

## Research Article

# Plasma Torch Height Tracking Based on Rolling Grey Prediction

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## Abstract

Among the parameters influencing plasma arc cutting, arc current, cutting speed, and plasma torch height act as the main factors. Among them, the plasma torch height plays an important role in improving the kerf width and cut quality, and the automatic control of the plasma torch height is essential due to the deformation of the workpiece during the cutting process. Therefore, according to the surface condition of the workpiece during plasma cutting, it is required to have automatic control so that the gap between the plasma nozzle and the cut workpiece remains constant. The plasma torch height control system in this paper consists of the sensing, controller, prediction, and stepper motor control system of the plasma torch height. Here, the rolling mode grey prediction algorithm is applied to predict the next state for the cutting forward direction and to control the previous data continuously updating. It is shown by the Simulink results of Matlab that the plasma torch height tracking with rolling grey prediction has better tracking accuracy than the general PID control method. In addition, the comparison between the plasma torch height tracking experimental results using the rolling grey prediction based method and the tracking experimental results using the general PID control method in the cutting test showed that the variation of the arc voltage is less, the cutting width is smaller, and the tracking performance is improved.

## Keywords

CNC Plasma Cutting, Height Control, Grey Prediction, Arc Sensing, Curve Approximation

## 1. Introduction

Plasma cutting is a thermal cutting process, and its quality can be altered due to the changes in the cutting parameters during plasma cutting and other some other reasons. When a power supply of the stable current output characteristics is used, torch height is an important factor affecting cutting capacity and cutting quality [1, 7-9, 14, 16].

In computer numerical control (CNC) plasma arc cutting

the plasma torch height monitoring and controlling are important as the plasma torch height is changed for some reasons such as an undulation and thermal deformation of the workpiece in the cutting condition etc. When the plasma torch height is kept constant, the quality of the cutting can be improved, the damage of the plasma electrode and nozzle can be prevented and their lifetime can be extended.

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**Received:** 11 October 2024; **Accepted:** 15 November 2024; **Published:** 13 December 2024



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During the plasma arc cutting process, the properties of cutting-generation sound are changed with the variation of arc voltage, cutting speed, air pressure and plasma torch height, especially frequency components and noise energy of sound are different. Therefore this properties can be used to monitor the cutting process [3-6].

The plasma torch height sensing method can generally be categorized into the contact and non-contact types. Of these, owing to the high tracking precision and the lack of problems of wear between the sensor and the cutting workpiece, much attention has been focused on the non-contact mode in arc welding [2].

In order to investigate the effectiveness of non-contacting sensors including laser and arc types.

The plasma cutting process is accompanied by a high temperature and strong arc light, is causing some sever conditions for the sensor applications.

Aiming this effect, the optical filter has been used to remove the disturbances and maintain a sufficient spacing between the arc and the projected light spot.

However, it raises a problem of discordance between the real arc position and the sensed one.

On the other hand, the arc sensing method based on the apparent altering of the arc voltage when plasma torch height changed is proposed to detect the torch height [10, 17].

To improve the tracking performance of plasma torch heights, a proportional control scheme using prediction terms has been proposed, and the experiments have shown that its tracking performance is improved compared to conventional proportional integral differential (PID) control.

Recently, the grey theory has effectively been applied to many forecasting problem. In [13], a grey predictive fuzzy control method (GPFC) was applied. Next, in view of the drawbacks of the conventional grey model GM (1, 1) model, a method using the genetic algorithm to adaptively change the model parameters is presented in order to increase the accuracy of the prediction [11, 13, 15]. The simulation results showed that the prediction accuracy of the improved grey prediction model is higher.

## 2. Prediction by Grey Model

### 2.1. General Grey Model GM (1, 1)

Grey model of GM (1, 1) form called “one variable first order model” has been used widely in papers. This model is time series prediction model. This model is updated with new data that is effective for the prediction model. To reduce randomness, convert the original data obtained from the system to an operator called Accumulating Generation Operator (AGO) to construct the GM (1, 1) model. By solving the differential equation, n-step forward prediction of the system is obtained. Finally, using the predicted value, the Inverse Accumulating Generation Operator (IAGO) is applied to find the predicted values of original data.

When let's assume non-negative primitive sequence

$\{X^{(0)}(k)\} = \{X^{(0)}(1), X^{(0)}(2), \dots, X^{(0)}(n)\}$  and this sequence is subjected to the AGO, the following sequence  $\{X^{(1)}(k)\} = \{X^{(1)}(1), X^{(1)}(2), \dots, X^{(1)}(n)\}$  is obtained.

The generated mean sequence of  $X^{(1)}$  is defined as.

$$Z^{(1)} = \{Z^{(1)}(1), Z^{(1)}(2), \dots, Z^{(1)}(n)\}$$

Where  $Z^{(1)}$  is mean value of adjacent data.

The least square estimate sequence of the grey difference equation of GM (1, 1) is defined as follows.

$$X^{(0)}\{k\} + az^{(1)}\{k\} = b \quad (1)$$

The first-order differential equation is therefore, as follows.

$$\frac{dx^{(1)}(k)}{dt} + ax^{(1)}\{k\} = b \quad (2)$$

where a is a developing coefficient and b represents the grey input.

In above,  $[a, b]^T$  is a sequence of parameters that can be found as follows.

$$[a, b]^T = (B^T B)^{-1} B^T Y \quad (3)$$

Where  $Y = [x^{(0)}(2), x^{(0)}(3), \dots, x^{(0)}(n)]^T$

$$B = \begin{bmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ \vdots & \vdots \\ -z^{(1)}(n) & 1 \end{bmatrix} \quad (4)$$

According to Eq. (2), the solution at time k can be found as.

$$\hat{x}^{(1)}(k+1) = [x^{(0)}(1) - \frac{b}{a}]e^{-ak} + \frac{b}{a} \quad (5)$$

To obtain the predicted value of the primitive data at time (k + 1), the IAGO is used to establish the following grey model.

$$x_p^{(0)}(k+1) = [x^{(0)}(1) - \frac{b}{a}]e^{-ak} (1 - e^a) \quad (6)$$

### 2.2. Rolling Grey Prediction

Discrete sequences that reflect the dynamics of the system have regular trends and irregular variability, and the regular trends provide useful information for constructing the dynamics of the system, irregular variability can be considered as disadvantageous information. The irregular variability makes the regular tendency obscure. Several transformations have

been proposed to weaken the irregular variability embedded in discrete sequences. In the traditional grey prediction model considered earlier, the adjacent average equivalence interval generation rule is used as a generation transform.

We use the adjacent average non-equivalence interval generation rule and define the smoothing process of adjacent three values, i.e., the three-point average process, as follows.

$$\begin{cases} x^{(0)}(1) = \frac{3x^{(0)}(1) + x^{(0)}(2)}{4} \\ x^{(0)}(i) = \frac{x^{(0)}(i-1) + 2x^{(0)}(i) + x^{(0)}(i+1)}{4} \\ x^{(0)}(n) = \frac{x^{(0)}(n-1) + 3x^{(0)}(n)}{4} \end{cases} \quad (7)$$

where  $i = 1, 2, \dots, n$

In this expression, we can see that the weight at the present time point has been increased.

When considering the dynamic characteristic of a state with time, generally predicting using GM (1, 1) models, only a few recent numerical data have a relatively high accuracy and the prediction accuracy of the model is increasingly weakened with time. To compensate for this deficiency, grey metabolism is introduced.

Considering the dynamic variation of the grey scale activity is important for increasing the prediction accuracy of the model and lowering the error. First, we construct a GM (1, 1) model that simultaneously optimizes the grey activity and time response function from the original sequence to obtain one prediction value. Then, in the original sequence, which adds this predictor, we simultaneously eliminate the previous data and keep the dimensions of this data sequence and the original one to be equal. Then, based on the sequence, the corresponding improved GM (1, 1) model is rebuilt to predict one data. In a sequence that adds the new predicted data, we remove the previous data and make the dimensions of the data sequences equal.

We calculate the  $\hat{x}^{(0)}(n+1)$  with initial original sequence and then remove the first value  $x^{(0)}(1)$  in the original sequence and make the following new sequence by adding newly predicted value  $\hat{x}^{(0)}(n+1)$ .

$$\{y^{(0)}(k)\} = \{x^{(0)}(2), x^{(0)}(3), \dots, x^{(0)}(n), \hat{x}^{(0)}(n+1)\} \quad (8)$$

Next, we determine the  $\hat{x}^{(0)}(n+2)$  by applying  $\{y^{(0)}(k)\}$  as the new original number sequence. In the same way, we determine.  $\hat{x}^{(0)}(n+3)$ ,  $\hat{x}^{(0)}(n+4)$ ,  $\hat{x}^{(0)}(n+5)$ ,...

### 3. Plasma Torch Height Control Based on Rolling Mode Grey Prediction Model

In the plasma torch height tracking, the tracking orbits

between the control cycles can usually be divided into three types. The shapes of the tracking orbit are shown in Figure 1. In this figure, 1-curve is linear approximation shape of tracking orbit, 2-curve is nonlinearly increasing approximation shape and 3-curve is nonlinearly decreasing approximation shape of tracking orbit.

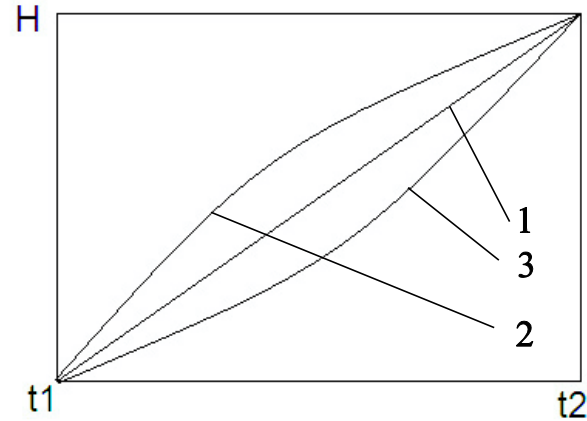


Figure 1. The tracking curve types of plasma torch height ( $t1$ ,  $t2$ -control point,  $H$ -plasma torch height).

This tracking orbit control function can be calculated as follows. If we assume the measured values of the previous plasma torch height as  $\{x^{(0)}(1), x^{(0)}(2), \dots, x^{(0)}(n)\}$ , the second-order polynomial approximation model can be obtained from these data.

$$H_i = a_1 \cdot x^{(0)}(i)^2 + a_2 \cdot x^{(0)}(i) + a_3, \text{ where } i = \overline{1, n} \quad (9)$$

The coefficient  $a_1$ ,  $a_2$ ,  $a_3$  are calculated by least squares method.

Based on this, we calculate the tracking curve up to predicted desired value  $\hat{x}^{(0)}(n+1)$ , the tracking orbit in the time interval between the previous control time  $t1$  and the next control time  $t2$ . This is to predict the next target value for each control cycle and derive a fractionated tracking orbit. Thus, approximating the tracking orbit during the whole control period can reduce the tracking error, compared to the linear approximation.

Next, the block diagram of plasma torch height control system based on rolling grey prediction is shown in Figure 2. The measurement of the plasma torch height is calculated by sensing the arc voltage, where it is analog-to-digital converted to 12 bits via digital filter and amplification circuits. The sampling period was 10 and the control period was set to be 500 Hz. In the figure, considering the errors between the set-point and the measured values and the predicted values, we calculate the new control error  $ee$  and perform the orbit interpolation via the tracking orbit approximation.

Next, we drive the z-axis controller to maintain the plasma torch height, the driving signal is the pulsed one for stepping

motor control. To consider the accuracy of rolling grey prediction and the height tracking using it, computer simulations

were performed.

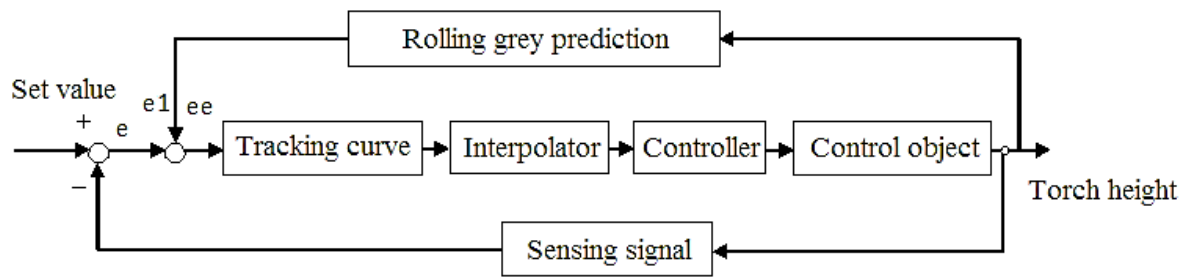


Figure 2. Block diagram of plasma torch height control system.

The data used in the simulations are the discrete data obtained from the following model discussed in the literature [12].

$$S(t) = \cos\left(\frac{t \times \pi}{25}\right) \sin\left(\frac{t \times \pi}{100}\right) + \frac{t}{1000} + 1, t \in [0, 2200] \quad (10)$$

Here, in order to evaluate the ability of grey prediction, random noise corresponding to about 10 percent of the amplitude was added.

Using these experimental data, the grey parameters are obtained as follow.

$$a = -0.0384, b = 0.6025$$

Hence, the grey dynamic sequence is

$$\hat{x}^{(0)}(k) = (1 - e^{-0.0384}) \left( x^{(0)}(1) + \frac{0.6025}{0.0384} \right) e^{0.0384(k-1)} \quad (11)$$

The relative error of this model is 0.874 and the above model is based on the calculation from 10 source data. As we use the rolling mode grey prediction, when we shift the following data, the parameters  $\alpha = [a, b]^T$  are changed according to the model.

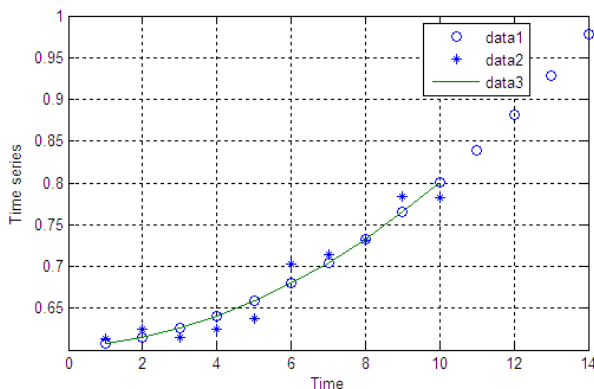


Figure 3. Grey prediction results (data1: predicted value, data2: original serial value, data3: approximate model value).

Figure 3 shows the calculated result predicted by the rolling mode grey prediction model. In the figure four information points predicted from 10 time series data are shown by labels (-o-).

We can see that the new data reflect the tendency of previous data.

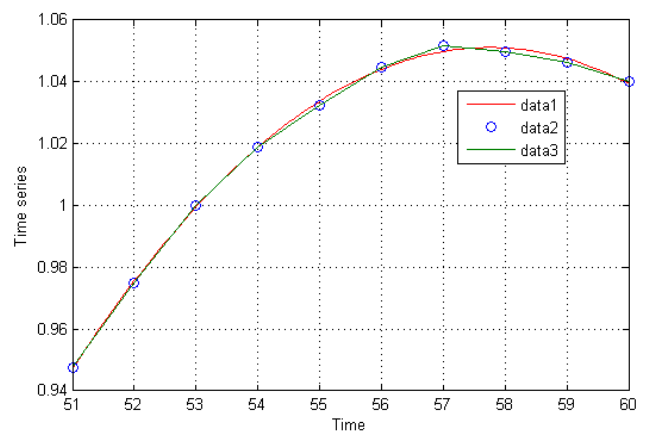


Figure 4. Tracking orbit approximation during the control cycle (data 1: tracing curve approximation, data 2: predicted point, data 3: linear approximation).

The aforementioned tracking based on rolling grey prediction and comparison with the general PID control method are carried out in Matlab Simulink.

The results are shown in Figure 5, where it can be seen that although the target arrival times are almost similar, the general PID control method has more overshoot and longer transient process than the rolling grey prediction.

This shows that the rolling grey prediction converges to the target point faster than the conventional PID method and the tracking error is small.

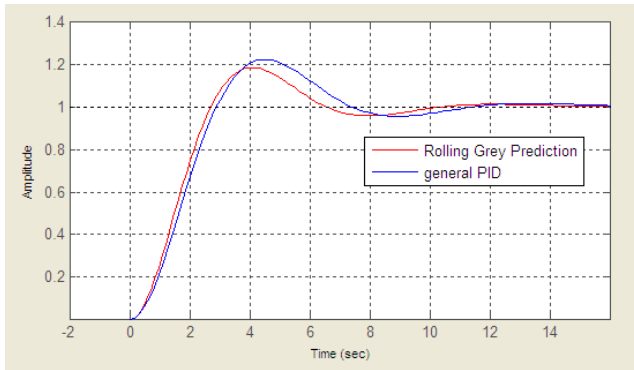


Figure 5. Simulation results in Simulink in Matlab.

Next, the performance of the plasma torch height tracking is investigated through the cutting experiments. The CNC plasma cutter used in the plasma cutting experiments and the test place are shown in Figure 6.



Figure 6. CNC plasma cutter and test place.

Since the plasma arc has a resistive action, its resistance varies significantly with the change in the distance between the cutting torch and the workpiece in the situation where the plate thickness, the cutting torch and other cutting technological parameters are determined, and this change can be calculated from the height through the measurement of the current and voltage of the arc.

The plasma arc resistance varies generally with the distance between the cutting plasma generator and the workpiece in situations where the plate thickness and the cutting generator and other cutting technique parameters are determined, and the torch height can be calculated by measuring the arc current and voltage. Plasma torch height is related to the plasma arc voltage. A separate plasma arc voltage sensing circuit was constructed to measure the plasma torch height, as shown in Figure 7.

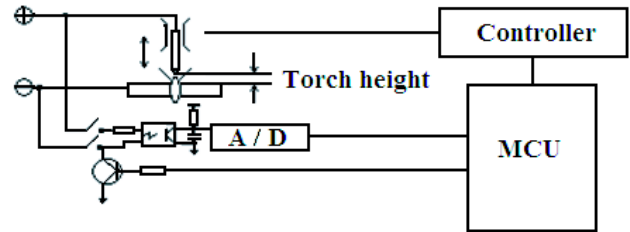


Figure 7. Plasma arc voltage measurement system.

Because we measure plasma arc voltage in plasma supply by connecting to output in parallel, during the automatic ignition, high voltage appears here and so we placed the electrical relay to measure the arc voltage in stable condition synchronizing with the ignition starting after the ignition.

The collector voltage versus the input signal voltage was converted to analog/digital (A/D) converted in a high-performance digital signal controller dsPIC, and the plasma torch height was measured with an accuracy of 0.1 mm as required by the design. In the cutting experiments, a transducer direct current (DC) plasma cutter was used, air cooling mode (air pressure: 0.4 MPa), and reference torch height was 4.0 mm. The cutting workpiece is 5 mm thick mild steel (1 200 mm × 400 mm). The cutting workpiece was placed at an inclined angle and plasma torch height was measured.

In order to reduce the amount of variation in the arc voltage measurement and increase the accuracy of the measurement, the locally varying voltage was filtered and digital filtering was also performed in the controller. When the current of the plasma cutter was set to 40 A, the arc voltage was measured to be 86 V for the plasma torch height of 1 mm and 138 V for the case of 8 mm during the workpiece cutting process. The measured arc voltage when varying the plasma torch height is shown in Figure 8.

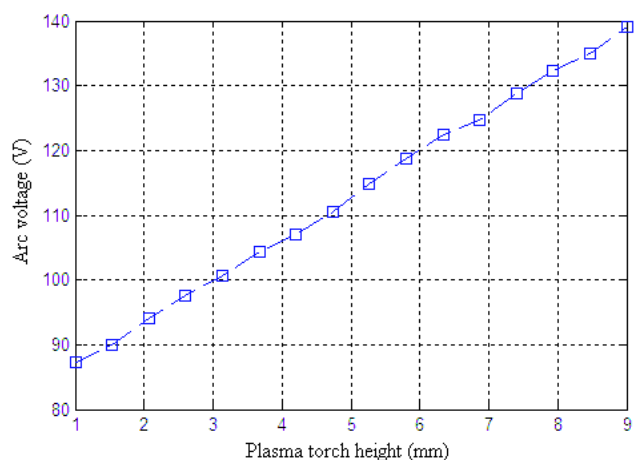


Figure 8. Arc voltage measurement curve according to plasma torch height.



The plasma cutting experiments were carried out at a cutting speed of 500 mm/min with the plasma torch height set at 2 mm, and the results of plasma torch height tracking are shown in Figure 9.

Three cases (A1-sliding grey prediction case, A2-conventional PID control case, and A3-height control case) are shown in Figure 9 (b), where the kerf width is 1 mm at the beginning and 1.9 mm at the end of the cut in the absence of height tracking, which clearly increases the kerf width. Also, comparing the case of A1-rolling grey prediction with the case of A2-general PID control, it can be seen that A1 has less variation in kerf width than A2.



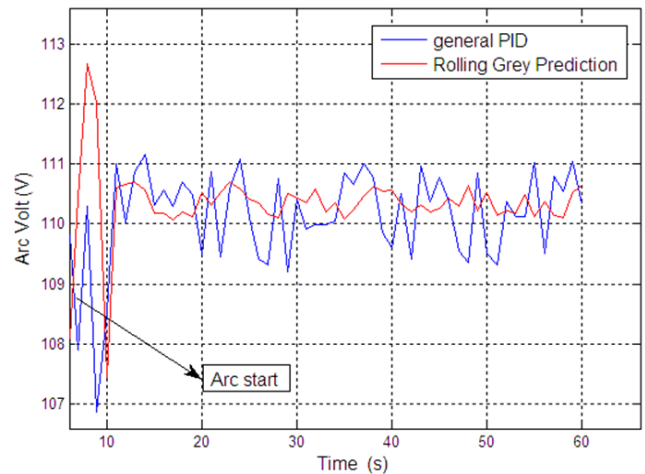
(a)



(b)

**Figure 9.** Results of plasma cutting experiments ((a): Test work-piece; (b): Cutting test result; A1: Rolling grey prediction; A2: General PID control; A3: No height control).

Next, to evaluate the height tracking results quantitatively, the arc voltage was measured during the cutting test, and the results are shown in Figure 10. As shown in this figure, red curve represent the tracking result that was performed cutting by using method based on rolling grey prediction, blue curve represent the tracking result by using PID control method. In the case of general PID control method the variation width of arc voltage was 1.9 V and in the case of rolling grey prediction method the variation width of arc voltage was 0.6 V. From the above results, we can see that accuracy of plasma torch height tracking was improved by using the rolling grey prediction method.



**Figure 10.** Plasma torch height tracking result.

## 4. Conclusion

The automatic control of the plasma torch height is essential due to the deformation of the workpiece during the cutting process. Therefore, according to the surface condition of the workpiece during plasma cutting, it is required to have automatic control so that the gap between the plasma nozzle and the cut workpiece remains constant.

In this paper a tracking method based on the rolling grey prediction for keeping cutting torch height in the plasma arc cutting is introduced. Through cutting experiment, we have confirmed that plasma torch height is related with plasma arc voltage and cutting speed.

We have established tracking algorithm based on the prediction to eliminate static error of control in the plasma arc cutting. It is confirmed by computer simulation and cutting experiments that the torch height tracking on rolling grey prediction has better tracking accuracy than the general PID control. In addition, the torch height control based on rolling grey prediction can predict the tracking error, realize the predictive control, and overcome some degree of noise. The comparison between the plasma torch height tracking experimental results using the rolling grey prediction based method and the tracking experimental results using the general PID control method in the cutting test showed that the variation of the arc voltage is less, the cutting width is smaller, and the tracking performance is improved. It is shown that the proposed torch height tracking algorithm based on the rolling grey prediction is an effective method.

## Abbreviations

CNC	Computer Numerical Control
PID	Proportional Integral Differential
GM	Grey Model
AGO	Accumulating Generation Operator
IAGO	Inverse Accumulating Generation Operator

A/D Analog/Digital  
DC Direct Current

## Availability of Data and Material

Not applicable.

## Code Availability

Not applicable.

## Author Contributions

**Yong Sik Kye:** Project administration, Investigation

**Yun Sik Choe:** Formal analysis

**Sung Chol Song:** Methodology

**Myong Guk Paek:** Software, Validation

**Gun Sik Ju:** Writing – review & editing

**Hae Hong:** Writing – review & editing

## Ethics Approval

Not applicable.

## Consent to participate

Not applicable.

## Consent for publication

Not applicable.

## Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

## Conflicts of Interest

The authors declare no conflicts of interest.

## References

- [1] R. Adalarasan, et al., Application of Grey Taguchi-based response surface methodology (GT-RSM) for optimizing the plasma arc cutting parameters of 304 L stainless steel. *The International Journal of Advanced Manufacturing Technology*. 2015, 78, 1 161-1 169.  
<https://doi.org/10.1007/s00170-014-6744-0>
- [2] J. Wang, K. Kusumoto, and K. Nezu. Plasma arc cutting torch tracking control. *Science and Technology of Welding and Joining*. 2001, 3, 154-158.  
<https://doi.org/10.1179/136217101101538695>
- [3] W. Xue, K. Kusumoto and K. Nezu. Analysis of acoustic characteristics for plasma arc cutting. *Science and Technology of Welding and Joining*. 2003, 8, 443-449.  
<https://doi.org/10.1179/136217103225005606>
- [4] W. Xue, K. Kusumoto and K. Nezu. Relationship between plasma arc cutting acoustic and cut quality. *Science and Technology of Welding and Joining*. 2005, 10, 45-49.  
<https://doi.org/10.1179/174329305x19376>
- [5] K. Kusumoto, Q. G. Chen, and W. Xue. Monitoring of plasma arc cutting process by cutting sound. *Science and Technology of Welding and Joining*, 2006, 11, 701-706.  
<https://doi.org/10.1179/174329306x150379>
- [6] J. Y. Wang, K. Kusumoto, K. Nezu. Modelling and prediction of cut shape for plasma arc cutting based on artificial neural network. *Science and Technology of Welding and Joining*, 1999, 4, 195-200.  
<https://doi.org/10.1179/136217199101537770>
- [7] K. P. Maity & Dilip Kumar Bag. Effect of process parameters on cut quality of stainless steel of plasma arc cutting using hybrid approach. *Int. J. Adv. Manuf. Technol*. 2015, 78, 161–175. <https://doi.org/10.1007/s00170-014-6552-6>
- [8] K. Kusumoto, J. Wang and K. Nezu. A Study on the Cut Surface Quality of Mild Steel Plate by Oxygen Plasma Arc Cutting. *Q. J. Jpn Weld. Soc*. 1999, 17, 201–208.
- [9] Jiayou Wang, Zhengyu Zhu, Conghui He, Feng Yang. Effect of dual swirling plasma arc cutting parameters on kerf characteristics. *Int. J. Mater. Form*. 2011, 4, 39-43.  
<https://doi.org/10.1007/s12289-010-0990-y>
- [10] Jeen Lin, Ruey-Jing Lian. Design of a grey-prediction self-organizing fuzzy controller for active suspension systems. *Applied Soft Computing*. 2013, 13, 4 162-4 173.  
<https://doi.org/10.1016/j.asoc.2013.06.003>
- [11] Erdal Kayacan, Baris Ulutas, Okyay Kaynak. Grey system theory-based models in time series prediction. *Expert Systems with Applications*. 2010, 37, 1 784–1 789.  
<https://doi.org/10.1016/j.eswa.2009.07.064>
- [12] Min Xia, W. K. Wong. A seasonal discrete grey forecasting model for fashion retailing. *Knowledge-Based Systems*. 2014, 57, 119-126.  
<https://doi.org/10.1016/j.knosys.2013.12.014>
- [13] Ruey-Jing Lian, Bai-Fu Lin, Jyun-Han Huang. A grey prediction fuzzy controller for constant cutting force in turning. *International Journal of Machine Tools & Manufacture*. 2005, 45, 1 047–1 056.  
<https://doi.org/10.1016/j.ijmachtools.2004.11.023>
- [14] Marin Gostimirovic, et al., An experimental analysis of cutting quality in plasma arc machining. *Advanced Technologies and Materials*. 2020, 45(1), 1–8.  
<https://doi.org/10.24867/ATM-2020-1-001>

- [15] P. P. Kapse, M. T. Telsang. Parametric investigation and optimisation of plasma arc cutting of structural steel St.52-3 using grey-based fuzzy algorithm. *International Journal of Manufacturing Research*. 2019, 14(2), 179–197.
- [16] H. Ramakrishnan, et al., Experimental investigation of cut quality characteristics on SS321 using plasma arc cutting. *Journal of the Brazilian Society of Mechanical Sciences and Engineering*. 2018, 40, 59-69.  
<https://doi.org/10.1007/s40430-018-0997-8>
- [17] Yan Lin, et al., Plasma cutting torch trajectory planning for main pipe hole cutting with welding groove and root face. *The International Journal of Advanced Manufacturing Technology*. 2017, 93, 4 329-4 343.  
<https://doi.org/10.1007/s00170-017-0843-7>