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INVESTIGATION OF YIELD STRENGTH OF STEEL BARS PRODUCED BY TEMPCORE PROCESS BYUSING RS METHODOLOGY AND ANN

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ABSTRACT

Weldable reinforcing steel bars are produced by quenching and self-tempering in Tempcore process. These steel bars are used in construction industry, and require high values of yield strength. Thus measuring and characterising yield strength represents one of the most important aspects in manufacturing process. In this paper, experiments are carried out using statistical three level full factorial design technique. During the experiments, process parameters, quenching time, flow rate of water, and inside diameter of the tube through which bar travels are varied. An artificial neural network (ANN) and response surface (RS) model are developed to predict yield strength of steel bars. In the development of predictive models, quenching time, flow rate of water, and inside of the tube through which bar travels are considered as model variables. A series of experiments are conducted and yield strength is measured to obtain the required data for predictive models. Good agreement is observed between the predictive models results and the experimental results. The ANN and RS models for steel bars are compared with each other for accuracy and computational cost.

Keywords: *Tempcore, ANN, RS, RMSE, R^2, MEP*

1. Introduction

In recent years, quench and self-tempering is very popular solution for producing weldable reinforcing bars. These reinforcing bars are produced by Tempcore process (Fig. 1). In Tempcore process reinforcing bars with high yield strength, good weld ability; superior ductility and high notch toughness are produced without addition of micro alloying elements [1,2]. The process consists of three stages. In the first stage, the bar leaving the last stand of the hot rolling mill passes thorough water cooling section. Here, the surface is quenched to form a predetermined thickness of martensite. At the end of this operation, the bar has an austenite core surrounded by a layer consisting of a mixture of austenite and martensite. In the second stage, the bar leaves the area of drastic cooling zone and is exposed to air. The core reheats the quenched surface layer by conduction. As a result, the martensite formed during the first stage is subjected to self-tempering. This ensures adequate ductility while maintaining a high yield strength level. The third stage occurs as the bar lies on the cooling bed. It consists of a quasi-isothermal transformation of the remaining austenite. The product of this transformation is a mixture of ferrite and pearlite or ferrite, pearlite and bainite, depending on the steel composition, bar diameter, quenching duration and its efficiency. Various researchers predicted the microstructure evolution and mechanical properties of steel bars produced by Tempcore process [3, 5].

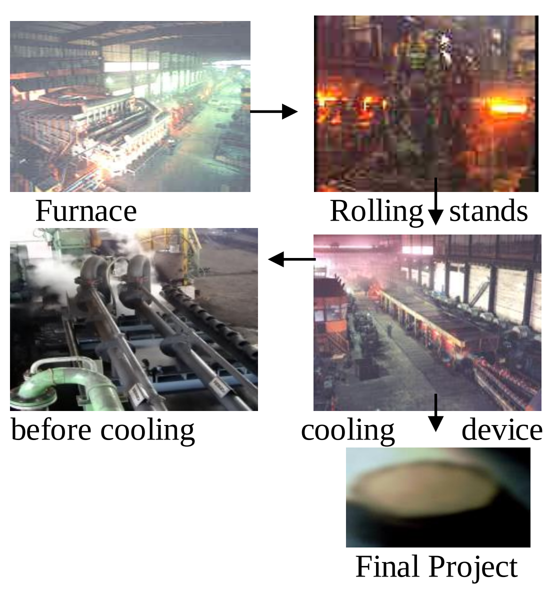

Fig.1 Flow chart for tempcore process

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composition, bar diameter, quenching duration and its efficiency. Various researchers predicted the microstructure evolution and mechanical properties of steel bars produced by Tempcore process by [3, 5]. In bars, it is observed that an increased amount of martensite, which results in increased amount of yield strength is a function of quenching time, flow rate of water, and inside diameter of the pipe through which bar travels. In this paper, an artificial neural network (ANN) and response surface (RS) model based on experimental results are developed to estimate yield strength of steel bars subjected to Tempcore process. In the development of predictive models, quenching time (T), flow rate of water (Q), and inside diameter of the tube through bar travels (ID) are model variables[9]. Good agreement is observed between the predicted and the experimental measurements. The ANN and RS models for steel bars are compared with each other for accuracy and computational cost.

2. Experimental Study

Steel bars of 12mm diameter, with chemical composition 0.17% C, 0.22%Si, 0.79% Mn, 0.036% P, are used as test material. Specimens are taken from bars produced by Tempcore process, are cut into 12mm long pieces and etched with 3% nital solution. Mechanical property, yield strength is measured with Universal tensile testing machine.

Experiments are conducted using design of experiments (DOE). Design of experiments is an analysis tool for modeling and analyzing the influence of process variables over some specific variable, which is an unknown function of these process variables (7). The three basic principles of experimental design are replication, randomization, and blocking. The first two help to increase precision in the experiment; the last is used to decrease bias. Several experiment design techniques are used to aid in the selection of appropriate design points. In a factorial design, the variable range is divided into levels between the lowest and highest values [8]. A three-level full factorial design creates 3^n training data, where n is the no of variables. In this study (9), three independent significant process parameters, such as quenching time (T), flow rate of water (Q), and inside diameter of the tube through which bar travels (ID) have a total of 3^3=27 experimental runs. Ranges of process parameters are shown in Table1. Experiments are conducted at least three times for each run and the average yield strength obtained is recorded. A measurement error of $\pm 1\%$ is accounted in the data. Experimental results obtained are shown in the Table 2.

Table 1: Levels of the variables

Factor	Level 1	Level 2	Level 3
T (sec)	1.0	1.4	1.6
Q (m3/hr)	30	40	60
ID (mm)	18	27	30

3. Testing the Accuracy of Both ANN and RS Models

In order to understand whether an ANN or a RS model is making good predictions, the check data, which was never presented to the network is used and the results are checked. The statistical methods of Root Mean Square Error (RMSE), Absolute fraction of variance (R^2), and Mean Error Percentage (MEP) values is used for making the comparisons (10). In statistics, the root mean squared error or RMSE of an estimator is one of many ways to quantify the amount by which an estimator differs from the true value of the quantity being estimated . The difference occurs because of randomness or because the estimator doesn't account for information that could produce a more accurate estimate. Two or more statistical models may be compared using their RMSEs as a measure of how well they explain a given set of observations: The unbiased model with the smallest RMSE is generally interpreted as best explaining the variability in the observations. R^2 is a measure of the amount of variation around the mean is explained by the model. The higher the R^2, the better the model fits your data. Thus a value of R^2 predicts the model with 90% accuracy. MEP measures the accuracy of fitted value. It is expressed in percentage.

The same data obtained from the RS model is used to determine the mentioned values. These values are determined by the following equations:

$$RMSE = \left(\left(\frac{1}{p} \right) \sum_j \left(t_j - o_j \right)^2 \right)^{\frac{1}{2}}$$

$$R^2 = 1 - \left(\frac{\sum_j \left(t_j - o_j \right)^2}{\sum_j (o_j)^2} \right) \quad \text{--- (1)}$$

$$MEP = \frac{\sum_j \left(\left(\left(t_j - o_j \right) / t_j \right) * 100 \right)}{p}$$

Where t - target value, o - output and p - number of samples.

4. Artificial Neural Network Model for Prediction of Yield Strength

ANN has two functions: learning and recalling [11]. It can learn from past experience and provide new results, just like the neural networks of living creatures. Multilayer perception trained by back propagation is among the most popular and versatile forms of neural networks and can deal with nonlinear models with high accuracy [12]. The input vector representing the pattern to be recognized is incident on the input layer and distributed to subsequent hidden layers and finally to the output layer via weighted connections. Each neuron in the network operates by taking the sum of its weighted inputs and passing the result through a nonlinear activation function. This is shown mathematically as

$$O_i = f(\text{net}_i) = f\left(\sum_j w_{ij} O_j + \theta_i\right) \qquad \text{--(2)}$$

Where O_i is the output of the i_{th} neuron, f(x) is the activation function and w_{ij} represents the weight connection to the i_{th} neuron from the j_{th} source. O_j is the output of j_{th} source and θ_i is the bias on hidden unit j.

The activation function, f (x) introduced in this paper use the modified sigmoid function s follows:

$$f(x) = \frac{1}{(1 + e^{-(x/t)}} \qquad \text{--(3)}$$

The term t in Equation (3) is referred to as the temperature of the neuron. The higher the temperature the more slowly the sigmoid changes. The network computes the weighted connections, minimizing the total mean squared error between the actual output of the network and the desired output. The weights are adjusted in the presence of momentum by,

$$\Delta_p W_{kj}(n) = \eta \partial_{pk} O_{pj} + \alpha \Delta_p W_{kj}(n-1) \quad \text{-- (4)}$$

Where η is the gain term, ∂_{pk} is an error term for node k, α is a momentum term. The momentum term is added for fast convergence. ANNs are able to:

1. Learn arbitrary nonlinear input-output mapping directly from training data.
2. Sensibly interpolate input patterns that are new to the network.
3. Automatically adjust their connection weights, for network structures to optimize their behavior as controllers, predictors and decision makers [13] In present work, a multiplayer perception (figure 2) and a back propagation algorithm by supervised training is used. There are three input variables and one output variable. Quenching durations, flow rate of water, and inside diameter of the tube are inputs to the network and yield strength is output to the network. The general aim in the training process is to teach the relations between input and output values to the program and get the results with the lowest possible errors. Authors developed a computer program in C language for this application. The input and output values are normalized, dividing each row by its absolute maximum value and keeping it within ± 1 for better speed and success of the network training. The training process is always by 'trial and error '. The learning rates (α), momentum rate (ε) and no of nodes of hidden layers are varied during Training iterations. The minimized error obtained in this way is best architecture. The optimum values α , ε , no of hidden layers and no of neurons in hidden layers after 30,000 training iterations are 0.6, 0.9, 1 and 8 respectively. After running the program, the average percentage error and the difference between the given output values and the values after training iterations are determined. The training process takes about 4 minutes of CPU time on HP-P4 Pentium processor for 30,000 iterations.

4.1 ANN approach: Results and comparison

Training of the neural network model is performed using 24 experiments data out of 27 data points from table 2.The trained network model is tested using three experimental data points (check data), which are not used in the training process. The results predicted from the ANN model are compared with those obtained from experimental results in table 3 for 3 check data sets and table 4 for 24 training sets. Table 3 and 4 show that ANN prediction is in good agreement with experimental results. Figures 3 and 4 compare the neural network yield strength prediction with experimental test results for training and check data sets respectively.

It is found that the developed ANN model developed has good interpolation capability and can be used as an efficient predictive tool for yield strength.

Table 2: Experimental Results

Sl.no.	T(sec)	Q(m^3/h)	ID(mm)	YS(N/mm^2)
1	1.6	60	30	587
2	1	60	18	440
3	1	60	30	410
4	1.6	30	18	610
5	1.6	30	30	510
6	1	40	18	420
7	1.6	60	18	680
8	1.6	60	27	624
9	1.4	40	27	490
10	1.4	30	18	495
11	1	30	27	360
12	1.6	40	18	645
13	1.4	60	18	595
14	1	30	18	390
15	1	60	27	422
16	1.4	40	30	460
17	1	40	30	375
18	1.4	60	30	480
19	1	60	18	440
20	1.6	30	30	510
21	1.6	60	18	680
22	1	30	18	390
23	1.4	30	27	470
24	1.6	40	27	640
25	1	60	30	410
26	1.6	30	18	610
27	1	30	30	353

Table 3: Comparison of the neural network predictions with check data

Test No	ANN results (Check data)	Experimental Result(check Data)	Error(%)
1	404.47	410	1.348
2	579.52	610	2.550
3	355.52	353	1.989

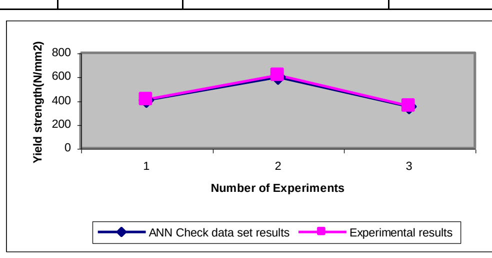

Fig. 3 Comparison of NN predictions with check data Set

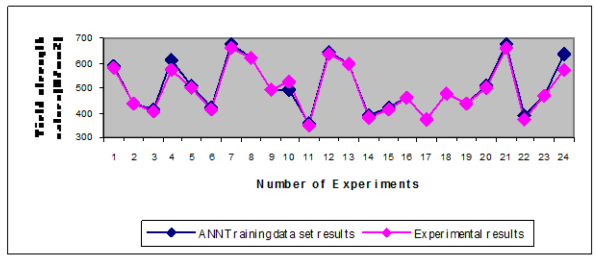

Fig. 3 Comparison of NN predictions with training data Set

Table 4: Comparison of Neural network with training data set

Sl. No.	Exp. results (Training data)	ANN results (Training data)	Error %
1	587	582.84	0.708688
2	440	435.26	1.077273
3	410	401.04	2.185366
4	610	571.20	6.360656
5	510	501.90	1.588235
6	420	411.70	1.97619
7	680	663.92	2.364706
8	624	620.02	0.637821
9	490	488.71	0.263265
10	495	525.40	-6.14141
11	360	348.36	3.233333
12	645	638.31	1.037209
13	595	594.59	0.068908
14	390	380.80	2.358974
15	422	413.44	2.028436
16	460	456.63	0.732609
17	375	371.28	0.992
18	480	475.70	0.895833
19	440	436.56	0.781818
20	510	501.96	1.576471
21	680	663.95	2.360294
22	390	373.11	4.330769
23	470	469.20	0.170213
24	640	572.00	10.625

5. Results and Discussion

5.1 Response surface approach for prediction of yield strength

Response Surface Methodology (RSM) is a collection of statistical and mathematical techniques useful for developing, improving, and optimizing processes [14]. Box and Wilson [15] introduced the Response Surface Methodology (RSM) and others developed it for designing experiments and subsequent analysis of experimental data. The method uses Design of Experiments techniques or DOE [16], such as Two-level Full and Fractional Factorial Designs, as well as regression analysis methods [17], where DOE techniques are employed before, during, and after the regression analysis to evaluate the accuracy of the model. The main idea is to replace a complicated response function with an approximate function by studying the relative significance of the effects of several factors supposed to have influence on the response of interest. Assume that the true response, *y*, of a system depends on *k* controllable input variables (or factors)

$\xi_1, \xi_2 ....., \xi_k$ as (18)

$$y = f(\xi_1, \xi_2, ..., \xi_k) + \varepsilon \qquad \text{--- (5)}$$

The function *f* is called the true response function, form of which is unknown and usually complicated, and ε is a term representing sources of variability not accounted for in *f*. The term ε is treated as a statistical error. For two factors, (i.e. *k=2)*, a second-order polynomial approximation of the true response function is:

$$y^- = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_{12} x_1 x_2 + \beta_{11} x_1^2 + \beta_{22} x_2^2 \qquad \text{--- (6)}$$

Where x_i are called 'coded variables', which are transformed values of the 'actual variables', ξ_i to the domain of [-1, 1]; and β_{ij} are called regression coefficients. In some cases, the first four terms of the above equation can satisfactorily predict the response, i.e. quadratic terms are not necessary. In most cases, the second-order model is adequate for well-behaved responses.

This empirical model is called a 'response surface model'. Steps taken in the construction of response (RS) approximations for objective and constraints using RSM [19] are illustrated in figure 5. In creating RS models, 27 data exploiting experimental measurements obtained from the effective quenching time (T), flow rate of water (Q), and inside diameter of the tube (ID) versus yield strength are compared with predicted in the RS method as shown in the table 6and figure 6. To check the accuracy of the RS model created, 3 data sets, which are not, involved in the training sets are employed and the results are shown in table 5 and Figure 7.

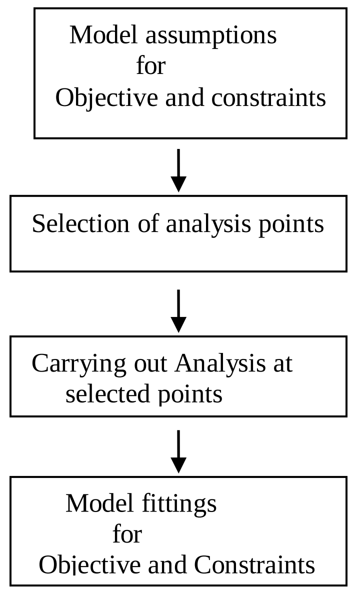

Fig. 5 Steps taken in the con- structing Response surface approximations [19]

6. Comparison of ANN and RS Models for Yield Strength

Construction of an artificial neural network needs a large number of iterative computations while on the contrary it is only a single step computation for a response surface model. High computational cost is required to generate an ANN model, depending on the number of variables and parameters and the nonlinearity. In the yield strength calculation an ANN model took 4 minutes of CPU time to create, whereas the RS model took just a couple of seconds. Models are also compared to predict yield strength accurately within a wide range of rolling parameters based on DOE (see Figs.8 and 9). The maximum test errors for ANN and RS model are 10.625 and 5.82 respectively. The comparison of accuracy values of ANN and RS models are presented in Table 7. As seen from the table RS model has provided better results than ANN.

Table 5: Comparison of RSM predictions with check data set

SL NO	RSM results (check data)	Experimental results (check data)	Error %
1	400.391	410	-2.399904094
2	610.6	610	0.098264003
3	342.555	353	-3.049145393

Table 6 Comparison of RSM predictions with training data set

SL NO.	RSM results (Training data)	Experimental results (Training data)	Error %
1	586.297	587	0.119761499
2	444.73	440	-1.075
3	400.391	410	2.343658537
4	610.6	610	-0.098360656
5	515.381	510	-1.055098039
6	423.33	420	-0.792857143
7	684.606	680	-0.677352941
8	631.31	624	-1.171474359
9	504.201	490	-2.898163265
10	500.029	495	-1.015959596
11	373.303	360	-3.695277778
12	654.485	645	-1.470542636
13	569.674	595	4.256470588
14	383.805	390	1.588461538
15	431.911	422	-2.348578199
16	464.2	460	-0.913043478
17	381.05	375	-1.613333333
18	489.355	480	-1.948958333
19	444.73	440	-1.075
20	515.381	510	-1.055098039
21	684.606	680	-0.677352941
22	383.805	390	1.588461538
23	462.542	470	1.586808511
24	602.734	640	5.8228125

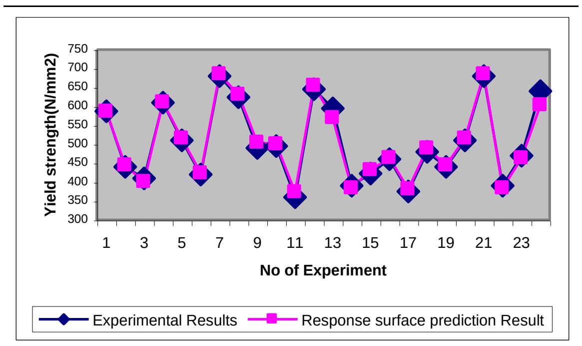

Fig. 6 Comparison of RSM predictions with Experimental data set

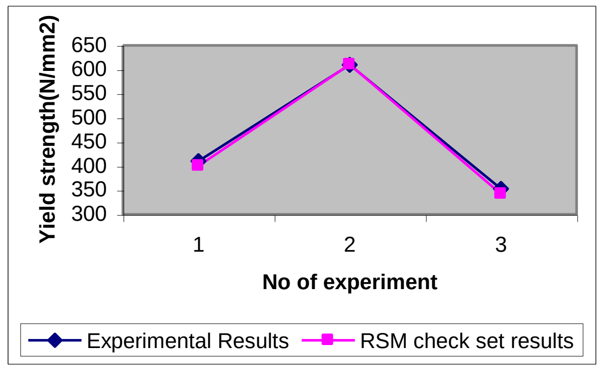

Fig. 7 Comparison of experimental measurements with predicted check set results from RSM

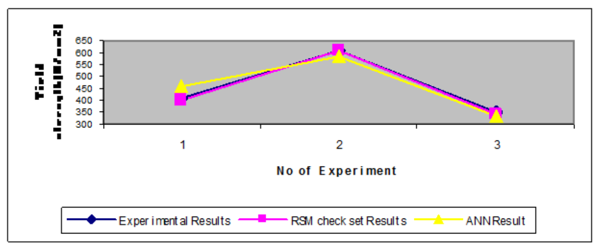

Fig. 8 Comparison of experimental measurement s with predicted check results from RSM and ANN

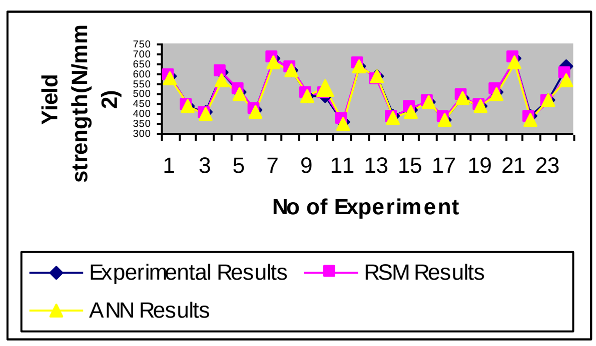

Fig. 9 Comparison of experimental measurements with predicted training results from RSM and ANN

Table 7: Comparison of accuracy values of models

Model		RESE	R	MEP
ANN	Training	18.94	0.9985	1.7588
	Check	10.11	0.9985	1.7488
RS	Training	11.54	0.9994	0.2614
	Check	8.201	0.9996	1.7340

7. Concluding Remarks

In this study, the experimental observations are incorporated into the ANN model for the steel bars produced by Tempcore process. A feed forward neural network model and RS model are developed to predict yield strength of steel bars. Models are also compared to predict yield strength accurately within a wide range of rolling parameters based on DOE. The predictive models results and the experimental results show Good agreement. The ANN model involves more computational time than a response model. Based on statistical error analysis methods, using ANN model for yield strength, the R^2 value for training data set is 0.9985, while for check data is 0.9954; the RSME values are 18.94 and 10.11; and the mean error values are1.7588 and 1.7488. Similarly for RS model the R^2 value for training data set is 0.9994, while for check data is 0.9996; the RSME values are 11.54 and 8.201; and the mean error values are 0.2614 and 1.734. Therefore yield strength of steel rods in Tempcore process are predicted with less error in RS model than compared to error of ANN model. However the degree of error can be ignored. RS model requires an explicit function to be defined before least square fitting, while a neural network depends more on training data and learning algorithm. Although RS model seems to give better predictions than ANN model, both methods can be used for the same purpose, because the difference in R^2 is very small.

References

1. *Econompolous, M. Application of the Tempcore process to the fabrication high yields Strength concrete-reinforcing bars. CRM Report, 1-17,1975.*
2. *Simon.P, Economopoulos M. Iron steel engineer, 61, 1984.*
3. *Chatterjee. S. , Kundu, S. et al . Modeling of Micro structural Evolution during Controlled cooling of TEMPCORE Rebar. Tata search, 265-272, 2005.*
4. *P. Simon . Optimization of Tempcore installations for rebars. Metallurgical plant and Technology 1990,pp.61-70.*
5. *Cetinel,H. ,Toper, M. and Ozsoyeller,L. Artificial neural networks modeling of mechanical property and microstructure evolution in the Tempcore process. Computers and Structures 80 ,213-218, 2002.*
6. *Hicks ,Charles. R. Fundamental concepts in the design of experiment. New York,Holt, Rinehart and Winston,1973.*
7. *Myers, RH, Montgomery DC Response surface methodology process and product optimization using designed experiments. Wiley, New York ,USA, 1995.*
8. *Youngseog ,lee. Rod and Bar rolling Theory and Applications. Marker Dekker Inc New York.*
9. *E.Arcaklioglu, "Performance comparison of CFCs with their substitutes using artificial neural network", International journal of Energy Research, Vol.28 (12), 1113-1125, 2004.*
10. *Ham FM :Principles of neurocomputing for science and engineering ,Mcgraw-Hill, New York, 2001.*
11. *P.lippmann :"An introduction to computing with neural nets",IEEE ASSP Magazine,2, 4-22,1987.*
12. *D.E.Rummelhart, G.E. Hinton and R.J.Williams:" Learning internal representation by error propagation",Parallel Distribution processing ,MIT press, Cambridge, MA, 318-362,1986.*
13. *Myers Raymond H. & D.C. Montgomery, 2002. "Response Surface Methodology: process and product optimization using designed experiment" A Wiley-Interscience Publication.*
14. *Box, G.E.P., and Wilson, K.B. "On the experimental attainment of optimum conditions", Journal of the Royal Statistical Society, B, 13, 1-45, 1951.*
15. *Montgomery, D.C.. Design and Analysis of Experiments. John Wiley & Sons New York, 1997.*
16. *Montgomery, D.C., Peck, E.A., and Vining, G.G. 2000. Introduction to Linear Regression Analysis, New York, John Wiley.*
17. *Myers, R.H. and Montgomery, D.C. Response Surface Methodology. John Wiley & Sons, New York, 1995.*
18. *Kurtaran H, Dissertation, design optimization of structures under impact loading with approximation methods. George Washington University, Washington, C, USA, 2001.*

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