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The Statistical Models for Estimating the Amount of Spatter in the Short Circuit Transfer Mode of GMAW

A study shows the optimal model for estimating the amount of spatter when considering arc extinction in short circuit transfer mode, using multiple regression analysis

BY M. J. KANG AND S. RHEE

ABSTRACT. Arc stability in the short circuit transfer mode of gas metal arc welding (GMAW) has a close relationship with the regularity of metal transfer, and metal transfer depends on several physical quantities (voltage, current, materials, etc.) related to the growth and transfer of the metal droplet. When the metal droplets uniformly transfer to the weld pool, the welding current and arc voltage waveforms become regular. When they are not uniformly transferred, the shape of the waveforms become very irregular, and hence, much more spatter is generated. The purpose of this study was to develop a statistical model able to estimate the amount of spatter quantitatively using the waveforms in short circuit transfer mode of GMAW. In this study, the spatter was gathered under several welding conditions, and, at the same time, the waveforms were measured. The factors representing the characteristics of the waveforms were calculated from the measured waveforms. Four different linear and nonlinear regression models were proposed to estimate the amount of spatter, performing the multiple regression analysis between each model and the amount of spatter. The estimated results were compared to the amount of spatter under several welding conditions, and the best model, which appropriately estimates the amount of spatter, was developed.

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Introduction

The GMAW process characteristically changes metal transfer modes due to complex actions of forces related to the melting phenomena of the electrode. Recently, much research has been performed on the arc stability estimation and the metal transfer phenomena as measuring technologies have developed. Adam and Siewert (Ref. 1) performed a statistical analysis for parameters from the measured signals of welding current and arc voltage, then classified the metal transfer modes. Ogunbiyi and Norrish (Ref. 2) proposed a mathematical index model, which consisted of some significant variables, and classified the metal transfer mode using the proposed index. Arai, *et al*. (Ref. 3), showed there was a close relationship between the standard deviation of arc time and arc stability based on human experience in short circuit transfer mode of CO_2 arc welding. Lucas (Ref. 4) revealed the distribution for the standard deviation of the short circuit peak current and the short circuit period under various welding voltage conditions, using several types of welding power sources, and proved there was a relationship between these standard deviations and arc stability. Mita, *et al.* (Ref. 5), obtained the standard deviations of the waveform factors (the arc time, the short circuit time, the average arc current and the average short circuit current, etc.) from the measured waveforms for welding current and arc voltage. He proposed several regression models, which were composed of the waveform elements and their standard deviations. He also developed an optimal regression model among the models by using multiple regression analysis, based on the assessment of some experienced workers, and considered the model as the arc stability estimation index. He showed if the index was high, then the arc would become unstable, and if it was low, the arc could be estimated as stable. Shinoda and Nishikawa (Ref. 6) proposed an index that could distinguish the arc stability by using welding current and arc voltage waveforms in short circuit transfer mode. Rehfeldt, *et al.* (Ref. 7), distinguished the arc stability using the signals of arc volt-

KEY WORDS

Transfer Mode
Short Circuiting
GMAW
Spatter
Regression Analysis
Arc Stability

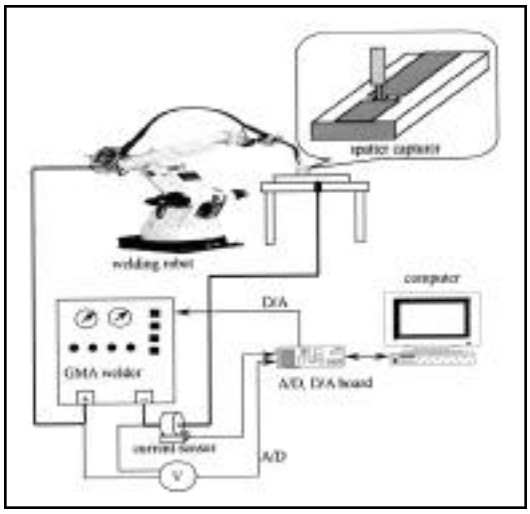

Fig. 1 — The experimental apparatus setup used in this study consists of a welding robot, a welding power source, sensors for measuring the signals of welding current and arc voltage, an A/D converter and a computer to gather the signals and to analyze the waveform characteristics from the signals.

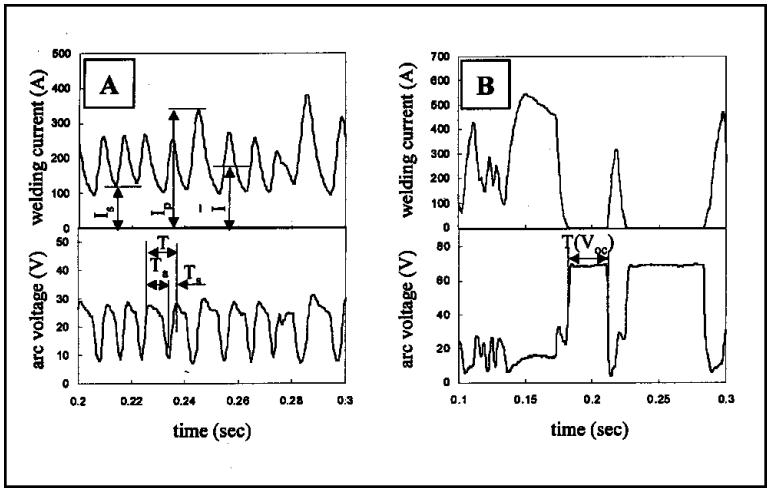

Fig. 2 — Waveforms of the arc voltage and welding current at a wire feed rate of 3.4 m/min. A — 22 V; B — 19 V.

Table 1 — Welding Conditions and the Number of Experiments per Setting Condition

Wire Feed Rate (m/min)	CTWD (mm)	Welding Voltage (V)	No. of Welding Experiments per Setting Condition
3.4	15	19V ~ 25V	6
	15	20V ~ 26V	6
6.0	20	21V ~ 27V	3
	25	21V ~ 27V	3
	15	21V ~ 27V	3
7.3	20	22V ~ 28V	4
	25	21V ~ 27V	3
8.6	20	23V ~ 27V	6

age in short circuit transfer mode. Most results reported so far were based on arc stability or the metal transfer mode, using the regularity of waveform factors or relationships between the welder's knowledge and some models in order to estimate the arc state. But the models were not explained quantitatively and even lacked statistical verifications. There is a possibility a large error can occur in predicting the arc stability with these models.

In short circuit transfer of GMAW, the spatter, as well known, is generated at the instant the short circuit begins, or when the short circuit finishes and the arc is ignited again. If the short circuit time or the arc time is irregular, much more spatter will be generated than when it is regular. Hence, it can be said the amount of spatter is closely related to arc stability. The main factors that influence the generation of the spatter are the metal droplet size and the magnitude of forces acting on the droplet. Droplet size and force magnitude are dependent on welding current and arc voltage waveforms. Therefore, when these elements are statistically analyzed and when the correlation between the amount of spatter and the many regression models composed of these elements are investigated, an index to quantitatively estimate arc stability can be developed. The model to predict the amount of spatter can become a quantitative criterion to estimate arc stability since arc stability is closely related to the amount of spatter. In addition, the model can become an important means to predict weld quality. It can also be used as an index to determine what changes in welding parameters must be made for good weld quality.

Therefore, the aim of this study was to develop a statistical model consisting of several waveform factors that closely represent waveform characteristics of arc voltage and welding current to predict the amount of spatter in short circuit transfer for GMAW. Spatter, under several welding conditions, was gathered and the amount was measured. At the same time, the signals for welding current and arc voltage were measured, and the waveform factors (the waveform elements and the standard deviations of those elements) were obtained from the measured signals. Four different linear and nonlinear regression models composed of the waveform factors are proposed. A correlation analysis between the amount of spatter and the constitution factors of each model was executed, and some factors that cause multicollinearity were eliminated. Multiple regression analysis was performed on the four regression models composed of the remaining factors that were not eliminated. Also, the factors that have high probability values were removed. Hence, each estimation model that can predict the amount of spatter is proposed. The estimated results predicted by the models were compared to the amount of spatter. Finally, the best model for estimating the amount of spatter was proposed.

Experimental Procedure

The shielding gas used in the welding experiments was 100% CO_2 with a flow rate of 20 L/min, and the electrode used was AWS ER70S-6 with a diameter of 1.2 mm. The workpiece was ASTM A36M with a thickness of 6 mm. The welding speed was set at 5 mm/s and the total welding time was 60 s (300 mm in length). The bead-on-plate welding was performed under various welding conditions, as shown in Table 1. Four wire feed rates of 3.4, 6.0, 7.3 and 8.6 m/min (Table 1) were used. With the 3.4 m/min wire feed rate, welding experiments were performed in 1-V increments from 19 to 25 V with a contact tube-to-work distance (CTWD) of 15 mm. To reduce experimental error, welding was performed six times under the same conditions. With the wire feed rate of 6.0 m/min, welding experiments were performed in 1-V increments from 20 to 26 V with a CTWD of 15 mm. Welding was performed six times under the same conditions. Welding experiments with a 20-mm CTWD were performed three times at 1-V increments from 21 to 22 V. The number of experiments performed for this study was 226.

The welding voltage and current were used as setting variables. Welding cur-

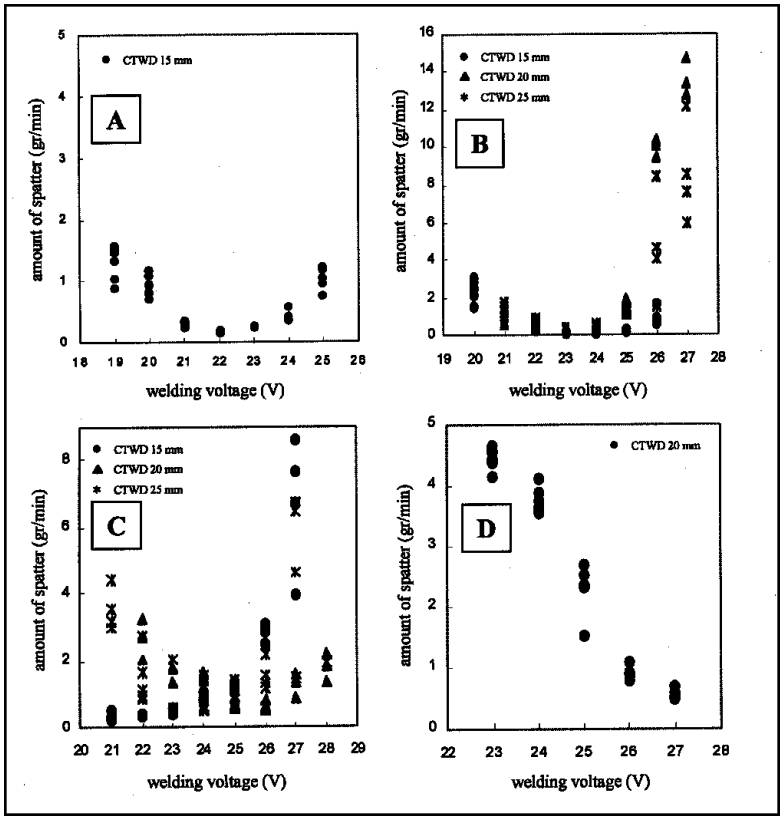

Fig. 3 — The amount of spatter as the welding voltage changes at different wire feed rates. A — Wire feed rate 3.4 m/min; B — 6 m/min; C — 7.3 m/min; D — 8.6 m/min.

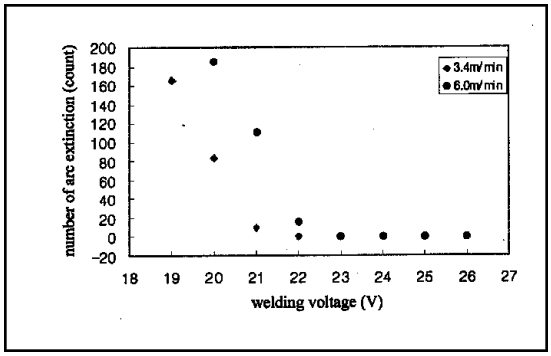

Fig. 4 — Number of arc extinctions with respect to welding voltage at a CTWD of 15 mm.

rent was measured with a Hall sensor attached to an earth cable. Arc voltage between the output terminals of the welding power source was measured. The measured signals were transferred into the computer via an A/D converter, which has a maximum sampling rate of 200 kHz. The noise on the signals was removed by a digital low-pass filter with 200 Hz cut-off frequencies. The welding process was performed using a welding robot and a constant-voltage-controlled welding power source of transistorized inverter type. In addition, spatter generated during welding was captured using a brass device. It was not splashed out during welding since this device was designed to envelop the torch and the workpiece completely. The sampling rate for measuring the waveforms was 5000 samples/s. The waveform signals were collected 10 s after the beginning of the welding at 20-s intervals.

Waveform Factors in Short Circuit Transfer Mode

In short circuit transfer mode, the arc voltage and welding current waveforms become regular under optimal conditions — Fig. 2A. If welding voltage is too low, arc extinction occurs (Fig. 2B), and the waveforms are very irregular. In this study, waveform characteristics that expressed the short circuit transfer mode obtained to develop the spatter prediction model used the following signal processing methods.

Threshold voltage and average arc voltage were used to distinguish the arc time and the short circuit time from the filtered signals. The positions calculated were the rising one or the falling one to threshold voltage. If average arc voltage between two positions was higher than the threshold voltage, the period when the voltage was maintained higher than the threshold voltage was regarded as the arc time (T_a). If the voltage was lower than that, the period was regarded as the short circuit time (T_s). Adding the arc time to the short circuit time was regarded as a period of short circuit transfer (T). The maximum and minimum currents for a period of short circuit transfer were regarded as the short circuit peak current (I_p) and the instantaneous short circuit current (I_s), respectively. The average current during a short circuit transfer ($\bar{I}$) was calculated. The time interval where arc voltage was maintained higher than 50 V was regarded as the arc extinction time [$T(V_{oc})$], and it was removed in calculating the above waveform elements (T_a, T_s, T, I_p, I_s and $\bar{I}$). Then, the number [$N(V_{oc})$] and the sum [$T(V_{oc})_{sum}$] of these time intervals during 20 s were calculated. When arc voltage became higher than 50 V, it indicated the voltage between the contact tube and the workpiece became the open circuit voltage, and welding current during this period became zero. In addition, the standard deviations of waveform elements, such as s[T], s[T_a], s[T_s], s[I_p], s[I_s] s[$\bar{I}$] and s[$T(V_{oc})$] were obtained as other waveform factors to express the waveform characteristics of short circuit transfer mode precisely.

Development of Models for Estimating the Amount of Spatter

The Characteristics of the Spatter Generation

Figure 3 shows the amount of spatter under several welding conditions. According to Fig. 3, it can be seen that little spatter is generated at optimal welding voltage, and that much spatter is generated when welding voltage is higher or lower than the optimal voltage.

Linear Regression Model in Overall Region

A linear regression model was composed as Equation 1, using the 16 factors obtained during 20 s of welding. A correlation analysis was performed to investigate how much influence these factors had on the amount of spatter. Table 2 shows the correlation coefficients between each factor and the amount of spatter, and between the factors with each other overall.

$$Y = a + bT + cT_a + dT_s + eI_p + fI_s + g\bar{I} + hs[T] + is[T_a] + js[T_s] + ks[I_p] + 1s[I_s] + ms[\bar{I}] + nN(V_{oc}) + oT(V_{oc}) + ps[T(V_{oc})] + qT(V_{oc})_{sum} \quad (1)$$

According to Table 2, the factors having a high correlation coefficient with the

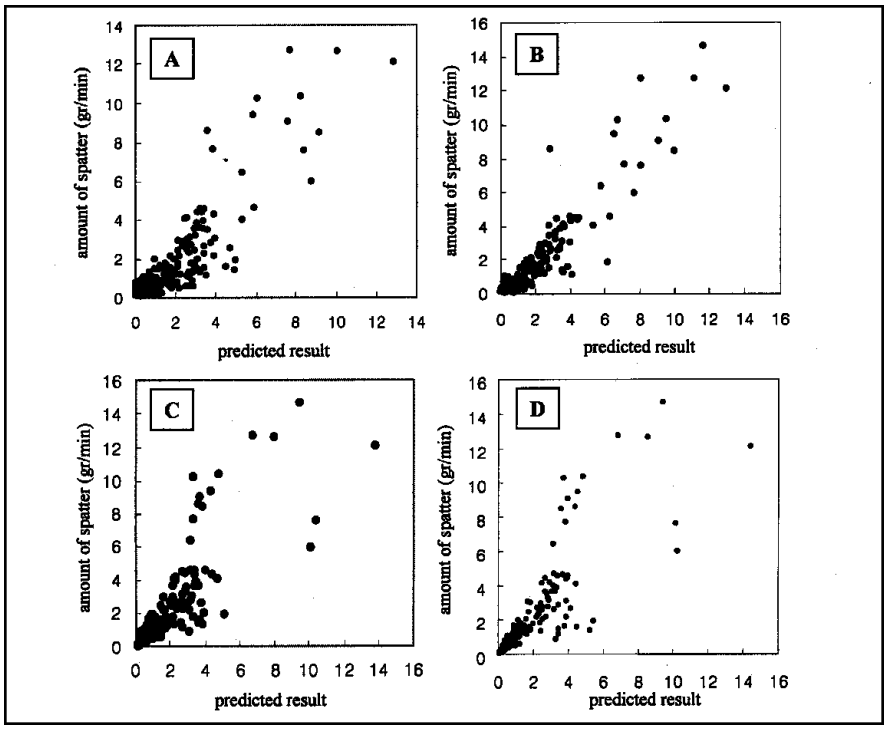

Fig. 5 — Comparison between predicted results by several proposed estimation models and the amount of spatter. A — Linear regression model for the region overall; B — combined linear regression model; C — nonlinear regression model for the overall region; D — combined nonlinear regression model.

amount of spatter were T, T_a, s[T], s[T_a] and s[I_p] . In addition, the correlation coefficients between T and T_a, s[T] and s[T_a], and N(V_{oc}) and T(V_{oc})$_{sum}$ were nearly 1. Hence, it can be regarded these factors have the same influence on spatter generation. That is, these factors can bring about the multicollinearity. Thus, T, s[T] and T(V_{oc})$_{sum}$ were eliminated in this study. So, we can make a linear model to predict the amount of spatter using the remaining 13 factors, as shown in Equation 2.

$$Y = a + bT_a + cT_s + dI_p + eI_s + f\bar{I} + gs[T_a] + hs[T_s] + is[I_p] + js[I_s] + ks[\bar{I}] + 1N(V_{oc}) + mT(V_{oc}) + ns[T(V_{oc})] \quad (2)$$

If some constitution factors in Equation 2 produce an error in predicting the amount of spatter, then those factors must also be eliminated. So, a hypothesis test with respect to the factors in Equation 2 was performed. In order to decide the acceptance or the rejection of the null hypothesis, a significant probability on the t-distribution was examined, as shown in Table 3. In this study, it was assumed the significance level was 5%. According to Table 3, the observed probability values of I_p, $\bar{I}$, s[T_s], s[$\bar{I}$], N(V_{oc}), T(V_{oc}) and s[T(V_{oc})] were 62.03%, 74.83%, 13.54%, 17.55%, 37.41%, 80.71% and 19.51%, respectively. As the observed probability values of these factors are much higher than the 5% significant level, the null hypothesis must be accepted and the factors were eliminated in a model equation, as shown in Equation 3.

$$Y = a + bT_a + cT_s + dI_s + es[T_a] + fs[I_p] + gs[I_s] \quad (3)$$

The multiple correlation coefficients between the prediction by Equation 3 and the amount of spatter was 0.874. The significant probability on the factors

Table 2 — Correlation Coefficients between Each Factor and the Amount of Spatter, and between the Factors with Each Other in the Linear Regression Model

Factors	T	T_a	T_s	I_p	I_s	$\bar{I}$	s[T]	s[T_a]	s[T_s]	s[I_p]	s[I_s]	s[$\bar{I}$]	N(V_{oc})	T(V_{oc})	s[T(V_{oc})]	T(V_{oc})$_{sum}$
T	1															
T_a	0.9921	1														
T_s	–0.0528	–0.177	1													
I_p	0.4154	0.3573	0.4161	1												
I_s	0.37417	0.4283	–0.475	0.54561	1											
I	–0.0524	–0.058	0.0475	0.6639	0.6528	1										
s[T]	0.94708	0.9367	–0.026	0.32129	0.2815	–0.191	1									
s[T_a]	0.95742	0.9542	–0.085	0.31803	0.3214	–0.183	0.9961	1								
s[T_s]	0.0752	–0.024	0.7847	0.33896	–0.311	–0.034	0.2389	0.1634	1							
s[I_p]	0.33501	0.286	0.3523	0.3620	0.1085	0.0822	0.5085	0.4574	0.7222	1						
s[I_s]	–0.091	–0.159	0.5543	0.2569	–0.155	–0.095	0.1171	0.0634	0.7805	0.7104	1					
s[$\bar{I}$]	–0.1568	–0.249	0.7528	0.4116	–0.219	0.089	–6E-06	–0.059	0.8464	0.6985	0.9231	1				
N(V_{oc})	–0.1363	–0.202	0.5374	0.1448	–0.257	–0.201	0.0666	0.015	0.7266	0.662	0.9517	0.8847	1			
T(V_{oc})	–0.0437	–0.122	0.6315	0.1552	–0.419	–0.234	0.1459	0.0909	0.7855	0.6051	0.7762	0.8015	0.7569	1		
s[T(V_{oc})]	–0.1628	–0.243	0.6564	0.1438	–0.432	–0.203	0.0271	–0.029	0.7865	0.5884	0.8186	0.8466	0.8121	0.9262	1	
T(V_{oc})$_{sum}$	–0.1405	–0.199	0.4815	0.1168	–0.241	–0.227	0.0649	0.0153	0.6896	0.655	0.9412	0.8598	0.9815	0.7535	0.804	1
Spatter	0.91983	0.723	–0.109	0.1746	0.2615	–0.163	0.7457	0.7361	0.1749	0.5019	0.1986	0.0423	0.1799	0.0893	0.0129	0.1797

Table 3 — Observed Probability Values of Factors in Linear Regression Model (Ref. 2)

Factors	T_a	T_s	I_p	I_s	$\bar{I}$	s[T_a]	s[T_s]	s[I_p]	s[I_s]	s[$\bar{I}$]	N(V_{oc})	T(V_{oc})	s[T(V_{oc})]
P-value	5.8E-20	0.0009	0.6203	0.00522	0.7483	7.2E-13	0.1354	0.0029	2E-05	0.1755	0.3741	0.80714	0.19516

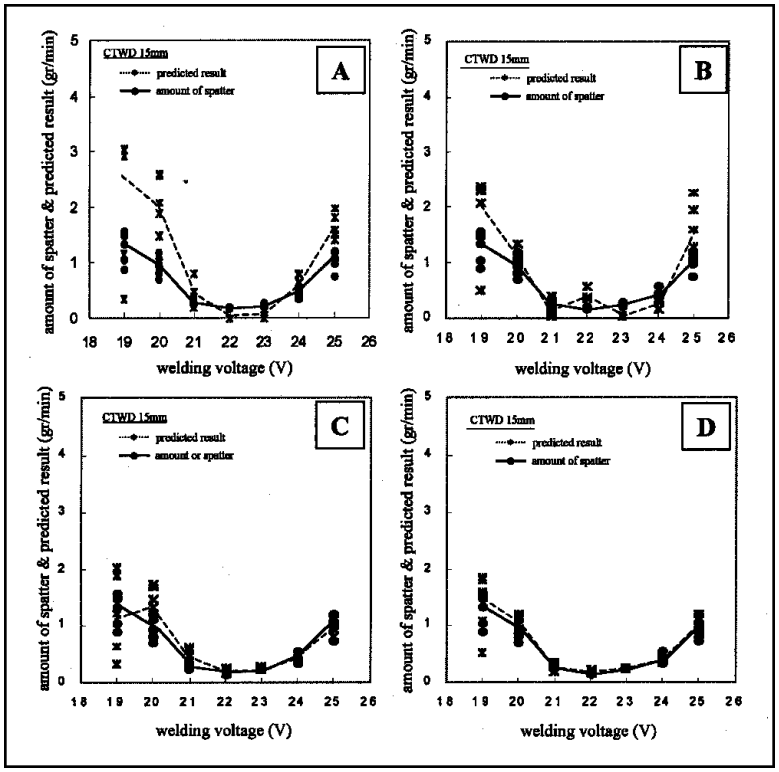

Fig. 6 — Comparison of the prediction by the linear/nonlinear regression models and the amount of spatter at a wire feed rate of 3.4 m/min. A — Linear regression model for the overall region; B — combined linear regression model; C — nonlinear regression model for the overall region; D — combined nonlinear regression model.

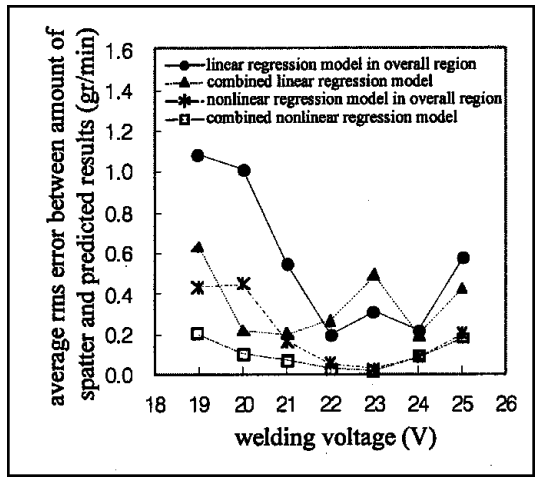

Fig. 7 — Average rms errors between the predicted results and the amount of spatter at a wire feed rate of 3.4 m/min.

Table 4 — Observed Probability Values of Factors in Linear Regression

Factors	Y-intercept	T_a	T_s	I_s	$s[T_a]$	$s[I_p]$	$s[I_s]$
P-values	0.001478	5E-26	2.1E-19	3E-14	1E-15	6.21E-07	3E-18

of Equation 3 was reassessed, as shown in Table 4. With these coefficients, the linear regression model shown in Equation 4 was developed.

$$Y = 2.8768 + 0.8658T_a - 1.42T_s - 0.04I_s - 0.89s[T_a] + 0.0281s[I_p] + 0.052s[I_s] \quad (4)$$

Linear Regression Model in the Separated Region

Figure 4 shows the number of arc extinctions with respect to the welding voltage when the CTWD was set at 15 mm and the wire feed rates were set at 3.4 and 6.0 m/min. In Fig. 4, it is revealed arc extinction takes place much more when the voltage is lower than the optimal voltage, and it does not take place when the voltage is higher than the optimal voltage. Considering the results of Figs. 2 and 4, it can be seen the mechanism for spatter generation is different depending on the welding voltage. Thus, it is necessary to separate the region where arc extinction exists or does not exist in order to develop the regression models for estimating the amount of spatter. In this case, the factors that establish each regression model may become different.

Linear Regression Model in the Region with Arc Extinction

A correlation analysis with 16 factors was performed in the region where arc extinction occurs. Like the overall region, the correlation coefficients between T and T_a, s[T] and $s[T_a]$, and $N(V_{oc})$ and $T(V_{oc})_{sum}$ were nearly 1, and then the factors T, s[T] and $sT(V_{oc})_{sum}$ were eliminated in Equation 1. Table 5 shows the correlation coefficients between each factor and the amount of spatter in the region with arc extinction.

In Table 2, T, T_a, s[T] and $s[T_a]$ had high correlation coefficients with respect to the amount of spatter. These factors in Table 5 showed very low correlation coefficients, whereas, $s[I_p]$, $s[I_s]$, $s[\bar{I}]$ and $N(V_{oc})$ showed high correlation coefficients. The significant probability on the remaining factors not eliminated was examined. The observed probability values of T_a, $\bar{I}$, $s[T_a]$, $s[T_s]$, $s[I_p]$, $s[I_s]$, $T(V_{oc})$ and $s[T(V_{oc})]$ were 38.25%, 2.3%, 21.7%, 59.9%, 99.76%, 7.97%, 7.42% and 40.015%, respectively. As these values were higher than the significance level, these factors were eliminated. Here, even though the observed probability value of the factor, $\bar{I}$, was 2.3%, the null hypothesis for the factor was accepted. This is because the observed probability value of the factor became higher than 5% when the factors were eliminated one by one from the highest value.

Equation 5 was obtained by applying the coefficients of the remaining factors in Equation 1. The multiple correlation coefficients between the estimated results of Equation 5 and the amount of spatter were 0.931. It was higher than the multiple regression coefficient of Equation 4, which was 0.874.

$$Y = -2.683 + 0.50103T_s - 0.014I_p + 0.04031I_s + 0.01568s[\bar{I}] + 0.0077N(V_{oc}) \quad (5)$$

Linear Regression Model in the Region without Arc Extinction

In the region without arc extinction, $N(V_{oc})$, $T(V_{oc})$, $s[T(V_{oc})]$ and $T(V_{oc})_{sum}$ were among the 16 factors of Equation 2 not generated; therefore, they must be eliminated from Equation 1. In addition, as the correlation coefficients between T and T_a, and between s[T] and $s[T_a]$ were near 1, T and s[T] were eliminated. Table 6 shows the correlation coefficients between each factor and the amount of spatter in the region without arc extinction.

Table 5 — Correlation Coefficients between Each Factor and the Amount of Spatter in the Region with Arc Extinction

Factors	T	T_a	T_s	I_p	I_s	$\bar{I}$	$s[T_a]$	$s[T_a]$	$s[T_s]$	$s[I_p]$	$s[I_s]$	$s[\bar{I}]$	$N(V_{oc})$	$T(V_{oc})$	$s[T(V_{oc})]$
Spatter	0.0593	0.0437	0.1235	0.230	0.351	–0.006	0.431	0.3666	0.6504	0.7650	0.8886	0.8816	0.8436	0.4949	0.483

Table 6 — Correlation Coefficients between Each Factor and the Amount of Spatter in the Region without Arc Extinction

Factors	T	T_a	T_s	I_p	I_s	$\bar{I}$	$s[T]$	$s[T_a]$	$s[T_s]$	$s[I_p]$	$s[I_s]$	$s[\bar{I}]$
Spatter	0.8165	0.8267	–0.1644	0.1757	0.2592	–0.2729	0.7914	0.7876	0.2565	0.6562	0.1398	–0.3033

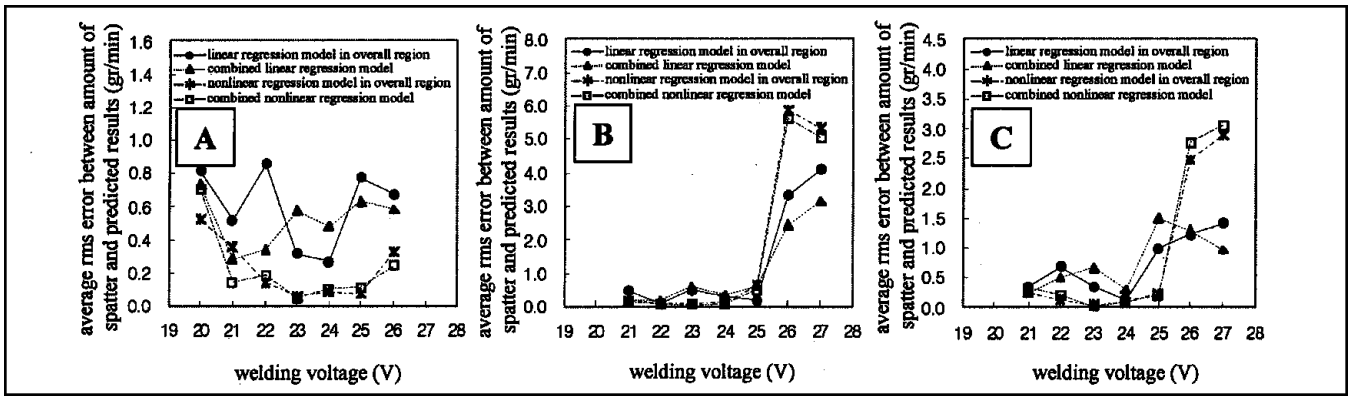

Fig. 8 — Average rms errors between the predicted results and the amount of spatter at a wire feed rate of 6 m/min. A — CTWD 15 mm; B — CTWD 20 mm; C — CTWD 25 mm.

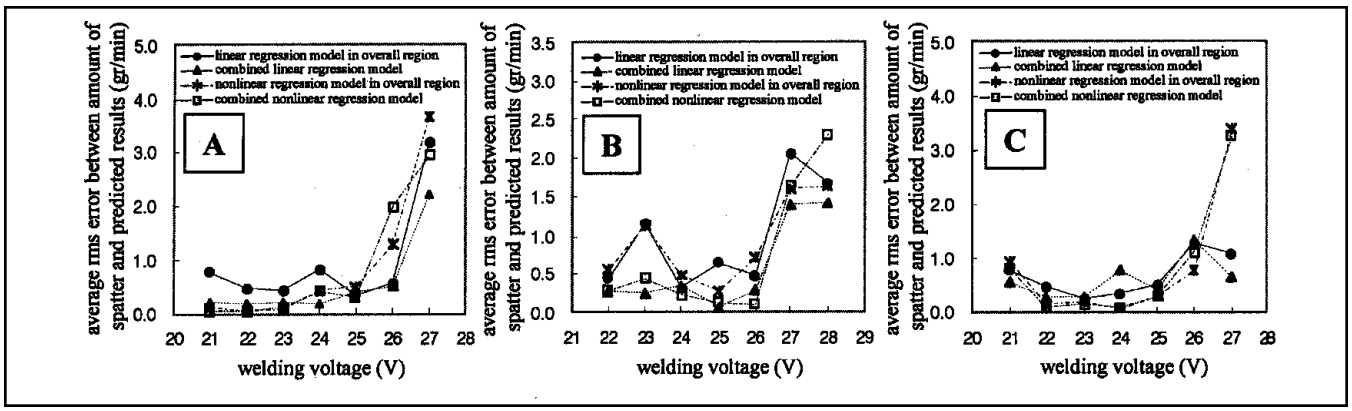

Fig. 9 — Average rms errors between the predicted results and the amount of spatter at a wire feed rate of 7.3 m/min. A — CTWD 15 mm; B — CTWD 20 mm; C — CTWD 25 mm.

The results of the correlation analysis for Table 6 were very different from those in the region with arc extinction, as shown in Table 5. Especially, the correlation coefficients of T, T_a, $s[T]$ and $s[T_a]$ with the amount of spatter (Table 5) are very low values, but they showed a higher value in the region without arc extinction. Thus, it can be seen the mechanism of spatter generation in the region without arc extinction differs from that in the region with arc extinction. The significant probability analysis on the remaining factors in Equation 1 was performed in the region without arc extinction. As a result of the analysis, T_s, I_s and $s[I_s]$ were eliminated since the observed probability values for them were larger than 5%. Applying the coefficients of the remaining factors to Equation 1, in the region without arc extinction, a linear regression model for estimating the amount of spatter was obtained (see Equation 6). The multiple correlation coefficient between the estimated results of Equation 6 and the amount of spatter was 0.9165. It is much higher compared to that of Equation 4, which was 0.874.

$$Y = 5.697 + 1.0534T_a + 0.0242I_p - 0.065\bar{I} - 1.5609s[T_a] + 2.5924s[T_s] + 0.0704s[I_p] - 0.1496s[\bar{I}] \quad (6)$$

Nonlinear Regression Model in the Overall Region

In the correlation analysis of Table 1, the correlation coefficients between each factor and the amount of spatter express only the linear relationship. Sometimes, it may have a high nonlinear correlation coefficient, although a factor has a low linear correlation coefficient. Hence, a nonlinear regression model could be considered, as shown in Equation 7.

$$Y = a \cdot T^b \cdot T_a^c \cdot T_s^d \cdot I_p^e \cdot I_s^f \cdot \bar{I}^g \cdot s[T]^h \cdot s[T_a]^i \cdot s[T_s]^j \cdot s[I_p]^k \cdot s[I_s]^l \cdot s[\bar{I}]^m \cdot N(V_{oc})^n \cdot T(V_{oc})_{avg}^{\ o} \cdot s[T(V_{oc})_{avg}]^p \cdot T(V_{oc})_{sum}^{\ q} \quad (7)$$

By taking the logarithm on both sides, Equation 8 is obtained. It becomes a linearized model similar to Equation 2.

$$\begin{aligned} 1nY &= a^* + b1nT + c1nT_a \\ &+ d1nT_s + e1nI_p + f1nI_s \\ &+ g1n\bar{I} + h1ns[T] + i1ns[T_a] \\ &+ j1ns[T_s] + k1ns[I_p] + l1ns[I_s] \\ &+ m1ns[\bar{I}] + n1nN(V_{oc}) \\ &+ o1nT(V_{oc})_{avg} + p1ns[T(V_{oc})_{avg}] \\ &+ q1nT(V_{oc})_{sum} \end{aligned} \quad (8)$$

Where a* is 1na . Since the correlation coefficient between 1nT and $1nT_a$, between 1ns[T] and $1ns[T_a]$, and among $1nN(V_{oc})$ $1nT(V_{oc})_{avg}$ and $1nT(V_{oc})_{sum}$ was almost 1, the factors, 1nT, 1ns[T] , $1nT(V_{oc})_{avg}$ and $1nT(V_{oc})_{sum}$ were eliminated. The significant probability of the remaining factors was checked. As a result, the observed probability values of $1nT_a$, $1nT_s$, $1nI_p$, $1nI_s$, $1ns[T_s]$, $1ns[\bar{I}]$ and $1nN(V_{oc})$ were larger than the significant level of 5%. So, these factors were eliminated. Therefore, Equation 9 was proposed as a nonlinear regression model for the overall region. The multiple correlation coefficient between the estimated result of the regression model, Equation 9, and the amount of spatter was 0.9109. This was much higher than the multiple correlation of Equation 4, which was 0.874.

$$\begin{aligned} Y &= 0.010451 \cdot \bar{I}^{-1.12761} \cdot s[T_a]^{1.214463} \\ &\cdot s[I_p]^{1.201309} \cdot s[I_s]^{0.644028} \\ &\cdot s[T(V_{oc})_{avg}]^{-0.02396} \end{aligned} \quad (9)$$

Nonlinear Regression Model in Separated Region

Nonlinear Regression Model in the Region with Arc Extinction

Equation 8 was also used as a nonlinear regression model in the region with arc extinction. As the correlation coefficients between T and T_a, between s[T] and $s[T_a]$, and between $N(V_{oc})$ and $T(V_{oc})_{sum}$ were near to 1, T , s[T] and $T(V_{oc})_{sum}$ were eliminated in Equation 8. In the region with arc extinction, the significant probability of the remaining factors was checked. As a result, a nonlinear regression model was established, as shown in Equation 10. The multiple correlation coefficient between the estimated result of Equation 10 and the amount of spatter was 0.9581. It was a better result than the linear regression model of Equation 5, 0.931, and of the nonlinear regression model of Equation 9, 0.9109.

$$\begin{aligned} Y &= 0.33823 \cdot T_a^{1.1681} \cdot T_s^{1.5313} \\ &\cdot I_p^{-4.3293} \cdot I_s^{1.7668} \cdot s[T_s]^{-0.5712} \\ &\cdot s[\bar{I}]^{2.6431} \cdot N(V_{oc})^{0.2315} \\ &\cdot s[T(V_{oc})_{avg}]^{-0.0119} \end{aligned} \quad (10)$$

Nonlinear Regression Model in the Region without Arc Extinction

In the region without arc extinction, the correlation coefficients between T and T_a, and s[T] and $s[T_a]$ were nearly 1; therefore, T and s[T] were eliminated in Equation 8. The significant probability was investigated with the remaining factors. From the results, the regression model of Equation 11 was established as a nonlinear regression model in the region without arc extinction. The multiple correlation coefficient between the estimated value of Equation 11 and the amount of spatter was 0.927. It can be considered that the estimated result of Equation 11 shows a better performance than that of the nonlinear regression model, Equation 6, whose coefficient was 0.9165 in the same region.

$$\begin{aligned} Y &= 0.011628 \cdot I_p^{1.12975} \\ &\cdot s[T_a]^{1.1481} \cdot s[I_p]^{1.45698} \\ &\cdot s[\bar{I}]^{-2.4543} \end{aligned} \quad (11)$$

Results and Discussion

Estimating Performance of Linear and Nonlinear Regression Models on the Amount of Spatter

Figure 5 shows the amount of spatter estimated by each proposed regression model. Figure 5A is the linear regression model for the overall region, Equation 4, and Fig. 5B is the combination of two separated linear regression models, Equations 5 and 6. Figure 5C is the nonlinear regression model, Equation 9, and Fig. 5D is the combination of two separated nonlinear regression models, Equations 10 and 11. According to Fig. 5, the estimating performance of these models have a linear relationship with the amount of spatter, as determined by experiment. The spatter estimation from the linear model of Equation 4 (Fig. 5A) showed a larger error than the other models where the amount of spatter was small. In that region, the estimating performance of the nonlinear regression models (Fig. 5C and 5D) is better than the linear models — Fig. 5A and 5B. However, when a large amount of spatter was generated, the estimating performance of these models was poor, while the combined linear regression model (Fig. 5B) had a much better estimating performance when compared to the others.

Fitness of Linear and Nonlinear Regression Models

Figure 6 shows how accurately the linear and nonlinear models estimated the amount of spatter with respect to the change in the welding voltage, when the wire feed rate was 3.4 m/min. Figure 7 shows the average root-mean-square (rms) errors between the amount of spatter and predicted results by the proposed models under those conditions. According to Figs. 6 and 7, it can be seen the nonlinear regression models express the amount of spatter more accurately than the linear regression models. Especially where the amount of spatter was small, the estimation errors by the nonlinear regression models were near zero. However, where the amount of spatter was large, the estimation errors by the nonlinear regression model were greater overall. Also, even in the nonlinear regression model, the estimation errors by the combined nonlinear regression model were much smaller than those of the nonlinear regression model for the overall region. Figure 8 shows the average root-mean-square (rms) errors between the amounts of spatter and predicted results by the proposed models, when the wire feed rate was set at 6 m/min.

As shown in Figs. 8 and 3, the estimating performance by the nonlinear regression models was better than the linear regression models when the amount of spatter was under 3 g/min. In the regions where the amount of spatter was greater than 3 g/min, the estimating errors by the nonlinear regression models were greater than those of the linear regression models. Also, in those regions, the estimating error by the combined linear regression model was smaller than the linear regression model overall. A similar tendency was shown with the higher wire feed rate. In Fig. 9, it was, on the whole, shown the estimating performance of the combined linear regression model was better than the others where the amount of spatter was greater than 3.0 g/min, and the combined nonlinear regression model was the best model where the amount of spatter was smaller than 3.0 g/min.

Selection of the Optimal Model for Estimating the Amount of Spatter

In the short circuit transfer mode of GMAW, the multiple correlation coefficient for each of the four proposed linear and nonlinear regression models and the amount of spatter was the greatest for the combined nonlinear regression model. The linear regression model showed the worst estimating performance overall. The best models for estimating the amount of spatter were the combined linear regression model when the amount of spatter

was greater than 3 g/min and the combined nonlinear regression model when the spatter was less than 3 g/min. Therefore, to estimate spatter more accurately, it is desirable to use the combined linear regression model and the combined nonlinear regression model alternatively according to the amount of spatter.

Conclusions

When welding with voltages above and below optimal levels, the arc becomes unstable and a large amount of spatter is generated. Also, when voltages were below the optimum, arc extinction took place. The more arc extinction, the more spatter. Therefore, the amount of spatter is dependent on the number of arc extinctions when the welding voltage is below the optimal. The factors with arc extinction, which have a high correlation coefficient on the amount of spatter, are different from those without arc extinction. Also, the regression models in each region are composed of different factors.

In order to estimate the amount of spatter, two linear and nonlinear regression models were made factoring in arc extinction. These models were compared to two linear and nonlinear models that did not consider arc extinction. The regression models that considered arc extinction estimated spatter much better than those that did not. Where there was a small amount of spatter, the combined nonlinear regression model showed the best performance in estimating the amount of spatter. In the region where there was a large amount of spatter, the combined linear regression model showed more accuracy.

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