MULTIVARIABLE INTELLIGENT CONTROL FOR M.A.G. WELDING PROCESS

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Abstract: A neural control technique, applied to the MAG (Metal-Active Gas) welding process, is presented in the paper. The static nonlinear model of welding process is based on experimental determinations. The geometric parameters of the welding beam are considered as output parameters of the MAG process (B_s, a, p), and they are measured for different step-variations of the input parameters (V_e, V_s, U_a). The analysis of the output dynamics was further used to model the MAG welding process using a 3-layer neural network with 6 hidden-layer neurons. In order to reject perturbations and cancel the stationary error, an error compensator was used, which consists of the reverse dynamic model connected to a proportional integrator controller. Simulation results for the multivariable neural controller are presented.

Keywords: welding process, intelligent control, nonlinear model, neural network, reverse dynamic model.

1. INTRODUCTION

The cross section geometry and metallographic structure characterize the quality of an electric welding process based on MAG procedure (Ogata, K.., 1990). Turbulence, unavoidable during welding, may modify both seam geometry, and metallurgic micro-structure. Such turbulence has to be perceived, and input parameters in the process have to be properly modified in order to maintain welding quality. In this paper, dynamic behavior of welding seam using MAG procedure is modeled, and a neural error compensator is designed.

2. MODEL OF MAG WELDING PEOCESS

The inputs and outputs of MAG welding model are illustrated in Figure 1.

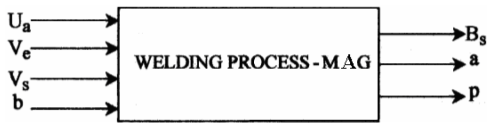

Fig.1. Input/Output of the MAG welding process

The model inputs, adjustable by means of welding equipment, are: arc voltage (U_a), wire electrode speed (V_e) and welding speed (V_s). The gap width (b) was considered as input variable, and its variation influences the performance of controller and model accuracy.

The model outputs are: seam breadth (B_s), weld thickness (a) and penetration (p), which are illustrated in Figure 2.

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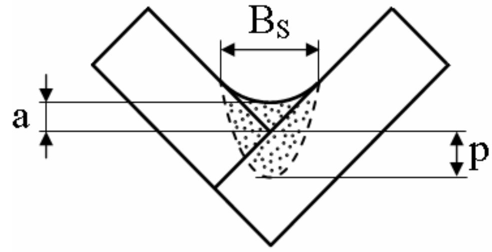

Fig.2. Fillet Weld Geometric Dimensions BS – width weld; a – throat thickness; p – penetration

From the set of seam geometric parameters, the seam breadth (B_s) is the only parameter, which can be on-line measured or estimated. In this paper it is estimated based on registered images produced by a video-camera. The other seam parameters (a and p) can be determined only off-line, after seam cross cutting.

2.1. Non-linear static model

In this paper, an empirical model based on neural network techniques has been represented. In order to generate a nonlinear static model, several experiments were performed. Each of the three inputs (U_a, V_e, V_s) has been modified in steps, measuring values of seam geometric parameters, including values of welding current. Constant free length of wire-electrode (L) was maintained during these experiments. For each value of gap width (b = 0 mm; b = 1.0 mm; b = 1.5 mm) one set of experiments has been performed. The input values are shown in Table 1 and output values are represented in Table 2 (Miholca, *et al*, 2000).

Comparative analysis shows that MAG welding is a nonlinear, continuous, multivariable process determined by non-stationary parameters.

The knowledge base about interaction between variables and dynamic response characteristics is incomplete.

Other welding characteristics were: type of joint: fillet welding; base material: marine steel grade A, S=7 mm; protection gas: Argon (82% Ar + 18% CO_2); flow gas: 22 l/min; welding source: ESAB-ARISTO LUD-320; nature and current polarity: DC^+; adding material: full wire S12 Mn2Si, ϕ 1,4 mm; welding position: horizontal in spot(Miholca, *et al*, 2003).

Table 1 Results of experiments on M.A.G. welding

Nr. crt.	b [mm]	U_a [V]	v_e [m/min]	v_s [mm/s]
0	1	2	3	4
1	0.0	28	5.0	8.5
2	0.0	32	5.0	8.5
3	0.0	28	6.0	8.5
4	0.0	32	6.0	8.5
5	0.0	28	6.5	8.5
6	0.0	32	6.5	8.5
7	0.0	28	5.0	10.0
8	0.0	32	5.0	10.0
9	1.0	28	5.0	7.0
10	1.0	32	5.0	7.0
11	1.0	28	5.6	9.5
12	1.0	32	5.6	9.5
13	1.0	28	6.0	7.0
14	1.0	32	6.0	7.0
15	1.0	28	5.6	7.0
16	1.0	32	5.6	7.0
17	1.5	28	6.0	9.5
18	1.5	32	6.0	9.5
19	1.5	28	5.0	7.0
20	1.5	32	5.0	7.0
21	1.5	28	5.6	9.5
22	1.5	32	5.6	9.5
23	1.5	28	5.6	7.0
24	1.5	32	5.6	7.0

Table 2 Results of experiments on M.A.G. welding

Nr. crt.	L [mm]	I_s [mm]	B_s [mm]	a [mm]	p [mm]
0	5	6	7	8	9
1	22	240	9.15	4.15	1.38
2	22	262	10.22	4.50	2.12
3	22	278	8.82	3.52	1.62
4	22	294	10.54	4.62	2.38
5	22	298	8.52	4.36	1.96
6	22	306	9.85	4.50	2.85
7	22	288	8.40	4.22	1.82
8	22	294	8.76	3.12	1.94
9	22	254	7.92	3.28	2.14
10	22	286	10.32	3.40	3.20
11	22	248	7.42	2.42	2.96
12	22	262	8.20	2.76	3.12
13	22	252	8.15	3.20	2.42
14	22	270	10.24	2.94	3.40
15	22	284	7.82	3.10	2.50
16	22	302	10.12	3.20	4.20
17	22	278	7.10	3.00	2.94
18	22	304	8.98	3.10	3.20
19	22	260	7.60	2.80	2.80
20	22	285	8.86	2.50	4.10
21	22	272	6.60	2.10	3.60
22	22	294	7.42	2.0	3.72
23	22	242	8.12	3.42	2.62
24	22	268	9.30	2.80	3.36

2.2. Dynamic model

The stationary response shown in Table 2 has been obtained using a neural network model composed of 3 layers with 6 hidden-layer nodes. To estimate output dynamics (transitory times and gain factors), variations of seam width (B_s) have been off-line measured at different step variations on each input.

During tests, each input was modified with small permitted values between minimum and maximum level, so that the nonlinear model to be considered as linear around operating point. Hence, dynamic analysis was performed using super-position principle. Results of experiments are shown in figures 3, 4, 5 and 6.

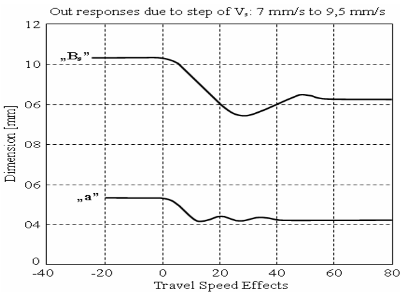

Fig.3. Travel Speed Effects

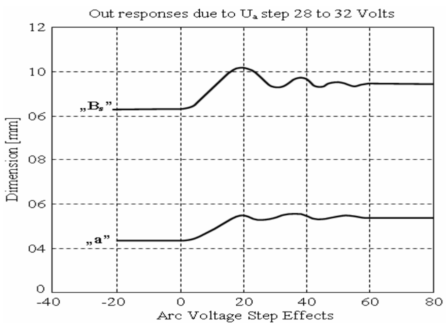

Fig.4. Arc Voltage Step Effects

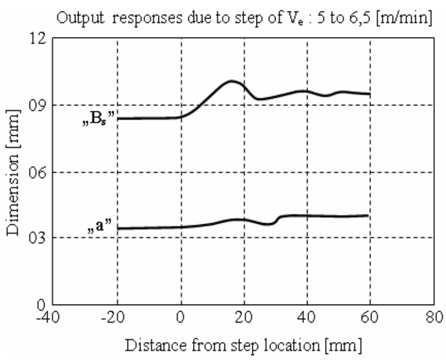

Fig.5. The Effects of the Step Wire Speed

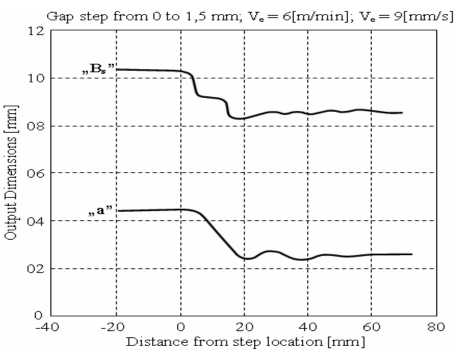

Fig.6. Root Gap Step Effects

2.3. Identification of output dynamics

Output variations (B_S and a) were measured starting from the moment when the corresponding input was modified. Time constant value is recommended at 1/4 of settling time [3], and it was computed based on the time interval measured from the moment of input variation and up to the moment of reaching stationary value of welding speed (V_S). Dynamic model contains the four-dimension input vector, denoted u, and the two-dimension output vector, denoted y.

$$(1)\quad u = \begin{bmatrix} U_a \\ v_e \\ v_s \\ b \end{bmatrix} \quad ; \quad y = \begin{bmatrix} B_s \\ a \end{bmatrix}$$

In general, if u is a column p-dimension vector, and y is a (q x 1) vector, then the transfer matrix G(s) must have (q x p) dimension, where each element is a first degree transfer function:

$$(2)\quad g_{ij}(s) = \frac{K_{ij}}{s + 1/\tau_{ij}}$$

where k_{ij} is gain factor, and τ_{ij} is time constant of the transfer function corresponding to the element.

After experimental identification of time constants for each element of transfer matrix, the matrix of time constants with (2 x 4) dimension results:

$$(3)\quad \begin{bmatrix} \tau_{11} & \tau_{12} & \tau_{13} & \tau_{14} \\ \tau_{21} & \tau_{22} & \tau_{23} & \tau_{24} \end{bmatrix} = \begin{bmatrix} 0{,}88 & 1{,}75 & 0{,}92 & 1{,}08 \\ 0{,}78 & 0{,}86 & 1{,}24 & 0{,}51 \end{bmatrix}$$

Using final value theorem for Laplace transformation, results:

$$(4)\quad \Delta y_{st} = \lim_{s\to 0} s \cdot \begin{bmatrix} \frac{K_{11}}{s+1/\tau_{11}} & \frac{K_{12}}{s+1/\tau_{12}} & \frac{K_{13}}{s+1/\tau_{13}} & \frac{K4}{s+1/\tau_{14}} \\ \frac{K_{21}}{s+1/\tau_{21}} & \frac{K_{22}}{s+1/\tau_{22}} & \frac{K_{23}}{s+1/\tau_{23}} & \frac{K_{24}}{s+1/\tau_{24}} \end{bmatrix}_{u=u_0} \cdot \frac{1}{s} \begin{bmatrix} \Delta U_a \\ \Delta V_e \\ \Delta V_s \\ \Delta b \end{bmatrix}$$

During stationary regime, it results:

$$(5)\quad \Delta y_{st} = \begin{bmatrix} \alpha_{11} & \alpha_{12} & \alpha_{13} & \alpha_{14} \\ \alpha_{21} & \alpha_{22} & \alpha_{23} & \alpha_{24} \end{bmatrix}_{u=u_0} \cdot \begin{bmatrix} \Delta U_a \\ \Delta V_e \\ \Delta V_s \\ \Delta b \end{bmatrix};$$

The gain factors are:

$$(6)\quad K_{ij} = \alpha_{ij} / \tau_{ij}$$

The values of gain factors for transfer matrix elements have been calculated based on experimental results shown in figure and 3, …,6:

$$(7)\quad K_{ij} = \frac{\Delta B_{si}}{\Delta u_i}, \, for \ \ j = 1,....,4$$

where ΔB_{SI} is variation of seam width to step signal of input i.

Dynamics of output ΔB_S for step variations of each input is expressed by formula:

$$(8)\quad \Delta B_s = f_{sc}\left[\begin{array}{l} K_{11}\left(1-\exp^{-\frac{t-t_0}{\tau_{11}}}\right)\Delta U_a + K_{12}\left(1-\exp^{-\frac{t-t_0}{\tau_{12}}}\right)\cdot \Delta V_e + \\ + K_{13}\left(1-\exp^{-\frac{t-t_0}{\tau_{13}}}\right)\cdot \Delta V_s + K_{14}\left(1-\exp^{-\frac{t-t_0}{\tau_{14}}}\right)\Delta b \end{array}\right]$$

where f_{sc} is computed for stationary regime ($t \to \infty$)

$$(9)\quad f_{sc} = \frac{\Delta B_s}{K_{11}\cdot \Delta U_a + K_{12}\cdot \Delta V_e + K_{13}\cdot \Delta V_s + K_{14}\cdot \Delta b}$$

3. CONTROLLER DESING

The MAG welding is a non-linear process with non-stationary parameters and coupled variable. Such characteristics of process impose the following requirements for a controller:

a) Reference follow up, which means that the output has to follow asymptotically the reference signal r(t) on the whole working range of process variables

$$(10)\quad \lim_{t\to\infty} e(t) = \lim_{t\to\infty}\left[r(t) - y(t)\right] = 0$$

b) Turbulence rejection: the effect of turbulence in output vector has to be null for the stationary regime.

$$(11)\quad \lim_{t\to\infty} \Delta y(t)_{r(t)=0} = 0$$

c) Robustness: controller has to be able to tolerate deviations of welding response, as a result from non-modeled process dynamics (variations of gap width).

d) Satisfactory transitory performance: over-adjusting and transitory time must be small when step signals are applied on inputs. As the outputs of MAG welding process are tight coupled, it is necessary a non-linear multivariable adjustment structure using a neural controller, illustrated in figure 7.

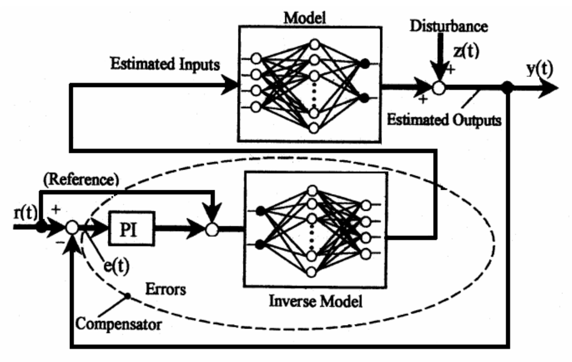

Fig.7. A Non – linear Neural Controller Framework

An error compensator was used to avoid stationary errors and to reject any perturbations. It contains a PI controller, coupled to the reverse dynamic model of welding process. An output feed-back is used to generate error signal e(t).

The weights of neural network representing reverse model of MAG process plays the role of matrixes A, B, C and D of linearised model of process:

$$(12)\quad \begin{cases} \Delta \dot{x} = A \cdot \Delta \underline{x} + B \cdot \Delta \underline{u} \\ \Delta y = C \cdot \Delta \underline{x} + D \cdot \Delta \underline{u} \end{cases}$$

The compensator model, illustrated in figure 7, is:

$$(13)\quad \begin{cases} \dot{\underline{x}}_c = A_c \cdot \underline{x}_c + B_c \cdot \underline{e} \\ \Delta \underline{u}(t) = K_c \cdot \underline{x}_c \end{cases}$$

4. SIMULATION RESULTS

The neural network was trained with data set from Table 1, adopting 0,001 value for minimum square error criterion. Simulation results led to a maximum error of ± 0,15 mm for seam width (B_s), and ± 0,06 mm for seam thickness (a).

The gain factors of transfer matrix elements (eq. 6) were computed by neural network model, so that the stationary error to be null.

Several neural network structures have been experimented for reverse process model and several conclusions have been reached:

- Convergence of 3 layers network is guaranteed.
- The most efficient training procedure for reverse model neural network is to modify the network parameters in each epoch.

A PI controller was taken into account for each of the two controlled outputs of process.

Simulation and experimental results (from Table 1) are compared and illustrated in figure 8, for the same operational conditions (b = 0, V_e = 6,0 m/ min and V_s = 9 mm/s).

Differences between real- and simulated-responses are due to different values in Table 1 used for neural network training.

Output simulation for step change "B_s" and "a" are illustrated in figure 9.

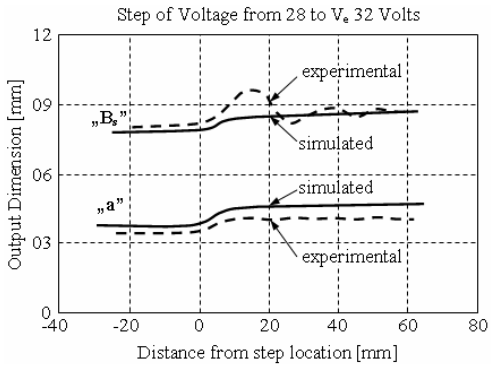

Fig.8. Experimental and Simulated Voltage Step

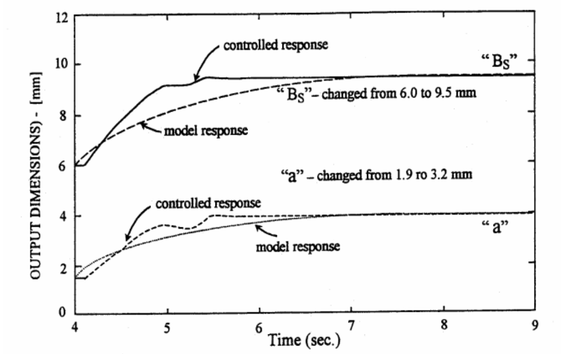

Fig.9. Output Simulation for Step Change "BS" and "a"

The step variations ΔB_s and Δa have been applied after min 5 seconds of stationary functioning.

Magnitude matrix of PI controller is:

$$(14)\quad K_{PI} = \begin{bmatrix} K_p & K_I/D & K_D \cdot D \\ K_p' & K_I'/D & K_D' \cdot D \end{bmatrix} = \begin{bmatrix} 2.2 & 0.03/D & 0 \cdot D \\ 2 & 0.02/D & 0 \cdot D \end{bmatrix}$$

where: K_p, K_I, K_D are proportional, integrator and derivative gain factors of welding width "B_s", and K_p', K_I', K_D' are the corresponding gain factors of welding thickness "a". The D variable is a parameter of multivariable linear model.

Estimation errors (e_{Bs} and e_a) of width and thickness welding with PI controller are computed:

$$(15)\quad \begin{bmatrix} e_{Bs} \\ e_a \end{bmatrix} = \begin{bmatrix} K_p & K_I / D \\ K_p' & K_I' / D \end{bmatrix} \cdot \begin{bmatrix} \Delta B_s \\ \Delta a \end{bmatrix}$$

Simulation results with and without controller, for a step increasing of gap width from 1 mm to 1,5 mm, are illustrated in figure 10.

The adjustment error of welding thickness "a" can be decreased by modifying controller gains.

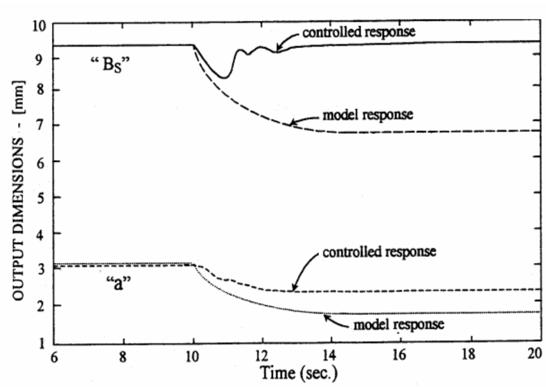

Fig.10. Output Simulation for the Step Change of gap width from 1 mm to 1.5 mm

5. CONCLUSIONS

- A multivariable neural controller is used for intelligent control of MAG welding process, which works well for the whole value range of model inputs.

- In contrast with a locally-linear controller, which requires a set of nominal inputs, the neural compensator computes directly the necessary inputs from the reference outputs of welding process.

- In addition, data obtained during welding process can be used immediately for refining of neural weights. This can be used to implement an adaptive neural controller.

- Simulation results show that the designed neural controller satisfies the performance criterion for multivariable control of MAG welding process.

6. REFERENCES

Miholca C. (2000). Representation of the Electrical Spot Welding Process by a Neural Network Based on Experimenral Investigations. Project Tempus PEC-12018/97 Bulletin Informative, no.1, pp.79-85 – Bucharest.

Miholca C., Mihăilescu D., Mihăilescu A. (2003). "Tehnological Parameters influence on the Welding Process Stability and Seam Geometry Under Pulsatory Current Tube Wire MAG Welding". ASR International Conference – 11-th July 2003, Bucharest, pp. 371-382.

Ogata, K., (1990). "Modern Control Engineering" – second Edition, Prentice Hall Inc.