doi.org/10.15407/tpwj2017.05–06.14

INFLUENCE OF FLASH BUTT WELDING PROCESS PARAMETERS ON STRENGTH CHARACTERISTICS OF RAILWAY RAIL BUTTS

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The analysis of basic parameters of flash butt welding was carried out according to the data of current technological reports formed by the computer control system during welding of rails. The opportunity to develop the model for predicting the output quality index of welded butt of a rail, i.e. fracture load of specimen and deflection, was shown based on the parameters of welding process applying different methods of statistical analysis, in particular, correlation and regression analysis and neural networks. The calculations were carried out according to the experimental data obtained at the Kiev rail welding enterprise during welding of rails in the welding machine K1000. 6 Ref., 2 Tables, 5 Figures.

Keywords: *flash butt welding, statistical models of monitoring and control, monitoring of process parameters, statistical control*

During welding of railway rails in the stationary and suspended flash butt welding machines, the monitoring of the mode technological parameters is carried out with their registration by the computer system for each welded butt. Simultaneously, ultrasonic testing of these butts is carried out. Periodically, mechanical tests of welded rails are carried out and the conclusion on the conformity of this technological mode to the required welding quality is issued. The monitoring of the process is carried out by checking the presence of mode parameters in the allowances preset by technical specifications (TS) [1].

At the present time the stationary and mobile rail welding machines of the new generation of K1000, K920, K922 types are equipped with the computerized control systems. The schemes for control of the machines are designed on the basis of SIEMENS industrial controllers. The modern element base allowed a high accuracy reproducing the values of the mode parameters, regulated by TS for welding of railway rails. However, even in this case, it is impossible to exclude the probability of defects arising in welded joints, if under the influence of random external factors the heating zone, plastic deformation or stability of flashing changed. In the industrial conditions different technological and electrical disturbances arise, which lead to violation of the process stability and deterioration of the welding quality. It is necessary to find new parameters and algorithms of control which increase the probability of predicting the quality of welded joints.

The aim of this work is the development of algorithms for control of flash butt welding process in the stationary and field conditions, providing the control of quality of butts based on the process parameters and monitoring the technical condition of welding equipment. These algorithms are embodied into a two-level system of monitoring and control. Such system besides a direct digital control of welding process and monitoring of process parameters in accordance with allowances, performs the following functions:

● prediction of the quality of welded butt by the process parameters and increase in its validity due to application of more advanced algorithms and involving the qualified specialists in the prediction;

● monitoring of technical condition of welding equipment, systematization of types of wear of welding equipment components, their dividing into common ones for all machines of the given type and specific ones for definite machines, working out of recommendations and planning the maintenance of welding equipment;

● detection and recognition of emergency situations (inadmissible deviations in welding process parameters, technical condition of equipment, performance of auxiliary technological operations, data of mechanical tests, inadmissible voltage deviation, cooling, etc.) for immediate intervention to the technological process;

● systematization of deviations of welding process parameters, which can lead to deterioration of the quality indicators of welded joints, working out of recommendations on the correction of welding mode parameters;

● indirect control during welding process deviations in the implementation of auxiliary technological operations (preparation of edges for welding), in the state of auxiliary objects (transformer substation, equipment for edges preparation).

The control algorithms are based on the analysis of welding process parameters, which are displayed in the technological report of the computer control system. An example of the report is given below: v_{fl} — 0.108 mm/s; S — 26.1 mm; T — 67 s; U_1 — 412 V; U_2 — 320 V; I — 359 A; v_f — 1 mm/s; P_a — 136 atm; L_{ups} —15.5 mm; T_{upsI} — 1.4 s; $Z_{sh.-c}$ — 104.5 μOhm; Q — 2271 W·h; v_{ups} — 68 mm/s; P_{fr} — 2400 kN; L_{defl} — 48 mm.

Here, v_{fl} is the flashing speed; S is the allowance for flashing; T is the welding duration; U_1 is the voltage at the 1st stage; U_2 is the voltage at the 2nd stage; I is the welding current; v_f is the forcing speed; P_a is the pressure; L_{ups} is the allowance for upsetting; T_{upsI} is the upsetting duration; $Z_{sh.-c}$ is the short circuit resistance of the machine circuit; Q is the total energy; v_{ups} is the upsetting speed; P_{fr} is the fracture load; L_{defl} is the deflection.

The aim of investigations was checking the opportunity to develop a model for predicting the output quality index of welded butt of a railway rail, i.e. the fracture load of specimen and deflection according to the parameters of welding process using different methods of statistical analysis, in particular, correlation and regression analysis and neural networks. The design strength of welded rails is determined by testing for static transverse bending. Here the value of fracture load P_{fr} and deflection of the rail L_{defl} are registered under the action of this load. The admissible values of these parameters are regulated by TS. The experiments were conducted at the Kiev rail welding enterprise in the welding machine K1000. The data of process parameters (162 sets) were measured and monitored by the monitoring and control system of welding machine. All the further investigations were carried out with the help of programs Excel 2010 (Microsoft) and Statistica v.10 (StatSoft, Dell) [2].

Each of the controlled parameters determines the course of the process at separate stages: 1 — fusion of the bevel (U_1); 2 — flashing (U_2, I, v_{fl}, Q); 3 — forcing (v_f, $T_{sh.-c}$); 4 — upsetting (v_{ups}, L_{ups}, P_a, T_{upsI}).

The parameter S characterizes the process before upsetting (1, 2, 3 stages), T characterizes the process over the welding time (1, 2, 3, 4); $Z_{sh.-c}$ — technical condition of welding machine.

To control the process the presetting of each stage is carried out according to the travel of a moving column, i.e. on achievement of the preset S (typical mode for the machines K920 and K1000). Thus, the parameter S, as well as U_1, U_2, L_{ups}, P_a, T_{upsI} are stabilized by the control system. Other parameters like I, v_{fl}, Q, v_f, $T_{sh.-c}$, v_{ups}, $Z_{sh.-c}$, T are determined by the conditions of running process (presence of disturbances, technical condition of welding equipment, qualification of welder and auxiliary workers).

If a particular parameter has a constant value, there is no sense to introduce it into the model [3, 4]. However, all the abovementioned parameters except of $T_{sh.-c}$ have scattering from ±8 to ±100 % and are appropriate for study.

The deviation of the process parameters (±) in the investigated experiments is the following: v_{fl} — 99 mm/s; S — 17 mm; T — 68 s; U_1 — 8 V; U_2 — 8 V; I — 41 A; v_f — 67 mm/s; P_a — 9 atm; L_{ups} — 14 mm; T_{upsI} — 56 s; $Z_{sh.-c}$ — 9 μOhm; Q — 49 W·h; v_{ups} — 79 mm/s; P_{fr} — 38 kN; L_{defl} — 39 mm.

From the data of correlation analysis (Table 1) the following parameters in the descending order (Figure 1) have the greatest relation with the output–fracture load P_{fr} (Figure 1): U_1 ,U_2, I, L_{ups}, S, v_{ups}, T_{upsI}, P_a, v_{ups}, $Z_{sh.-c}$, Q, T, v_f. The latter two of them are lower than the Student's value (0.159) and 6 are lower according to the Chaddock 0.3). To evaluate the relation strength in the theory of correlation, the scale of the English statistician Chaddock is applied: weak — from 0.1 to 0.3; moderate — from 0.3 to 0.5; significant — from 0.5 to 0.7; high — from 0.7 to 0.9; very high (strong) – from 0.9 to 1.0.

From the coefficients of mutual correlation between the parameters, it follows that:

● high relation (0.7–0.9) between U_1, U_2, I, L_{ups}, S;

● high relation of v_{fl} with this group except of S (0.67) and Q (0.64);

● Q has a high relation with T (0.8) and an average one with v_{fl} (0.64);

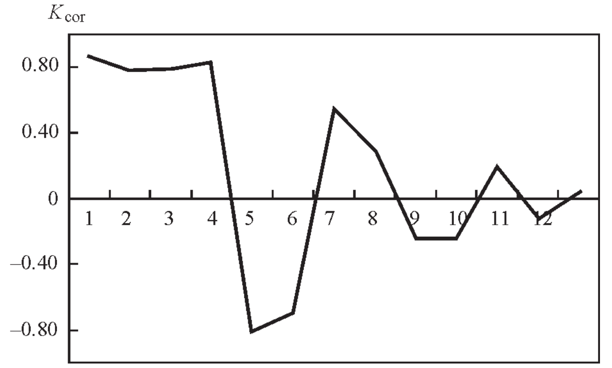

Figure 1. Correlation coefficients of process parameters with the value of fracture load of specimen in descending order: *1* — U_1; *2* — U_2; *3* — I; *4* — L_{ups}; *5* — S; *6* — v_{fl}; *7* — T_{upsI}; *8* — P_a; *9* — v_{ups}; *10* — $Z_{sh.-c}$; *11* — Q; *12* — T; *13* — v_f

Table 1. Correlation coefficients between welding process parameters

v_{fl}	S	T	U_1	U_2	I	v_f	P_a	L_{ups}	T_{upsI}	$Z_{sh.-c}$	Q	v_{ups}	P_{fr}	L_{defl}	
1.00	0.67	–0.34	–0.78	–0.67	–0.70	–0.14	0	–0.82	–0.45	0.12	–0.64	0.15	–0.69	–0.46	v_{fl}
	1.00	0.30	–0.89	–0.82	–0.88	0.13	–0.46	–0.74	–0.38	0.37	–0.05	0.35	–0.81	–0.54	S
		1.00	–0.09	–0.16	–0.23	0.14	–0.35	0.05	0.03	0.35	0.80	0.17	–0.13	–0.04	T
			1.00	0.87	0.83	–0.03	0.32	0.91	0.62	–0.28	0.25	–0.29	0.86	0.59	U_1
				1.00	0.74	–0.09	0.32	0.81	0.62	–0.18	0.15	–0.20	0.78	0.47	U_2
					1.00	0.07	0.22	0.75	0.33	–0.40	0.27	–0.34	0.79	0.51	I
						1.00	–0.49	0.10	0.09	–0.03	0.31	0.07	0.03	0.13	v_f
							1.00	0.11	0.17	–0.32	–0.37	–0.13	0.29	0.13	P_a
								1.00	0.72	–0.14	0.39	–0.17	0.82	0.58	L_{ups}
									1.00	0.10	0.24	0.05	0.55	0.37	T_{upsI}
										1.00	0.13	0.22	–0.24	–0.16	Z
											1.00	0.01	0.19	0.12	Q
												1.00	–0.24	–0.14	v_{fl}
													1.00	0.67	P_{fr}
														1	L_{defl}

- rest parameters T_{upsI}, P_a, v_{ups}, $Z_{sh.-c}$, T, v_f have a relation with other parameters below the average one.

Checking the correlation relations of second-order parameters at the stage of flashing showed that these parameters changed little the pattern of relation with P_{fr}.

The analysis of data with deflection shows a clearly worse dependence, which can be connected with the measurement accuracy.

Taking into account the data of theoretical and experimental investigations, at the first stage the linear regression from the following parameters was plotted:

$$v_{fl}, S, U_2, I, P_a, L_{ups}, Z_{sh.-c}, v_{ups}.$$

Further, taking into account the correlation coefficients, the models with different combinations of parameters were calculated:

$$v_{fl}, S, U_2, I, P_a, L_{ups}, Z_{sh.-c}, Q, v_{ups}; v_{fl}, S, U_2, P_a, L_{ups};$$
$$v_{fl}, S, P_a, L_{ups}; v_{fl}, S, U_2, I, L_{ups}, S, L_{ups}.$$

All the mentioned models have a root-mean-square-deviation (RMSD), which equals to 73 kN for P_{fr} and 2.35 mm for L_{defl}.

Table 2. Neural networks based on MLP for the value of fracture force P_{fr} and deflection L_{defl} of specimens

Number	Output variable networks	Input variable networks	Structure	RMSD
1	P_{fr}	v_{fl}, S, L_{ups}, U_2	4-8-1	66.4
2	L_{defl}	v_{fl}, S, L_{ups}, U_2	4-10-1	2.27
3	P_{fr}	v_{fl}, S, L_{ups}	3-4-1	66.1
4	L_{defl}	v_{fl}, S, L_{ups}	3-3-1	2.33
5	P_{fr}	S, L_{ups}	2-4-1	66.8
6	L_{defl}	S, L_{ups}	2-4-1	2.3

Neural networks for modeling the process. Artificial neural network is a mathematical dependence which models a method for processing a definite problem. Obviously, it is considerably simplified and primitive as compared to the biological neurons [5, 6].

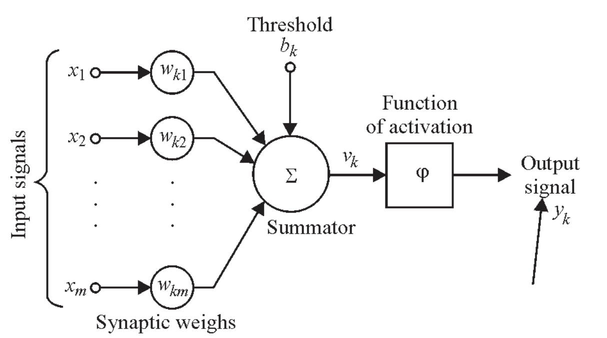

Figure 2. Schematic diagram of artificial neuron

Input signals

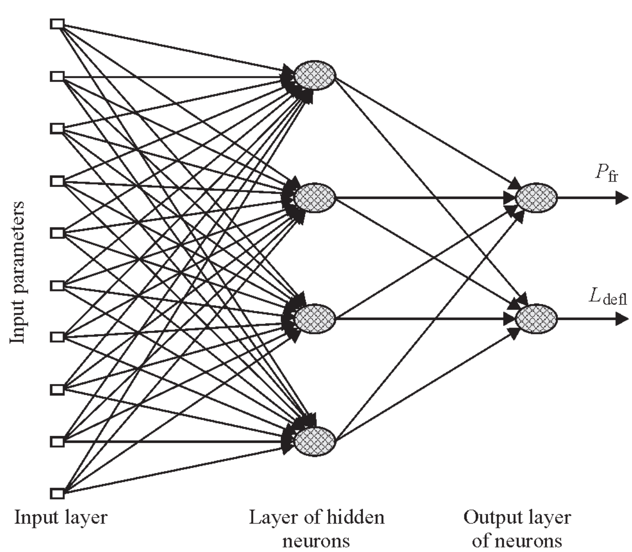

Figure 3. Multilayer perceptron MLP

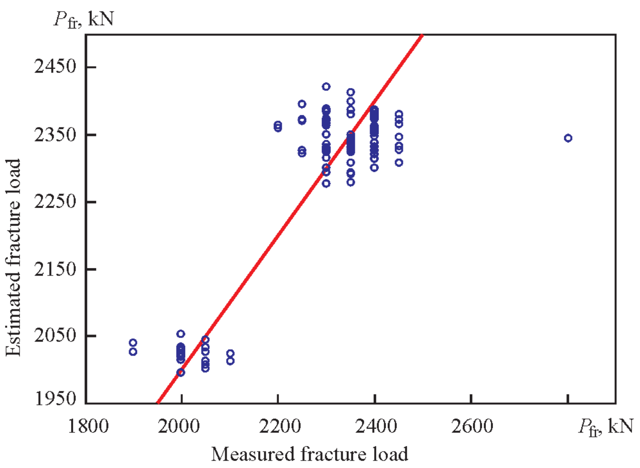

Figure 4. Prediction error P_{fr} by networks 3-4-1, 0.87, 79 kN

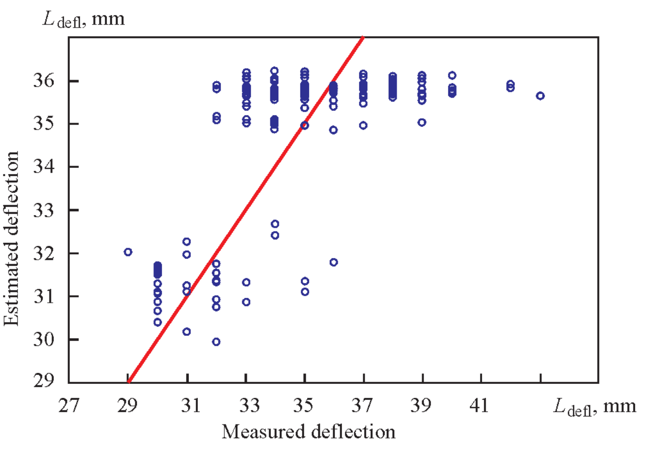

Figure 5. Prediction error L_{defl} on networks 4-10-1, 0.88, 2.27

Having signals or their numerical values at the input of the network, the output signal is uniquely determined by the formula (Figure 2):

$$v_k = \sum_{j=1}^{m} w_{kj} x_j + b_k, \quad y_k = \varphi(v_k).$$

Error of prediction according to the neural network

$$e_k(n) = Y_k(n) - y_k(n),$$

where $Y_k(n)$ is the actual value of output; $y_k(n)$ is the estimated value.

The cost function where the number of step n of the iterative process of adjustment of synaptic weights of the neuron k.

When developing the neural networks, the same input parameters were used as for nonlinear regression without second-order terms. The network structure was in MLP with a one hidden layer, in which non-linearities of approximated dependence are worked out. As a function of activation of internal neurons the hyperbolic tangent and output — identity function [6] were used. The initial weight coefficients were not preset. The training was conducted according to the algorithm BFGS. First, the search for the best network was performed in ANS (automated network search) mode, and then in CNN (custom neural networks) to select the same structure of the hidden layer. The results of calculation are given in Table 2. The prediction errors were shown in the diagrams (Figures 4, 5).

Conclusions

1. The regression models and neural networks with input parameters v_{fl}, S, L_{ups}, U_2, which are included in the technological report of the system for control of welding machine, can be used to predict the strength characteristics of welded butts of railway rails.

2. The developed models have approximately the same prediction error, and a root-mean-square-deviation (RMSD) equals to 73 kN for P_{fr} and 2.35 mm for L_{defl}.

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Received 12.05.2017