WELDING PROCESS OPTIMIZATION WITH ARTIFICIAL NEURAL NETWORK APPLICATIONS

*Adnan Aktepe**, *Süleyman Ersöz**, *Murat Lüy*†

Abstract: Correct detection of input and output parameters of a welding process is significant for successful development of an automated welding operation. In welding process literature, we observe that output parameters are predicted according to given input parameters. As a new approach to previous efforts, this paper presents a new modeling approach on prediction and classification of welding parameters. 3 different models are developed on a critical welding process based on Artificial Neural Networks (ANNs) which are (i) Output parameter prediction, (ii) Input parameter prediction (reverse application of output prediction model) and (iii) Classification of products. In this study, firstly we use Pareto Analysis for determining uncontrollable input parameters of the welding process based on expert views. With the help of these analysis, 9 uncontrollable parameters are determined among 22 potential parameters. Then, the welding process of ammunition is modeled as a multi-input multi-output process with 9 input and 3 output parameters. 1st model predicts the values of output parameters according to given input values. 2nd model predicts the values of correct input parameter combination for a defect-free weld operation and 3rd model is used to classify the products whether defected or defect-free. 3rd model is also used for validation of results obtained by 1st and 2nd models. A high level of performance is attained by all the methods tested in this study. In addition, the product is a strategic ammunition in the armed forces inventory which is manufactured in a limited number of countries in the world. Before application of this study, the welding process of the product could not be carried out in a systematic way. The process was conducted by trial-and-error approach by changing input parameter values at each operation. This caused a lot of costs. With the help of this study, best parameter combination is found, tested, validated with ANNs and operation costs are minimized by 30%.

Key words: *Artificial neural networks, welding process control, weld operation*

Received: March 8, 2013 **DOI:** 10.14311/NNW.2014.24.037
Revised and accepted: December 17, 2014

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1. Introduction

Control of the input and output parameters are important problems for welding processes. This is a multi-input multi-output process. In order to control the process, the interaction among input and output parameters must be predicted. The problems for which a linear model cannot be built are examples of those kinds of problems. In addition, the mass number of parameters in the model increases the run time of the algorithms so that AI techniques are used for practical solution.

In the literature, statistical and numerical techniques are used for optimization of welding processes [2]. In their study, factorial design, linear regression, response surface methodology, Taguchi experimental design, Artificial Neural Network (ANN) and hybrid techniques are used for handling the welding process control problem. For example, expert systems are used for classification of welding defect types [7]. In another study, a comparison is conducted among results of Genetic Algorithms (GA), Simulated Annealing (SA) and ANN for stainless steel welding process [17]. In their studies, the effect of input parameters such as heating time, heating pressure, upset pressure and upset time on output variables such as tensile strength and metal loss are discussed.

ANN models provide effective solution approach to problems faced in material science. ANN models have a wide application area on casting, welding, analysis of interaction among input and output parameters and analysis of quality control specifications. ANN models on welding process control are summarized in the Tab. I below.

In the literature it is observed that welding process control problem is mostly solved for one aspect: Output parameter prediction. However in our study we address the problem with 3 different approaches: Output parameter prediction, input parameter prediction and classification. We develop 3 different ANN applications for welding process control of the product. 1st model is used for prediction of output parameters according to given input parameter values. Here the objective is to find the value of output parameters before production and determine whether the product will is defected or not. 2nd model is used for input parameter prediction (reverse of Model 1). This model helped us to find the best input parameter combination for producing a non-defective product. Finally 3rd model is developed for classification of products as defective or non-defective according to input parameter values.

The models are applied on 155 mm artillery ammunition, which is produced in Mechanical and Chemical Industry Corporation (MKEK) Ammunition Factory, located in Turkey. In the welding process there were critical problems (which are detailed in the next section) and 30% of the products were defective. With our study now this ratio is decreased to 1–2% with great success and minimum error rates. The paper is organized as follows: In the next section we give information about the welding process control problem. In the 3rd section solution approach is given with reduced number of uncontrollable input parameters. In the 4th section we discuss ANN applications and in the last section we finalize the paper with concluding remarks.

Authors	Year	Scope of the study	Type of Study		
			Output parameter prediction	Input parameter prediction	Classification
[19]	1997	Welding process modeling and optimization	+		
[5]	2004	Optimization of controlling robotic arc welding	+		
[8]	2005	Laser welding defect diagnosis	+		
[13]	2007	A novel system which allows arc-welding defect detection and classification	+		+
[10]	2007	Defect detection in spot welding	+		
[1]	2007	A novel technique based on ANN for prediction of gas metal arc welding parameters	+		
[15]	2008	A multilayer neural network model to predict the ultimate tensile stress (UTS) of welded plates	+		
[20]	2009	Prediction of mechanical properties of Cu-Sn-Pb-Zn-Ni alloys		+	
[11]	2010	Prediction of stainless steel spot welding parameters	+		

Tab. I *Summary of literature on ann models developed for solving welding problems.*

2. Welding Problem

In the welding process a rotating band is welded to the body of ammunition. After welding channel is created on the body in a Computer Numerically Controlled (CNC) station, it is transferred to the welding machine. After preheating operation, the body is transferred to the welding workbench. In this station, firstly the body is tied between stitch and panel. Then rotating manually, the welding channel is rubbed down, cleaned by an alcohol-soaked cloth and the body gets ready for welding operation. Meanwhile copper and brass wires are prepared. The welding machine gets these wires and welding operation is realized with these metals. After cleaning process on the body, the torch distances for copper and brass wires, water discharge, gaseous fill rate, copper and brass wires' speed, torch-nozzle distance are controlled and values are entered to the control panel manually. Finally welding operation starts. Welding operation carried out in the welding workbench is a gas metal arc welding. The operation is carried out creating arc between Argon gas and metal wires. This type of welding is also called Metal Inert Gas (MIG) welding. When the welding operation is started, firstly an arc is formed at the torch where copper metal wire meets. And after 3-4 oscillations, as a second torch with brass metal wire, an alloy is created in weld zone. When the torches make 120-140 oscillations where copper and brass metal wires meet, weld zone is filled and the operation ends automatically. After welding operation the ammunition body is picked up from welding workbench and weld zone is grinded at beginning, middle and end parts. A chemical analysis is applied to these three zones. In quality control operation, the zinc (ZnR), iron (FeR) and copper ratio (CuR) of weld is measured. According to quality control specifications, metal ratios in the weld must be between lower and upper limits. For a defect-free weld ZnR must be between 8–12%, FeR must be between 0.5–4% and CuR must be between 84–91.5%.

The rotating band is the part that enables the ammunition to rotate in the barrel and it affects the velocity and quality of the ammunition. After welding treatment, the metal proportions (ZnR, FeR, CuR) in the weld region must be at the required level. For a defective product, for example if the iron ratio is lower, the rotating band may detach in the barrel. If the ratio is higher, the barrel may be ruined.

In the current situation, the loss rates in the production are high for 155 mm artillery ammunition. There are problems about production of the product that has been produced since January 1st 2009. The main problem is: The interaction among input and output parameters of welding process cannot be predicted and therefore optimum parameter configuration cannot be found.

The product is highly demanded due to its strategic importance and because of the problems in welding process, more than 50% of the annual demand cannot be matched. In addition, because 30% of the products are defective, the reproduction and salvage costs are incurred. The product cannot be used when it doesn't satisfy the quality requirements and only 18% of the defective products can be retrieved. The retrieval costs are incurred because of retrieval processes. After retrieval processes, if ZnR, FeR and CuR are not in the specified level, the products are scrapped and the retrieval process cannot be applied to these products for the second time. The scrap rate after retrieval process is 2%. In other words, for 18% of the products retrieval costs are incurred, for 10% of the products scrap costs are incurred and for 2% of the products both retrieval and scrap costs are incurred.

3. Parameter Analysis

For solving the welding problems discussed in the previous section, firstly the input parameters are analyzed with experts (a group of 10 people consisting mechanical, industrial and chemical engineers-with managers of the factory). The input analysis process is carried out with Pareto Analysis. Pareto Analysis is a simple quality tool. It is a graphical method of comparing and sorting a set of measures. Pareto Analysis uses the '80/20 Rule' to select the 'vital few' items for further action [14]. Benefiting from this property of Pareto Analysis we detected the controllable (unimportant) and uncontrollable (important) parameters of the model (Pareto Analysis results are shown on Fig. 1. The x-axis shows the number of input variables given in

Tab. II). In Tab. II, the list of 22 input parameters, output parameters and the reduced list of parameters found with Pareto Analysis are displayed (Uncontrollable inputs are in grey).

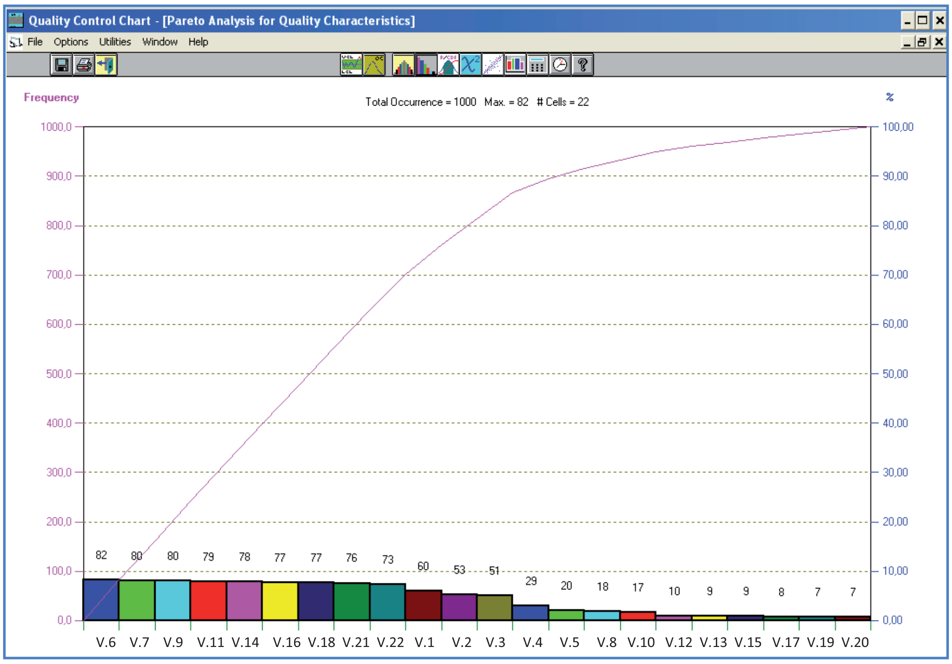


Fig. 1 *Results of Pareto analysis.*

The input parameters are evaluated by expert team with an evaluation form. Each expert gave scores for each parameter between 1 to 10 according to characteristic of the input. If the input is controllable the importance scores were low, if the input is uncontrollable the scores were high. This evaluation is carried out to find the uncontrollable parameters because there is no need of modeling for manually controllable parameters.

After determining 9 uncontrollable input parameters and previously known output parameters, 3 different ANN models are developed. Fig. 2 summarizes the solution approach developed in this study.

4. Neural Network Models Developed for Welding Process Control

In this study, 3 different models have been developed for welding process control problem defined in Section 2. For solving addressed problems, Backpropagation Neural Networks (BPNN) are used in the study. Model 1 is used for output parameter prediction, Model 2 is used to predict input parameter values given the

INPUT PARAMETERS				
No	**Input Name**	**Input**	**Unit**	**Uncontrollable**
V.1	Chemical analysis of copper wire-I	CCW1	%	
V.2	Chemical analysis of copper wire-II	CCW2	%	
V.3	Chemical analysis of copper wire-III	CCW3	%	
V.4	Zinc ratios of brass wire	ZBW	%	
V.5	Copper ratio of brass wire	CBW	%	
V.6	Brass wire drawing speed	BDS	m/min	+
V.7	Copper wire drawing speed	CDS	m/min	+
V.8	Brass torch rate	BTR	mm	
V.9	Copper torch rate	CTR	mm	+
V.10	Brass torch angle	BTA	angle	
V.11	Copper torch angle	CTA	angle	+
V.12	Furnace temperature	FUT	°C	
V.13	Beginning oscillation rate	BOR	mm	
V.14	Final oscillation rate	OSR	mm/min	+
V.15	Maximum oscillation rate	MOR	mm/min	
V.16	Center deviation of wires	CDW	mm	+
V.17	Gaseous flow rate	GFR	lt/dk	
V.18	Water discharge	WAD	lt/min	+
V.19	Nozzle length	NOL	mm	
V.20	Body rotating speed	BRS	cycle/min	
V.21	Welding current	WCU	ampere	+
V.22	Voltage	VOL	volt	+

Tab. II *The list of controllable and uncontrollable parameters.*

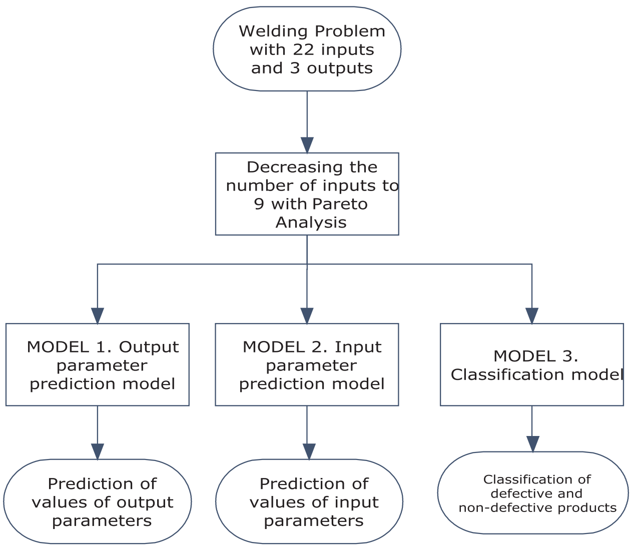


Fig. 2 *Solution approach used in the study.*

output values (a reverse BPNN application) and Model 3 is used for classification of defective and defect-free products.

Backpropagation algorithm is one of the well-known algorithms in neural networks [6, 16, 18, 21]. In this study, feed forward multi layered perceptrons are used for modeling. The reason for using this type of neural network is that it is a standard in the solution of problems related with identifying figures by applying the supervised learning and the backpropagation of errors together. The training of a network by backpropagation involves three stages: the feed forward of the input training pattern, the calculation and backpropagation of the associated error and the adjustment of the weights [3].

An activation function is used to transform the activation level of a neuron into an output signal. Activation functions can take several forms. The type of activation function is indicated by the situation of the neuron within the network. The most widely used activation function for the output layer is the linear function, because non-linear activation function may introduce distortion to the predicated output. The logistic and hyperbolic functions are often used as hidden layer transfer function that are shown in Equations (1) and (2), respectively. Other activation functions can also be used such as linear and quadratic, each with a variety of modeling applications [4]. In this study log-sigmoid, hard limit, hyperbolic tangent sigmoid transfer functions are used as follows:

$$\mathrm{Sig}(x) = 1/(1 + (\exp(-x)) \tag{1}$$

$$\mathrm{Tanh}(x) = (1 - \exp(-2x))/(1 + \exp(-2x) \tag{2}$$

4.1 Data: Descriptives of Input and Output Variables

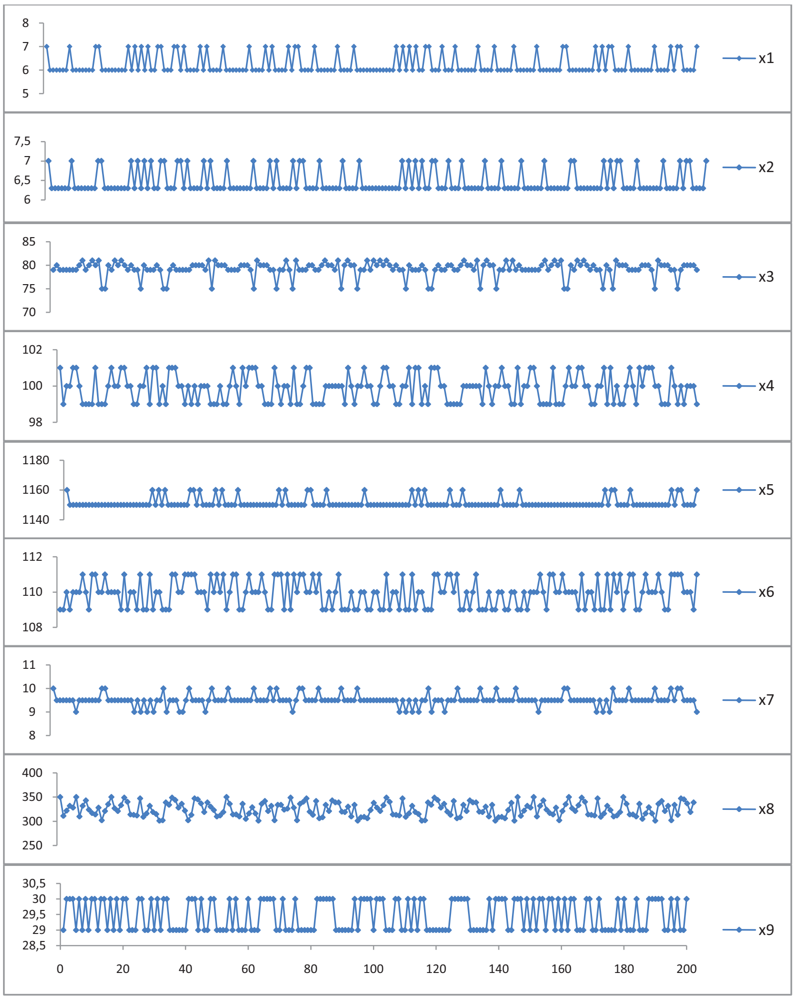
The input variables of the model are copper wire drawing speed (CDS), brass wire drawing speed (BDS), copper torch rate (CTR), copper torch angle (CTA), oscillation rate (OSR), center deviation of wires (CDW), water discharge (WAD), welding current (WCU) and voltage (VOL). The output variables are zinc ratio (ZnR), iron ratio (FeR) and copper ratio in percentages (CuR) of the weld. In this study data of 200 products are used for modeling. Descriptive statistics of input and output variables are shown on Tab. III. Tab. III shows range, minimum, maximum, mean, standard deviation and variance values of each input (x_i) and output variables (y_i).

After obtaining descriptive statistic values for each variable, we plot input and output data in order to show distribution of application data. Input variable distribution is shown in Fig. 3(a) below. There are 9 different input variables from x_1 to x_9. In Fig. 3(b), we plot data for 3 different output variables. The x-axis on the graphs shows the values of each variable. Y-axis on the graph shows the number of data.

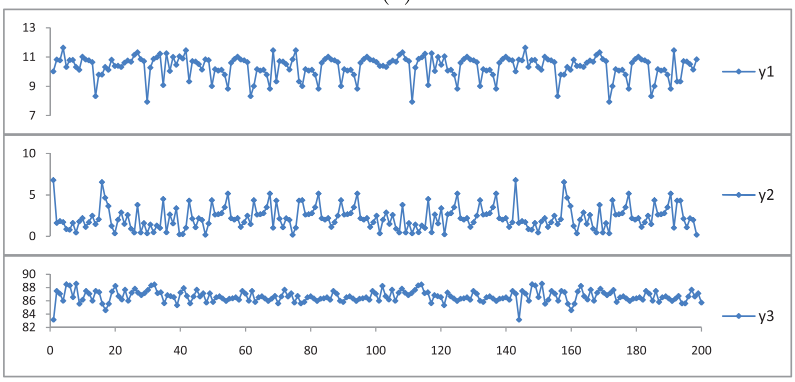
In the application stage, we developed 3 different ANN models (i) Output parameter prediction model (Model 1), (ii) Input parameter prediction model (Model 2) and (iii) Classification model (Model 3) for different purposes. Purpose of each model is explained in sub-sections 4.1, 4.2 and 4.3 below respectively.

Input (x) and Output (y)	**Units**	**N**	**Range**	**Min.**	**Max.**	**Mean**		**Std. Deviation**	**Variance**
Parameters		**Statistic**	**Statistic**	**Statistic**	**Statistic**	**Statistic**	**Std. Error**	**Statistic**	**Statistic**
x_1 (CDS)	*m/min*	200	1,00	6,00	7,00	6,2475	0,04316	0,43373	0,188
x_2 (BDS)	*m/min*	200	0,70	6,30	7,00	6,4733	0,03021	0,30361	0,092
x_3 (CTR)	*mm*	200	6,00	75,00	81,00	79,1881	0,16211	1,62919	2,654
x_4 (CTA)	*angle*	200	2,00	99,00	101,00	99,8713	0,07664	0,77024	0,593
x_5 (OSR)	*cycle/min*	200	10,00	1150,00	1160,00	1151,5842	0,36513	3,66952	13,465
x_6 (CDW)	*mm*	200	2,00	109,00	111,00	109,9802	0,07832	0,78715	0,620
x_7 (WAD)	*lt/min*	200	1,00	9,00	10,00	9,5248	0,02475	0,24876	0,062
x_8 (WCU)	*ampere*	200	49,00	301,00	350,00	325,1386	1,43858	14,45754	209,021
x_9 (VOL)	*volt*	200	1,00	29,00	30,00	29,4653	0,04988	0,50129	0,251
y_1 (ZnR)	%	200	3,70	7,94	11,64	10,3322	0,07458	0,74953	0,562
y_2 (FeR)	%	200	6,60	0,19	6,79	2,2961	0,14000	1,40697	1,980
y_3 (CuR)	%	200	5,44	83,14	88,58	86,6297	0,08467	0,85092	0,724

Tab. III *Descriptive statistics for input and output variables.*



(a)



(b)

Fig. 3 *Distribution of data for (a) input variables, (b) output variables.*

- In Model 1, we have 9 different input variables (x_1 to x_9) and 3 different output variables (y_1 to y_3). In this model, there are 3 hidden layers with 10 neurons in first hidden layer, 10 in second hidden layer and 5 neurons in third hidden layer.

- In Model 2, we have 3 input variables (y_1 to y_3) and 3 different output variables (x_2, x_3 and x_5). In this model, there are also 3 hidden layers with 10 neurons in first hidden layer, 10 in second hidden layer and 5 neurons in third hidden layer.

- In Model 3, we have 9 different input variables (x_1 to x_9) and 3 different output variables (y_1 to y_3). In this model, there is 1 hidden layer with 10 neurons.

The generalized ANN architecture used in the models is shown in Fig. 4 below. We show the number of inputs as 1 to m, the number of neurons in hidden layers as 1 to n_i and the number of outputs as 1 to o.

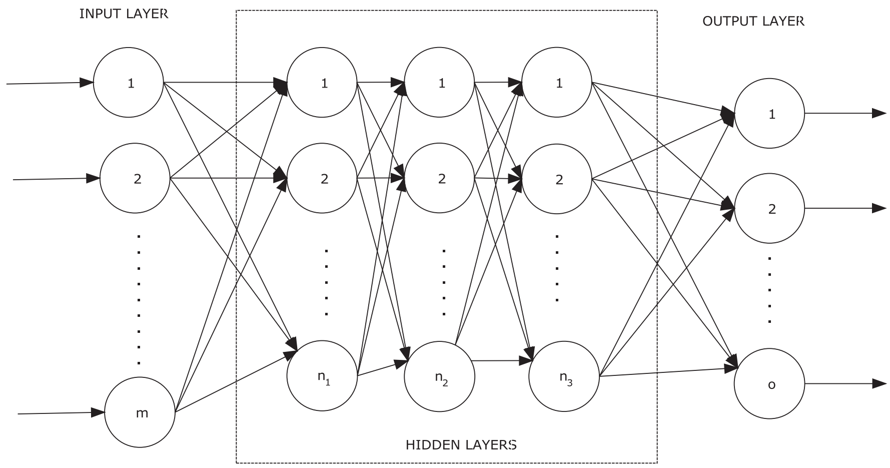


Fig. 4 *Generalized ANN architecture.*

4.2 MODEL 1. Output Parameter Prediction Model

In this model, values of 3 output variables (ZnR, FeR and CuR) are predicted according to given input variables. For this reason a BPNN model is used. Here the aim is to find the values of output values before production and determine whether the product will be defective or not. The best structure of network is found by trial and error under several scenarios (by changing the number of hidden layers, neurons, type of transfer functions each layer etc.). The summary of trial and error results is given in Tab. IV. The output values can be predicted with approximately 99% as seen in Tab. IV.

The network is trained with Levenberg–Marquardt Algorithm (LMA). LMA provides a numerical solution to the problem of minimizing a function, generally nonlinear, over a space of parameters of the function. These minimization problems arise especially in least squares curve fitting and nonlinear programming [9]. Primary application of LMA is in the least squares curve fitting problem: Given a set of m empirical datum pairs of independent and dependent variables, $(x_i,\ y_i)$, optimize the parameters β of the model curve $\mathrm{f}(x, \beta)$, so that the sum of the squares of the deviations becomes minimal as follows:

$$\mathrm{S}(\beta) = \sum_{i=1}^{m} [y_i - \mathrm{f}(x_i, \beta)]^2 \tag{3}$$

In order to measure the network performances Mean Squared Error (MSE) is used as a performance measure. MSE is a network performance function. It measures network's performance according to the mean of squared errors.

The MSE of a estimaton λ with respect to the estimated paramete θ is defined as follows:

$$\mathrm{MSE}(\lambda) = \mathrm{E}([\lambda - \theta]^2) \tag{4}$$

For training Model 1, data are partitioned into 4. The training performance of Model 1 is shown in Tab. V. For modeling ANN, MATLAB software is used [12].

4.3 MODEL 2. Input Parameter Prediction Model

In this model, values of 3 input variables (BDS, CTR and OSR), which are 3 important classifiers, are predicted according to given output variables. For this reason a reverse BPNN model is used.

Here the purpose is determining the values of most important input variables according to given output values and finding best values for a defect-free product. For this model a $3 \times 10 \times 10 \times 5 \times 3$ model structure is used. In this model, we use 3 inputs which are ZnR, FeR and CuR. There are 3 hidden layers in the model. First hidden layer is composed of 10 neurons, second hidden layer is composed of 10 neurons and third hidden layer is composed of 5 neurons. Model 2 is developed to find best values for 3 critical parameters which are BDS, CTR and OSR.

Here as a reverse application of 1st model, output variables are used as inputs. Because we know the optimum values for output variables (which are predetermined by Quality Control department) for a defect-free product, we use the numerical values of outputs as input and try to predict the input values. Here using outputs and inputs in a reverse provided the advantage of finding best values of input variables for a defect-free product. This also enabled us to tackle the problem with a different perspective. In the 1st model, we found the unknown values of output parameters for each product; However in Model 2, we use quality specification values of outputs (For a defect-free weld ZnR must be between 8–12%, FeR must be between 0.5–4% and CuR must be between 84–91.5%) as inputs.

For Model 2, a different structure from Model 1 is developed. The best structure is found by trial and error under several scenarios (by changing the number of

Number of Hidden Layers	Activation Functions	Number of neurons in each layer	Iteration Number	MSE Value	r Value
One	Sigmoid	1	1000	0.02399	0.490
	Sigmoid	5	1000	0.00862	0.858
	Sigmoid	10	1000	0.00420	0.934
	Sigmoid	15	1000	0.00376	0.945
	Sigmoid	15	1500	0.00376	0.945
	Hiperbolic Tangent	15	1000	0.09997	0.836
	Sigmoid	16	1000	0.00377	0.944
	Sigmoid	20	1000	0.00718	0.903
	Sigmoid	20+	1500	0.00718	0.903
Two	Sigmoid (1)–Sigmoid (2)	1–1	1000	0.01444	0.617
	Sigmoid (1)–Sigmoid (2)	5–5	1000	0.01025	0.842
	Sigmoid (1)–Sigmoid (2)	10–10	1000	0.00320	0.957
	Sigmoid (1)–Hyperbolic Tangent (2)	15–15	1000	0.01112	0.834
	Sigmoid (1)–Sigmoid (2)	15–15	1000	0.00259	0.968
	Sigmoid (1)–Sigmoid (2)	16–16	1000	0.00224	0.969
	Sigmoid (1)–Sigmoid (2)	20–20	1000	0.00224	0.969
	Sigmoid (1)–Sigmoid (2)	20+ – 20+	1500	0.00224	0.969
Three	Sigmoid (1)–Sigmoid (2)–Sigmoid (3)	1–1–1	1000	0.01698	0.699
	Sigmoid (1)–Sigmoid (2)–Sigmoid (3)	5–5–5	1000	0.01321	0.747
	Sigmoid (1)–Sigmoid (2)–Sigmoid (3)	10–5–5	1000	0.00138	0.968
	Sigmoid (1)–Sigmoid (2)–Sigmoid (3)	10–5–5	1500	0.00138	0.968
	Sigmoid (1)–Sigmoid (2)–Sigmoid (3)	10–10–5	1000	0.00551	0.936
	Sigmoid (1)–Hyperbolic Tangent (2)–Sigmoid (3)	10–10–5	1000	0.00111	0.969
	Sigmoid (1) – Hiperbolic Tangent ***(2)–Linear (3)***	***10-10-5***	***1000***	***0.00002***	***0.999***
	Sigmoid (1) – Hiperbolic Tangent ***(2)–Linear (3)***	***10+–10+–5+***	***1500***	***0.00002***	***0.999***

Tab. IV *Results of trial and error for best ANN architecture for Model 1.*

hidden layers, neurons, type of transfer functions at each layer etc.). The structure giving minimum MSE in selected. The training performance of Model 2 is shown in Tab. V.

According to results of Model 2; OSR must 1155 mm/min, CTR value must be equal 77 mm and BDS value must be 6,65 m/min.

4.4 MODEL 3. Classification Model

Neural networks have proven themselves as proficient classifiers and are particularly well suited for addressing non-linear problems. Given the non-linear nature of real world phenomena, neural networks is certainly a good candidate for solving the problem [4].

The classification model is built with 3 different approaches in this work. First application is carried out to determine which input parameter set results with a defective product and which ones with a defect-free product. In order to solve this problem three different BPNN models (Model 3.1: Feed forward backpropagation network, Model 3.2: Cascade-forward backpropagation network and Model 3.3: feedforward backpropagation network with feedback from output to input) are developed for classifying the products. In feed-forward backpropagation networks, the first layer has weights coming from the input. Each subsequent layer has a weight coming from the previous layer. In cascade forward backpropagation networks, the first layer has weights coming from the input. Each subsequent layer has weights coming from the input and all previous layers. In feed-forward backpropagation networks, with feedback from output to input, the first layer has weights coming from the input. Each subsequent layer has a weight coming from the previous layer and there exists a feedback from output layer to inputs. For all 3 models all layers have biases, the last layer is the network output.

ANN model architectures used in Model 3 are composed of an input layer, 1 hidden layer and an output layer. There are 9 neurons (9 input parameters) in input layer, 10 neurons in hidden layer, and 3 neurons (3 output parameters) in output layer ($9\times10\times3$). The best network architecture is found with trial and error. Several runs are conducted and the structure with minimum Mean Squared Error (MSE) is chosen. Performance of networks is discussed in "Results and Discussion" section. The outputs in ANN model are represented by unit vectors as: [1 1 1] = defective weld, [0 0 0] = defect-free weld. Each neuron in the output vector represents a situation whether ZnR, FeR and CuR is between quality specifications respectively. Therefore [1 1 1] means that output quality specifications are not met and [0 0 0] means output quality specifications are met.

The network is trained with Levenberg–Marquardt Algorithm (LMA). For this "trainlm" learning function is used in the MATLAB software. "trainlm" is often the fastest backpropagation algorithm and it is highly recommended as a first-choice supervised algorithm, although it does require more memory than other algorithms.

In Tab. V, training performances of Model 1, Model 2 and Model 3 are given respectively. Here epoch shows the number of iterations of neural network algorithm. Time shows total running time of algorithm in seconds in an Intel Core Duo, 2.13 Ghz, 2 GB RAM desktop computer. MSE, which is a common measure of performance, shows the mean squared error of training performance (explained in Section 4.2). SSE shows the sum of squared error of training performance. With correlation coefficient (r) we have information about the training of network. It takes values between -1 and 1. If r is close to 1, it shows success rate of the learning.

Performance criteria for training performance of Model 1, 2 and 3		**Model 1***	**Model 2**	**Model 3**		
				3.1	**3.2**	**3.3**
1. Epoch		50	100	32	100	18
2. Time (seconds)		28	52	34	65	10
3. Training Performance	**Mean Squared Error (MSE)**	$1{,}56*10^{-6}$	$8{,}99*10^{-3}$	$2{,}02*10^{-18}$	$2{,}95*10^{-12}$	$5{,}87*10^{-21}$
	Sum of Squared Errors (SSE)	$3{,}1*10^{-4}$	$1{,}8*10^{-2}$	$4*10*10^{-16}$	$6*10^{-10}$	$1{,}2*10^{-20}$
4. Correlation coeff. (r)		0,99	0,95	0,99	0,99	0,99

*4 different models (by choosing different parts of data for training and test) are developed for Model 1. Best performance results among 4 different models are shown in the table for Model 1.

Tab. V *Training performance of Models 1, 2 and 3.*

5. Results and Discussion

This paper presents results of the research on development of a new approach based on 3 different ANN models to predict best input-output parameter combination and to classify products. In this new modeling approach, prediction and classification capabilities of ANNs are used together with input-output interactions for developing a defect-free welding operation. Another innovation point in the study is a reverse application of ANN method as shown in the 2nd model. In the ANN models, the training and testing results have shown a strong potential for prediction of best parameter interactions. It is discovered that a high level of performance is accomplished by all the methods used in this study. In virtue of this study, the reproduction, salvage, scrap and retrieval costs for 155mm artillery ammunition are minimized.

Model 1 is used for output parameter prediction and a model with 99% success rate is created; Model 2 is used for input prediction as a reverse ANN application and values of 3 important input parameters are found; Model 3 is used for classification of defective and defect-free products and a classification model with 95% success rate is found. For all of the models, welding operation data of 200 ammunitions are used for prediction and classification analysis. %75 of the data are used for training of the networks. Remaining 25% are used for testing the network performance.

The main quality indicator of a neural network is to predict accurately the output of unseen test data. In this study, we have benefited from classification and prediction success of BPNNs. The classification and prediction performance results show the advantages of Backpropagation neural networks: it is rapid, noninvasive and inexpensive. Another advantage of the models is, with any input parameter combination, we can execute the model and find the output values in a few seconds.

In addition, BPNN does not explain the classification results by rules. In order to create rules from ANN results, intelligent classification algorithms can be integrated to ANN codes. And the final algorithm can find best classifiers, which is considered as a future study.

Acknowledgement

This study was financially supported by a grant from Republic of Turkey Ministry of Science, Industry and Technology with Grant No.: 00748.STZ.2010-2.

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