in the case of edge waves or long edges, as shown in Figure 3a, it is required to stretch the center until it is the same length as the edges [28]. In this scenario, the backup rollers are adjusted to be tight on the edges and loose in the center. This means that we will stretch the edges in a controlled manner. There are examples in the literature that have addressed backup roll design [28,29]. However, backup roll adjustments for lateral leveling have been limited. This is a common practice in the coil leveling industry from machine operators with years of experience. Therefore, utilizing the regression method for parameter prediction for backup adjustments is the motivation of this research.

3. Materials and Methods
3.1. Experiment Instruments

In this research, five laser sensors were used to measure the sheet metal surface during a leveling process with a line speed of 12 m/min as shown in Table 1. As shown in Figure 4a,
each of the sensors was placed on the sensor bar in line with where the backup roll set was placed; that is, the five laser displacement sensors were installed along with the backup set along the steel sheet’s lateral direction. Therefore, in such placement, the sensors could measure the waviness or flatness of the sheet and be used as a feedback signal to the system to adjust the actuation of each of the five backup rolls. Figure 4b is shown to demonstrate where the sensor was placed in the system. The sensors’ readings were based on the triangulation principle [30], where the laser beam is enlarged into a line and projected onto the surface of the object to be measured. The root mean square and average height deviation were calculated within the system.

Table 1. Laser sensor specifications.

| Brand Measure Range (Z-Axis) | Baumer 100–150 mm |
|-----------------------------|-------------------|
| Field of View (X-axis)      | 48–72 mm          |
| Resolution                  | 2–4 µm            |
| Measuring Rate              | <500 Hz           |
| Ambient Light Immunity      | <35 kLux          |
| Interface                   | Analog, RS485     |

![Figure 4](image.png)

**Figure 4.** (a) Schematic drawing of the sensors’ placement and (b) a photograph of the model lateral leveling sensor measurement system.

The laser sensors used in this research had the specifications shown in Table 1. The sensor had a measurement range of 100–150 mm and a resolution of 2–4 µm. The flatness variation of the steel sheet after the leveler ranged between 3.0 mm and 0.5 mm. Therefore, this sensor measurement system was capable of and suitable for providing meaningful and useful flatness measurements of the steel sheet through the model lateral leveling process.

3.2. Regression Analysis

In this paper, multiple linear regression (MLR) analysis was applied to determine the relationship between the dependent variables and independent variables [31–35]. As mentioned by Kim et al. [22], this multiple regression analysis can be used to estimate the value of a dependent variable by substituting the values of the independent variables. The dependent variables ($y_i$) in this paper are defined as the output of each backup roll adjustment value. The independent variables ($x_i$) are the measured input data and the specifications of the sheet metal coil. The backup set adjustment output is estimated using the MLR model as follows [31,32]:

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_p x_{ip} + e_i$$  (1)
where the $\beta_k$ ($k = 0, 1, 2, \ldots, \rho$) coefficients are unknown parameters and $e_i$ is a set of random error terms. The subscript $i$ indicates the observational unit from which the observations of $y$ and the $\rho$ independent variable were taken [34].

In this case, the relationship between the target and predictor variables is unknown. Therefore, it is often required to estimate this relationship or to equivalently estimate the unknown parameters $\beta_k$. To achieve this goal, least squares regression is used for estimation, in which the sum of the squares of the residuals is a measure of the discrepancy between the data and an estimation model mentioned by Weisberg [31], such as linear regression. A small sum of the squared residuals (SSR) indicates a tight fit of the model to the data, which mathematically can be expressed as

$$SSR = \sum_{i=1}^{n} e_i^2 = \sum_{i=1}^{n} [y_i - (\beta_0 + \beta_1 x_{1i} + \cdots + \beta_\rho x_{\rho i})]^2$$

or simply as

$$SSR = \sum_{i=1}^{n} e_i^2 = e_1^2 + e_2^2 + \cdots + e_n^2$$

As demonstrated by Chatterjee et al. [32] and Raschka [35], to measure the strength of the regression relationship $R^2$, this is expressed as the fraction of the regression squared residuals over the corrected total squared residuals as

$$R^2 = \frac{\sum (\hat{y}_i - \bar{y})^2}{\sum (y_i - \bar{y})^2} = \frac{\text{Regression SS}}{\text{Corrected total SS}}$$

where $\hat{y}_i$ is the fitted value and $\bar{y}$ is the sample mean of the target value. This $R^2$ value (also called the coefficient of determination) estimates the population proportion of variability in $y$ accounted for by the best linear combination of the predictors. Its value being closer to 1 indicates a good deal of predictive power from the predictors for the target variable, while a value closer to 0 indicates little predictive power.

Multiple regression analysis has two or more independent variables. It is necessary to consider the adjusted coefficient of determination, denoted as $R_a^2$, as $R^2$ is an estimate of the population proportion of variability accounted for by the regression. $R_a^2$, in fact, compensates for the characteristic of $R^2$ and corrects this bias as expressed by the following equation [32]:

$$R_a^2 = R^2 - \frac{p}{n - p - 1} \left(1 - R^2\right)$$

where $(n - p - 1)$ is the degree of freedom, $n$ is the number of samples, and $p$ is the number of independent variables.

### 3.3. Machine Learning Workflow

In this research, the training data used were the previously recorded data from flatness verification against the machine operator’s input value while applying the leveling process during production. The sample data were then applied using multiple regression as a training model to predict the parameters for the leveling process. The machine learning workflow of this research was based on a flowchart, as shown in Figure 5. The measuring system was set up at the exit side of the leveler, and each of the sensors was placed at the same position as each of the backup sets. Therefore, each laser sensor could measure the flatness of the sheet at the location leveled or corrected by each of the backup sets. The system was initiated by receiving reading sample data from the laser sensor. After receiving the value, it checked whether the value was above the flatness threshold. If the value was above the threshold, the sensor reading was fed forward to the multiple regression model for the machine learning process. After the value was predicted, each backup set was adjusted based on the calculated value to achieve an optimized value for flatness. The backup set was adjusted up or down through the servo motor to deform the
work roll as shown in Figure 3 according to a different application. Finally, the learned regression model was validated in this research.

![Methodology flowchart used for leveling with the proposed machine learning method.](image)

4. Results and Discussion

After carrying out the experiment through machine learning using the multiple regression method, the results from the machine operator and the machine learning output are compared in this section. The experiment was carried out using the same input condition for both the machine operator’s method and the machine learning method. The sensor fed the sample data into the machine learning section to train and predict the backup roll set parameters for the corresponding scenario. On the other hand, the experienced machine operator also put down the recommended parameters based on years of experience.

Each of the backup sets from 1 to 5 was simulated with the MLR method as shown in Tables 2–6. Each of the regression models was simulated with the related independent variables. The independent variables were mostly sheet metal coil-related properties marked with line speed and flatness readings from the laser sensor in the system. In addition, it can be seen that the line speed of the production line had a lower coefficient than the other independent variables, as the line speed did not have much impact on how to level a coil sheet. On the other hand, the coil thickness and flatness readings had the
The strongest impact on the regression model, as they both had higher coefficients than the other independent variables. As shown from the results, all of the independent variables had p-values less than 0.05, and the null hypothesis could be rejected. This p-value was used in statistical testing to determine the probability of extreme results or inform a statistically significant relationship.

Table 2. Multiple linear regression model for backup set 1.

| Backup Set 1 | Coefficient | Standard Error | p-Value          |
|--------------|-------------|----------------|-----------------|
| Constant     | 20.52       | 6.2            | 3.5 × 10⁻¹⁶     |
| Coil thickness | −19.63     | 2.15           | 2.1 × 10⁻¹⁵     |
| Coil width   | 2.69        | 0.25           | 4.5 × 10⁻¹³     |
| Coil tensile strength | 7.32        | 0.86           | 5.9 × 10⁻¹³     |
| Coil yield strength | 6.27        | 0.18           | 7.8 × 10⁻¹⁵     |
| Coil outer diameter | 1.64        | 0.11           | 6.0 × 10⁻¹³     |
| Coil inner diameter | 3.52        | 0.42           | 7.5 × 10⁻¹⁶     |
| Line speed   | 0.24        | 0.12           | 8.7 × 10⁻¹³     |
| Flatness reading | 21.53       | 1.58           | 3.6 × 10⁻¹⁴     |

Table 3. Multiple linear regression model for backup set 2.

| Backup Set 2 | Coefficient | Standard Error | p-Value          |
|--------------|-------------|----------------|-----------------|
| Constant     | 18.64       | 4.52           | 4.2 × 10⁻¹⁴     |
| Coil thickness | −19.79     | 3.04           | 2.3 × 10⁻¹¹     |
| Coil width   | 2.42        | 0.58           | 5.2 × 10⁻¹³     |
| Coil tensile strength | 6.45        | 0.74           | 5.8 × 10⁻⁹      |
| Coil yield strength | 5.87        | 0.14           | 5.6 × 10⁻¹¹     |
| Coil outer diameter | 2.08        | 0.16           | 6.0 × 10⁻¹⁴     |
| Coil inner diameter | 3.87        | 0.34           | 1.0 × 10⁻¹⁶     |
| Line speed   | 0.21        | 0.18           | 7.6 × 10⁻¹²     |
| Flatness reading | 24.38       | 2.08           | 6.5 × 10⁻⁰⁹    |

Table 4. Multiple linear regression model for backup set 3.

| Backup Set 3 | Coefficient | Standard Error | p-Value          |
|--------------|-------------|----------------|-----------------|
| Constant     | 19.48       | 2.54           | 5.3 × 10⁻¹³     |
| Coil thickness | −19.45     | 2.85           | 1.4 × 10⁻¹¹     |
| Coil width   | 3.56        | 0.68           | 1.8 × 10⁻¹⁴     |
| Coil tensile strength | 6.53        | 0.62           | 1.9 × 10⁻¹³     |
| Coil yield strength | 5.92        | 0.23           | 1.8 × 10⁻¹⁶     |
| Coil outer diameter | 2.67        | 0.17           | 2.7 × 10⁻¹³     |
| Coil inner diameter | 3.5         | 0.42           | 1.8 × 10⁻¹³     |
| Line speed   | 0.278       | 0.17           | 6.8 × 10⁻¹⁴     |
| Flatness reading | 30.51       | 2.54           | 2.1 × 10⁻¹³     |

Table 5. Multiple linear regression model for backup set 4.

| Backup Set 4 | Coefficient | Standard Error | p-Value          |
|--------------|-------------|----------------|-----------------|
| Constant     | 16.55       | 5.73           | 1.8 × 10⁻¹⁰     |
| Coil thickness | −19.87     | 2.74           | 1.5 × 10⁻¹⁴     |
| Coil width   | 3.74        | 0.78           | 3.6 × 10⁻¹¹     |
| Coil tensile strength | 5.43        | 0.82           | 5.2 × 10⁻⁷      |
| Coil yield strength | 5.27        | 0.74           | 3.4 × 10⁻¹³     |
| Coil outer diameter | 2.85        | 0.19           | 2.5 × 10⁻¹²     |
| Coil inner diameter | 3.47        | 0.23           | 1.5 × 10⁻¹²     |
| Line speed   | 0.18        | 0.02           | 2.8 × 10⁻¹⁴     |
| Flatness reading | 26.45       | 2.15           | 7.8 × 10⁻¹²     |
Table 6. Multiple linear regression model for backup set 5.

| Backup Set 5                | Coefficient | Standard Error | p-Value       |
|-----------------------------|-------------|----------------|---------------|
| Constant                    | 20.75       | 4.32           | $6.9 \times 10^{-8}$ |
| Coil thickness              | $-19.67$    | 1.89           | $5.8 \times 10^{-13}$ |
| Coil width                  | 2.22        | 0.97           | $2.8 \times 10^{-13}$ |
| Coil tensile strength       | 7.62        | 0.62           | $5.4 \times 10^{-10}$ |
| Coil yield strength         | 7.15        | 0.45           | $2.2 \times 10^{-12}$ |
| Coil outer diameter         | 2.97        | 0.18           | $7.5 \times 10^{-11}$ |
| Coil inner diameter         | 4.08        | 0.43           | $4.5 \times 10^{-12}$ |
| Line speed                  | 0.22        | 0.15           | $8.2 \times 10^{-11}$ |
| Flatness reading            | 20.97       | 1.98           | $1.9 \times 10^{-12}$ |

Table 7 below shows the regression results for each of the five backup sets, namely backup set 1 to set 5. The $R^2$ and adjusted $R_a^2$ were all around 0.81–0.88, with slight variation between each of the backup sets. The values for the root mean square error (RMSE) and standard deviation error (Std. Error) were all within 30. Thus, it was considered as a good fit for the regression models.

Table 7. Regression results for each backup set.

|                  | $R^2$  | $R_a^2$ | RMSE | Std. Error |
|------------------|--------|---------|------|------------|
| Backup set 1     | 0.8856 | 0.8156  | 20.55| 19.52      |
| Backup set 2     | 0.8951 | 0.8513  | 21.54| 18.62      |
| Backup set 3     | 0.8125 | 0.8763  | 22.35| 20.56      |
| Backup set 4     | 0.8698 | 0.8865  | 26.25| 22.65      |
| Backup set 5     | 0.8725 | 0.8425  | 30.15| 26.79      |

From the above MLR model, the machine learning system was tested with two different common coil defects. The defects were based on the edge wave and center buckle of the sheet metal coil. The system was tested and recorded with different samples with training outputs, which were later compared with those from an experienced machine operator. The experiment was tested with a defined success rate of 100% being a flatness of 60 µm or lower, a flatness specification which is a common standard in the sheet metal leveling industry. After the flatness reading was recorded, it was calculated as a percentage against 60 µm as a reference. The experiment was conducted with 1000 test samples during coil leveling processing. The regression model was input to the system to train and provide a progressive output as shown in Figures 6 and 7 for leveling edge waves and center buckle, respectively.

During the leveling of edge waves, the backup sets need to provide slightly tight space in the middle and loose space at the edges so that the sheet can expand laterally toward its two edges and make it flat. The results, shown in Figure 6, indicate that as the number of samples increased, the regression model could offer a success rate over 96%, whereas the experienced machine operator apparently was capped by a ceiling. The experienced machine operator may have produced a relatively good success rate when the number of samples was small. However, when the number of samples increased, the operator’s “experience” may not have been good enough to make the proper judgement in adjusting the backup sets. In general, the experienced machine operator was shown to provide a success rate of around 80–90% during all of the 1000 test samples, which apparently was not as good as the results generated by the proposed method. Additionally, in comparing the results of the regression model and the machine operator, the regression model was shown to be more consistent for the success rate. Due to the edge wave possibly not being the same for both edges, it was harder for the machine operator to use solely experience for trials and errors to keep the leveling results consistent for the entire process. As a result, the regression model was shown to have a higher success rate and a more consistent for the edge wave leveling application.
In the center buckle leveling process, the backup roll set needs to be tight on the edges and loose in the center. The results, shown in Figure 7, offered a success rate over 97% with the regression model over 1000 samples. On the other hand, the machine operator was shown to have a success rate varying between 80% and 95% when the test samples became large. In this application, although the machine operator and regression model were shown to have similar outcomes, the consistency for the regression model was also shown to be greater for the buckle leveling process over 800 samples. From the results, it was observed that the machine operator was shown to produce fluctuating results, primarily because the trial-and-error approach based on experience could not show the ability to adapt to the variation as quickly as the regression method.

From the edge wave and center buckle lateral leveling, it can be seen that the machine learning model using the MLR method was shown to be consistent for the two applications when there were over 800 samples. The success rate was over 96% for both of the applications. They were also shown to be more consistent than the experienced machine operator, since the trial-and-error terms were neglected in the system.
5. Conclusions

In this research, a parametric study on lateral leveling with the adjustment of backup sets in the model industry leveling machine was achieved with the MLR machine learning method. The predicted results with the proposed method were compared with experienced machine operators, from which it was concluded that more consistent accurate results could be achieved with the proposed method, particularly for leveling or flattening the waviness of edge wave and center buckle in steel sheets. The results showed success rates over 96%, whereas the experienced machine operator’s success rate was shown to be around 80–90% during the leveling of edge waves. In the center buckle leveling process, the results showed over a 97% success rate, whereas the machine operator was shown to have a variation of 80–95% for their success rate. By increasing the success rate and consistency, the machine setting time was shortened compared with the conventional machine operator input value method. The proposed method was conducted with industrial leveling equipment to validate the effectiveness of the leveling process for edge wave and center buckle. Further research with the proposed method is possible for the consideration of leveling crossbow and twisted strip. In addition, different machine learning methods such as random forest regression and decision tree regression can also be applied to this application and compared with the MLR method used in this research for further accuracy improvement.

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