These four steps will be repeated until the items are packed. This method was tested on the literature instances, and we obtained encouraging results.

CIE00459 Identification of Run Length Distribution in Residual Control Chart While Monitoring Autoregressive and Moving Average Processes

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Introducing a definite mathematical relationship to calculate average run length (ARL) in residual control chart for autoregressive process of order p, is the main idea of this paper. In addition, a procedure is proposed to compute ARL in residual control chart for monitoring moving average process of order q. Also, tables of ARL values especially prepared for AR(1) and MA(1) processes are presented. Since 1988 which Special Cause Chart (SCC) was first introduced by Alwan and Roberts, though several researchers have investigated the probability distribution of residuals in AR(1) process, definition of a mathematical formula for ARL in autoregressive processes which is of great interest to compare different monitoring procedures for autocorrelated processes, has been seldom addressed. Invoking mathematical software providing quick solutions for systems of mathematical equations allowed us to implement the proposed approach as a computer program.

CIE00462 Multi-Component Preventive Maintenance Optimization Based on Availability

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In this paper the problem of preventive maintenance (PM) planning for a system with deteriorating components has been addressed. The problem involves a multi-component system with resource constraint and minimum availability requirements. The cost function is weighted summation of repair costs, system downtime cost and random failure cost. Maintenance and repair activities are divided into three actions; namely simple service (inspection), repair and replacement. During the planning horizon, inspections are performed on the regular basis. In each inspection period, one of the three PM activities is carried for each component. The objective is to maintain certain level of availability with minimal total cost. Since the problem is complicated in nature, Simulated Annealing (SA) algorithm is employed as the solution procedure. Computational results show that this algorithm has good performance in solving PM scheduling problems.

CIE00462_2 Evaluating the Discretization of Search Space in Continuous Problems for Ant Colony Optimization

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In this paper, after a beginning on the concept of ant algorithms, a brief survey of the ant-based methods proposed for optimization of problems with continuous design spaces is presented. As a common approach in continuous domains, discretizing the search space is the model presented to be appended to the original ant colony system (ACS) algorithm. Evaluating this method and comparing it to the standard simulated annealing shows that it is robust enough not to fall in local minima. However, when higher resolution is required, the algorithm fails to capture the global optimums and the computational costs rapidly increase. Therefore, it can be safely proposed for the problems in which a trade-off between time, solution accuracy and algorithm intricacy is needed.

CIE00462_3 A Genetic Algorithm Approach For Prediction Of Process Parameters In Submerged Arc Welding

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Among different welding techniques, Submerged Arc Welding (SAW) is one of the most widely used processes employed in metal forming industries. In this paper, a Genetic Algorithm approach is proposed to optimally determine SAW process parameters for any desired weld bead geometry. A five-level factorial technique is employed to relate the important process-control variables (welding voltage, wire feed rate, welding speed and nozzle-to-plate distance) to the bead-quality features (penetration, reinforcement, bead width, total volume of the weld bead and dilution). The adequacy of the proposed approach is verified with ANOVA. Then, the developed models embedded to a GA algorithm to determine the best SAW process parameters for any target values of weld bead geometries. Computational results show that GA method can be used effectively for solving complicated and highly non linear equations in prediction and optimization of welding process parameters.

A GENETIC ALGORITHM APPROACH FOR PREDICTION OF PROCESS PARAMETERS IN SUBMERGED ARC WELDING

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ABSTRACT

Among different welding techniques, Submerged Arc Welding (SAW) is one of the most widely used processes employed in metal forming industries. In this paper, a Genetic Algorithm approach is proposed to optimally determine SAW process parameters for any desired weld bead geometry. A five-level factorial technique is employed to relate the important process-control variables (welding voltage, wire feed rate, welding speed and nozzle-to-plate distance) to the bead-quality features (penetration, reinforcement, bead width, total volume of the weld bead and dilution). The adequacy of the proposed approach is verified with ANOVA. Then, the developed models embedded to a GA algorithm to determine the best SAW process parameters for any target values of weld bead geometries. Computational results show that GA method can be used effectively for solving complicated and highly non linear equations in prediction and optimization of welding process parameters.

KEYWORDS

Submerge Arc Welding, Prediction, modeling, Genetic Algorithm, Weld Bead Geometry, Process Parameters.

1. INTRODUCTION

Submerged Arc Welding (SAW) is one of the major fabrication processes in metal forming industry because of its inherent advantages, including deep penetration, complete fusion, and smooth weld bead (Houldcroft, P.T., 1989). In this technique, similar to other welding processes, the quality of weld joint can be defined in terms weld bead geometry. The weld bead geometry itself is directly influenced by the welding input parameters. In other words, welding can be considered as a multi-input multi-output process. Therefore, appropriate selection of process control parameters is very crucial for achieving required weld bead quality.

The important controlling parameters in SAW include welding voltage, wire feed rate, welding speed and nozzle-to-plate distance. The weld bead quality is specified by weld penetration, reinforcement, bead width, bead volume and the percentage of dilution. A common problem that faces many manufacturers is to select the process input parameters so as to obtain a welded joint with the required bead geometry. In the past, cost and time-intensive trial and error methods were used to determine the suitable process parameters for a desired bead specification. However, these methods were limited in the sense they were porn to errors and could not take into account process changes such as different materials and welding environments.

In recent years, various optimization methods have been applied to define the best output parameters through developing mathematical models to specify the relationship between the process parameters and the weld bead specifications. Design of Experiment (DOE) and numerical methods are employed to model welding processes. Evolutionary algorithms and Neural Networks (NN) have also been adopted to predict the best process parameters. Most models are developed based on regression analysis for a given set of experimental welding data.

For instance, Yang, L.J. et al., (1993) were among the first who used linear regression method for calculating the weld specifications from SAW process variables. They have shown that linear regression equations can be used for predicting various welding features in SAW technique. More recently, Xue, Y. et al., (2005) have employed a fuzzy linear regression approach to investigate the effects of process parameters on the bead width and weld quality in the robotic arc welding.

Kim, J. et al., (2003) carried out a set of statically designed experiments based on factorial technique to study the relationship between process variables and bead penetration for CO_2 arc welding. Murugan, N. et al., (2005) have employed statistically designed experiments based on the factorial technique to gather the required information about different process parameters and their mutual interactions. Numerous research works exist on the modeling and optimization of process parameters in welding. A comprehensive literature survey in this area can be found in (Benyounis, K.Y., and Olabi, A.G., 2007).

Nevertheless, most of the proposed models are complicated and highly non linear. They require comprehensive and time consuming mathematical manipulations. The new trend in welding parameters optimization is to use evolutionary algorithms such as Genetic Algorithm (Correia, C. V., et al., 2005) and Simulated Annealing (Tarng, Y. S. et al., 1999). Other search methods have also been used for this purpose (Kim, S., et al., 2002). Along this line, developing more accurate models and providing more efficient solution procedure is the main objective of this research. In this paper, a Genetic Algorithm (GA) approach is proposed to determine the best values for process parameters with respect to any desired bead geometry.

2. MODEL DEVELOPMENT

The following steps are needed in the proposed approach. First, the mathematical model to relate the bead geometry to the process parameters should be developed and verified. Then, a proper objective function is needed to facilitate the prediction process with respect to any desired Weld bead specification. The implementation of Genetic Algorithm to optimally determine process variables through minimization of such objective function is the final step.

The most important process parameters in SAW are the voltage (V); the wire feed rate (F); the welding speed (S) and the nozzle-to-plate distance (N). To develop the mathematical model with the minimum number of trial experiments, a design matrix should be constructed. Trial runs are then conducted based on this matrix by varying one of the process parameters at a time; while keeping the rest constant. To facilitate design matrix construction, a coding system is employed to indicate different ranges of parameters. The upper and lower limits are coded as +2 and −2, respectively. The intermediate values are calculated using the following formula:

$$X_i = \frac{2[2X - (X_{\max} + X_{\min})]}{(X_{\max} - X_{\min})} \qquad (1$$

Where X_i is the coded value of variable X, and X has a value between X_{min} and X_{max}. Using this procedure, the coded process parameters are given in Table 1.

Parameters	Units	Notation	–2	–1	0	+1	+2
Voltage	Volts	V	24	26	28	30	32
Feed rate	m/min	F	0.70	0.93	1.16	1.39	1.62
Speed	m/min	S	0.43	0.51	0.59	0.67	0.75
Distance	mm	N	30.0	32.5	35.0	37.5	40.0

Table 1 Process Parameters limits and codes

The design matrix, shown in Table 2, is a standard central composite rotatable four-factor five-level factorial design. These 31 experimental runs are sufficient to establish the relationship between weld bead characteristics and welding parameters.

The weld bead geometry includes penetration (P), width (W), reinforcement (R), area of penetration (AP), area of reinforcement (AR), percentage of dilution (D) and total volume (T.V) of the weld bead (assuming the length of the bead (L) as unity). The last seven column of Table 2 are the observed values for the weld bead geometry resulted from 31 trial runs adopted from Gunaraj, V., and Murugan, N., (2000). These data can be used to develop the mathematical models.

Any of the above weld bead characteristics is a function of process parameters ($Y = F(V, F, S, N)$) which can be expressed as:

$$Y = b_0 + b_1V + b_2F + b_3S + b_4N + b_{11}V^2 + b_{22}F^2 + b_{33}S^2 + b_{44}N^2 + b_{12}VF + b_{13}VS + b_{14}VN + b_{23}FS + b_{24}FN + b_{34}SN \qquad (2$$

Based on the above data, the coefficients values ($\boldsymbol{b}_i$) can be calculated using regression analysis.

No.	V	F	S	N	P (mm)	R (mm)	W (mm)	Ap (mm^2)	Ar (mm^2)	D (%)	T.v (mm^3)
1	–1	–1	–1	–1	3.52	1.70	10.15	20.7	24.48	42.40	48.8
2	+1	–1	–1	–1	3.40	1.51	13.47	22.1	21.52	46.80	47.3
3	–1	+1	–1	–1	4.75	2.32	11.05	24.5	22.80	47.50	51.5
4	+1	+1	–1	–1	4.10	1.85	15.64	26.3	24.15	50.30	52.2
5	–1	–1	+1	–1	3.25	1.38	08.28	18.3	23.17	40.70	44.9
6	+1	–1	+1	–1	3.18	1.18	10.10	19.5	23.42	41.90	46.5
7	–1	+1	+1	–1	3.52	1.50	09.15	21.5	18.90	48.60	44.3
8	+1	+1	+1	–1	3.33	1.82	09.86	23.2	19.25	49.80	46.6
9	–1	–1	–1	+1	3.85	1.61	10.66	20.2	27.48	39.40	51.3
10	+1	–1	–1	+1	3.60	1.48	14.55	21.8	26.24	40.50	53.8
11	–1	+1	–1	+1	4.10	1.92	13.38	23.1	27.82	42.10	54.9
12	+1	+1	–1	+1	3.80	1.80	15.96	26.5	31.16	42.90	61.8
13	–1	–1	+1	+1	3.20	1.37	08.70	17.7	24.52	38.60	45.5
14	+1	–1	+1	+1	3.00	1.10	09.28	18.9	25.34	39.70	47.6
15	–1	+1	+1	+1	4.10	1.75	09.01	20.3	25.55	40.80	49.8
16	+1	+1	+1	+1	3.88	1.50	10.00	21.1	23.87	42.30	49.1
17	–2	0	0	0	4.10	1.62	10.28	19.4	24.25	41.10	47.2
18	+2	0	0	0	3.75	1.43	15.30	25.4	29.45	42.90	59.2
19	0	–2	0	0	3.26	1.41	09.95	19.1	17.95	38.10	40.1
20	0	+2	0	0	4.97	1.75	10.96	27.7	21.53	51.00	54.3
21	0	0	–2	0	4.25	2.30	16.11	25.3	31.33	41.30	61.2
22	0	0	+2	0	3.48	1.40	08.50	18.4	21.05	43.00	42.8
23	0	0	0	–2	3.82	1.31	11.17	22.5	19.68	48.70	46.2
24	0	0	0	+2	3.58	1.27	12.05	23.2	27.83	42.50	54.6
25	0	0	0	0	3.45	1.15	11.20	20.9	21.80	47.10	44.4
26	0	0	0	0	3.47	1.30	10.58	21.7	21.40	46.50	46.6
27	0	0	0	0	3.66	1.27	09.92	21.9	19.80	48.20	45.4
28	0	0	0	0	3.60	1.31	11.13	21.2	19.90	47.60	44.5
29	0	0	0	0	3.30	1.16	10.56	20.5	21.10	45.70	44.9
30	0	0	0	0	3.60	1.27	10.84	22.6	21.50	47.30	47.8
31	0	0	0	0	3.92	1.45	11.05	22.1	24.60	48.50	47.6

Table 2 Design of experiments matrix for bead geometry parameters with respect to process parameters

The mathematical models representing the relationship between process parameters and weld bead geometry can be stated as follows:

Penetration (P_{mm}) $= 3.57 - 0.113V + 0.33F - 0.217S - 0.001N + 0.048V^2 + 0.1F^2 + 0.03S^2 - 0.01N^2 - 0.05VF + 0.06VS + 0.038VN - 0.011FS - 0.01FN + 0.083SN$ (3

Reinforcement (R_{mm}) $= 1.27 - 0.08V + 0.16F - 0.18S - 0.03N + 0.07V^2 + 0.08F^2 + 0.15S^2 + 0.01N^2 + 0.02VF + 0.03VS - 0.014VN - 0.003FS - 0.02FN + 0.03SN$ (4

Width of weld bead (W_{mm}) $= 10.76 + 1.19V + 0.45F - 1.9S + 0.23N + 0.41V^2 - 0.17F^2 + 0.29S^2 + 0.12N^2 - 0.05VF + 0.64VS - 0.15VN - 0.35FS + 0.091FN - 0.29SN$ (5

Area of penetration (Ap_{mm^2}) $= 21.56 + 1.05V + 1.85F - 1.61S - 0.21N + 0.041V^2 + 0.29F^2 - 0.097S^2 + 0.15N^2 + 0.14VF - 0.21VS + 0.056VN - 0.24FS - 0.16FN - 0.16SN$ (6

Area of reinforcement (Ar_{mm^2}) $= 21.44 + 0.443V + 0.187F - 1.76S + 2.11N + 1.39V^2 - 0.39F^2 + 1.22S^2 + 0.62N^2 + 0.41VF - 0.047VS + 0.14VN - 0.94FS + 0.77FN - 0.33SN$ (7

Percentage of dilution (Pd%) $= 47.27 + 0.74V + 2.5F + 0.25S - 2.23N - 1.31V^2 - 0.71F^2 - 1.31S^2 - 0.44N^2 - 0.09VF - 0.28VS - 0.31VN + 0.43FS - 0.9FN + 0.17SN$ (8

Total weld bead volume (Tv_{mm3}) $= 45.78 + 1.58V + 2.2F - 3.5S + 2.0N + 1.67V^2 + 0.17F^2 + 1.34S^2 + 0.97N^2 + 0.28VF - 0.21VS + 0.48VN - 0.87FS + 0.64FN - 0.77SN$ (9

To ensure the accuracy of these empirical models, analysis of variance technique (ANOVA) is performed. According to ANOVA, models are adequate within the confidence limit of 95%.

For any given weld bead geometry, this set of equations must be solved simultaneously to find the suitable process parameters. As can be seen, the only feasible way to solve these equations is the use of numerical methods. Such methods require large computational efforts and are porn to errors. In the following sections, we propose a GA based approach to predict the best values for process parameters by minimizing a fitness function.

2.1. The Prediction Function

The mathematical models furnished above provide one to one relationships between process parameters and weld bead geometry. They can be used in two ways; 1) predicting weld bead geometry based on input parameters and 2) predicting process parameters for a desired weld bead specification. The later one is more practical since the welding parameters are usually set based on desired bead geometry. For this purpose, the set of non-linear equations must be solved simultaneously for all the process parameters. Evolutionary algorithms are powerful optimization techniques widely used for solving combinatorial problems. Nevertheless, other capabilities of these techniques have rarely been explored. As a new and promising approach, one of these algorithms, called GA, is implemented for prediction purposes in this research.

To predict the process parameters based on a desired bead quality, we first define the prediction function as follow:

$$of(i) = \alpha_1 \frac{(P_t - P_{Equ})^2}{P_t} + \alpha_2 \frac{(R_t - R_{Equ})^2}{R_t} + \alpha_3 \frac{(W_t - W_{Equ})^2}{W_t}$$
$$+ \alpha_4 \frac{(Ap_t - Ap_{Equ})^2}{Ap_t} + \alpha_5 \frac{(Ar_t - Ar_{Equ})^2}{Ar_t} + \alpha_6 \frac{(Pd_t - Pd_{Equ})^2}{Pd_t}$$
$$+ \alpha_7 \frac{(Tv_t - Tv_{Equ})^2}{Tv_t}$$

(10

Where:

$P_{Equ}, R_{Equ}, W_{Equ}, Ap_{Equ}, Ar_{Equ}, Pd_{Equ}, Tv_{Equ}$ are bead specifications namely penetration, reinforcement, width of weld bead, area of penetration, area of reinforcement, percentage of dilution and total bead volume respectively which are given by Equations 3 to 9. In the same manner, we define $P_t, R_t, W_t, Ap_t, Ar_t, Pd_t, Tv_t$ as the target values for the desired weld bead geometry.

The coefficients α_i represent weighing importance of different parameters in the objective function. In the prediction process, the purpose is to minimize this objective function. By doing so, the process parameters are calculated in such way that the bead geometry parameters approach their desired values. A GA method is employed to find the best welding variables with respect to process specifications.

3. GENETIC ALGORITHM

Genetic Algorithm, first proposed by John Holland in 1975, has been adapted for large number of applications in different areas. This method has its philosophical basis in Darwin's theory of survival of the best and most fitted individuals. It belongs to a general category of stochastic search methods. This algorithm encodes a potential solution to a specific problem on simple chromosome string like data structure and applies specified operators to these structures so as to preserve critical information, and to produce a new set of population with the purpose of generating strings which map to high function values. The basic operations which affect the binary strings makeup in natural evolution are a selection, a crossover of genetic information between reproducing parents, a mutation of genetic information and an elitist strategy that keeps the best individual in the next generation.

The main characteristic of the GA and its several variations is that they operate simultaneously with a large set of search space points, instead of a single point (as the conventional optimization techniques). Besides, the applicability of the GAs is not limited by the need of computing gradients and by the existence of discontinuities in the objective function (performance indexes). This is so because the GAs works only with function values, evaluated for each population individual.

Genetic algorithm repeatedly modifies a population of individual solutions. At each step, it selects individuals at random from the current population to be parents and uses them to produce the children for the next generation. Over successive generations, the population "evolves" toward an optimal solution.

Genetic algorithm uses three main types of rules at each step to create the next generation from the current population:

Selection rules select the individuals, called parents, which contribute to the population at the next generation.
Crossover rules combine two parents to form children for the next generation.
Mutation rules apply random changes to individual parents to form children.

Genetic algorithm can be applied to solve a variety of optimization problems that are not well suited for standard optimization algorithms, including problems in which the objective function is discontinuous, non differentiable, stochastic, or highly nonlinear (Cheng, G.R., 1997). The major drawback of GA includes its many search parameters which need to be properly selected and tuned. A complete description of this algorithm and some of its applications can be found in (Goldberg, N., 1989)

4. AN ILLUSTRATIVE EXAMPLE

In this section a numerical example is presented to illustrate the performance of proposed procedure and solution technique. The target values for desired weld bead geometry are given in Table 3. (Gunaraj, V., and Murugan, N., 2000).

Weld Bead Geometry	Target Value
P_t (mm)	3.07
R_t (mm)	1.28
W_t (mm)	8.33
Ap_t (mm^2)	18.13
Ar_t (mm^2)	20.21
Pd_t (%)	38
Tv_t (mm^3)	41.33

Table 3 Target values for weld bead geometry

Without lose of generality, all elements of the bead geometry are assumed to be of the same importance and therefore constants α_1 to α_7 are set to unity.

The prediction function given in Equation 10 along with weld bead modeling equations 3 to 9 are embedded into GA algorithm. The parameters for the algorithm are set as follows:

Number of generations	200
Population size	30
Crossover rate	80%
Crossover mechanism	scatter
Mutation rate	1%

The objective is to minimize the perdition function which is used as the fitness criterion in evaluation each generation of solutions. The best values found by proposed GA for process parameters are presented in Table 4. By setting these parameters in SAW, the target weld bead geometry specifications may be achieved.

Process parameters	Predicted value by GA
Welding Voltage (V)	27.34102
Wire Feed Rate (m/min)	0.70055
Welding Speed (m/min)	0.63756
Nozzle to plate distance (mm)	34.36322

Table 4 Predicted values for process parameters

The performance of the solution procedure was tested by substituting parameters values obtained by GA into the weld bead models and comparing the results with the desired values of bead geometry. The comparison of the calculated and desired values is shown in Table 5. The largest error is around 5.5% while most parameters deviate much less than 1% from their desired values. The computational results show that GA can be used efficiently and with good accuracy as a prediction technique.

Weld Bead Geometry	Targets	GA Results	Error%
Penetration	3.07	3.193	-3.85
Reinforcement	1.28	1.213	5.52
Width of weld	8.33	8.35	-0.24
Area of Penetration	18.13	18.12	0.06
Area of Reinforcement	20.21	20.25	-0.19
Percentage of Dilution	38	37.94	0.10
Weld Bead Volume	41.33	41.41	-0.19

Table 5 Comparison between desired and predicted weld bead geometry values

5. CONCLUSION

Weld bead geometry is the most important quality measure in welding processes. In order to achieve a high quality weld, welding parameters should be set in such way that the desired bead geometry is obtained. The relationship between bead geometry and welding parameters is quite complicated involving many mutual interactions. The main trust of this research was to explore the possibility of using GA algorithm in predicting welding parameters values in Submerged

Arc Welding (SAW). Along this line, first the mathematical relationships between welding parameters and weld bead geometry were established. Then a GA based procedure was developed to predict the best process parameters values for desired weld bead specifications. Computational results show that the proposed GA method can efficiently and accurately predict welding parameters so that a desired weld bead is obtained. The extension of this research may include employing GA, and other heuristic techniques, to predict optimal parameters for other kinds of welding processes.

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