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Application of desirability function for optimizing the performance characteristics of carbonitrided bushes

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C H R O N I C L E

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A B S T R A C T

The performance of a product is generally characterized by more than one response variable. Hence the management often faces the problem of simultaneous optimization of many response variables. This study was undertaken to simultaneously optimize the surface hardness and case depth of carbonitrided bushes. Even though lots of literature has been published on various methodologies for tackling the multi-response optimization problem, the simultaneous optimization of heat treated properties of carbonitrided bushes are not reported yet. In this research the effect of four factors and two interactions on surface hardness and case depth of carbontirded bushes were studied using design of experiments. Based on the experimental results, the expected values of the heat treated properties of the bushes were estimated for all possible combination of factors. Then the best combination which, simultaneously optimized the response variables, was arrived at using desirability function. The study showed that the optimum combination obtained through desirability function approach not only minimized the variation around the targets of surface hardness and case depth but also was superior to the ones obtained by optimizing the response variables separately. Moreover this study provides a useful and effective approach to design the production process to manufacture bushes with customer specified surface hardness and case depth targets.

1. Introduction

The powder metallurgy technique is relatively cost effective and simple way to produce bushes with good wear resistance and better mechanical properties. The carbonitriding has become the most popular process for surface hardening of bushes. In carbonitriding, ammonia is added to the furnace atmosphere of endo gas and hydrocarbon. The ammonia dissociates at the metallic surface and atomic nitrogen is formed, which will diffuse into the material along with carbon. The nitrogen not only increases the surface hardness but also stabilizes the austenilite and thus increases the hardenability of sintered steel (Boby, 2012).

The specifications on surface hardness and case depth would vary from customer to customer based on the application of bushes. Hence the knowledge on the effect of various process parameters on the

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surface hardness and case depth was essential to quickly change the process setting to manufacture bushes with different customer requirements. The challenge was to simultaneously minimize the variation around customer specified targets on surface hardness and case depth. The studies on simultaneous optimization of heat treated properties of carbonitrided bushes were not reported yet. Hence this research was undertaken.

The methodologies used were design of experiments and desirability function. The design of experiments (Dal Re 1999; Baragetti & Terranova 2000; Surm et al., 2005; Wang et al., 2008; Bhuiyan et al, 2011; Boby, 2012, Murali Krishna et. al, 2013) was used to establish the relationship between the heat treated properties with carbonitriding process parameters. Then the best combination of significant process parameter values, which would simultaneously optimize surface hardness and case depth, were identified using desirability function.

The reminder of this paper is arranged as follows: in session 2, a brief description of various approaches for simultaneous optimisation problem is presented. The details of the desirability function approach are given in session 3. The experimentation and data analysis is shown in session 4. In session 5, the result obtained through the implementation of the solution is presented and the conclusions are given in session 6.

2. Simultaneous optimisation of response variables

The performance of a product or service is generally characterized by many response variables. In many situations these response variables or quality characteristics are controlled by a set of independent factors. Often the best values of these control parameters, which would simultaneously optimise the response variables, need to be identified.

A common approach for multi response optimisation is to identify one of the response variables as primary response and optimise it subject to the condition that the other response variables satisfy the specified requirements. In other words the problem is formulated as constraint optimisation problem (linear or nonlinear programming problem) with primary response as objective function and other responses as constraints. One major drawback of this approach is that it will not result in simultaneous optimisation of all responses.

Recently, several approaches to multiple response optimisation have been proposed in literature. For the optimisation of duel responses, Montgomery and Castillo (1993) suggested a non-linear programming solution. Myers and Carter (1973) proposed response surface techniques. Harrington (1965) and Derringer (1994) developed the desirability function approach for simultaneous optimisation of multiple responses. Koksoy and Yalcinoz (2006) presented a methodology for analysing several quality characteristics simultaneously using the mean square error criterion. Su and Tong (1997) proposed multi – response robust design using principal component analysis. Hsu (2004) presented an integrated optimisation approach based on neural networks, exponential desirability functions & tabu search.

Liao (2004) proposed data envelopment analysis ranking approach to optimise multi-response problems. Antony et al. (2006) used neuro-fuzzy model and Taguchi methodology to tackle multiple response optimisation problems. Saha and Mandal (2013) showed that the surface roughness, power consumption and frequency of vibration of turning process can be simultaneously optimized using gray relational analysis. Chakravorty et al (2013) published a comparative study on the effectiveness of various engineer friendly multi response optimization techniques for optimization of ultrasonic machining processes. Of all the aforementioned approaches, the utilization of desirability function is the most popular and strongly suggested method. This study used the desirability function approach to optimise the multiple responses of a carbonitriding process.

3. Desirability Function

In the desirability function approach, each response is transformed into a desirability value d and the total desirability function D, which is the geometric mean of the individual desirability values, is computed and optimised. The desirability is defined such that if a response is beyond the acceptable limit, then the corresponding desirability value will be 0. If the response is on target then the desirability value will be equal to 1. When the response falls within the tolerance interval but not on the target, the corresponding desirability will lie between 0 and 1. As the response approaches the target, the desirability value becomes closer and closer to 1.

The class of desirability functions is divided into three types, namely Nominal the best (NTB), Smaller the better (STB) and Larger the better (LTB). For the NTB type, the desirability function is defined as

$$d = \begin{cases} \left|\dfrac{y - LSL}{T - LSL}\right|^{\alpha} & LSL < y \leq T \\ \left|\dfrac{y - USL}{T - USL}\right|^{\beta} & T < y < USL \\ 0 & y \leq LSL \text{ or } y \geq USL \end{cases} \tag{1}$$

where LSL, USL and T are the lower specification limit, upper specification limit and target for the response y. The weights α and β needs to be specified depending on the desirability of response variable y with respect to USL, LSL and target.For the STB type, the desirability function is defined as

$$d = \begin{cases} \left|\dfrac{y - USL}{y_{\min} - USL}\right|^{\alpha} & y_{\min} < y < USL \\ 0 & y \geq USL \\ 1 & y \leq y_{\min} \end{cases} \tag{2}$$

where USL is the upper specification limit, α is the weight and y_{min} is the most desirable minimum value, which can be practically achievable. For the LTB type, the desirability function is defined as

$$d = \begin{cases} \left|\dfrac{y - LSL}{y_{\max} - LSL}\right|^{\alpha} & LSL < y < y_{\max} \\ 0 & y \leq LSL \\ 1 & y \geq y_{\max} \end{cases} \tag{3}$$

where LSL is the lower specification limit, α is the weight and y_{max} is the most desirable maximum value, which can be practically achievable.After transforming each response variable y_i to a corresponding desirability value d_i using Eq. (1), Eq. (2) or Eq. (3), the total desirability function D is computed as the geometric mean of these individual d_i's, $i = 1,2, - - - ,p$

$$\text{D} = \left(d_1 \times d_2 \times - - - \times d_p\right)^{1/p} \tag{4}$$

4. Experimentation and Analysis

The discussions with the technical personals of the company revealed that four parameters impacts the heat-treated properties of carbonitrided bushes. Accordingly an experiment was designed with soaking time (A), temperature (B), green density (C) and the material (D) as factors. It was decided to try out three levels for all the four factors in the experiment. The technical personals also suspected the interaction between soaking time & temperature (AxB) and the interaction between soaking time & green density (AxC). The full factorial design would require 81 experiments, which was not economically feasible under the given situation. Hence the experiment was designed using L_{27} orthogonal array (Phadke, 1989). The factors with levels chosen for experimentation are given in Table 1. The surface hardness (in HRD) and case depth (in mm) were taken as the responses. The responses with specified USL, LSL & target values are given in the Table 2.

Table 1
Factors with levels

SL No.	Factor Name	Code	Levels		
			1	2	3
1.	Soaking Time (Minutes)	A	Low	Medium	High
2.	Temperature (^oC)	B	Low	Medium	High
3.	Green Density (gm / cc)	C	Low	Medium	High
4.	Material	D	Type I	Type II	Type III

Table 2
Responses with Specification

SL No	Response	LSL	USL	Target
1.	Surface Hardness	420	580	500
2.	Case Depth	0.1	0.8	0.45

The experiments were conducted as per the design. Each experiment was replicated twice. The experimental layout is given in Table 3.

Table 3
Experimental Layout with Response values

Exp No.	Soaking Time	Temperature	Green Density	Material
1	Low	Low	Low	Type I
2	Low	Low	Medium	Type II
3	Low	Low	High	Type III
4	Low	Medium	Low	Type II
5	Low	Medium	Medium	Type III
6	Low	Medium	High	Type I
7	Low	High	Low	Type III
8	Low	High	Medium	Type I
9	Low	High	High	Type II
10	Medium	Low	Low	Type I
11	Medium	Low	Medium	Type II
12	Medium	Low	High	Type III
13	Medium	Medium	Low	Type II
14	Medium	Medium	Medium	Type III
15	Medium	Medium	High	Type I
16	Medium	High	Low	Type III
17	Medium	High	Medium	Type I
18	Medium	High	High	Type II
19	High	Low	Low	Type I
20	High	Low	Medium	Type II
21	High	Low	High	Type III
22	High	Medium	Low	Type II
23	High	Medium	Medium	Type III
24	High	Medium	High	Type I
25	High	High	Low	Type III
26	High	High	Medium	Type I
27	High	High	High	Type II

The responses were individually subjected to analysis of variance (Montgomery, 2001) to identify the significant main effects and interactions. The ANOVA table for surface hardness is given in Table 4 and the corresponding residual plots is given in Fig. 1.

Table 4
ANOVA table for Surface Hardness

Source	DF	SS	MS	F	p
Soaking Time	2	1612	806	0.8	0.458
Temperature	2	3231	1616	1.6	0.216
Green Density	2	20083	10042	9.92	0.000
Material	2	30112	15056	14.9	0.000
Soaking Time x Temperature	4	12524	3131	3.09	0.027
Soaking Time x Green Density	4	806	202	0.2	0.937
Error	37	37436	1012		
Total	53	105805			

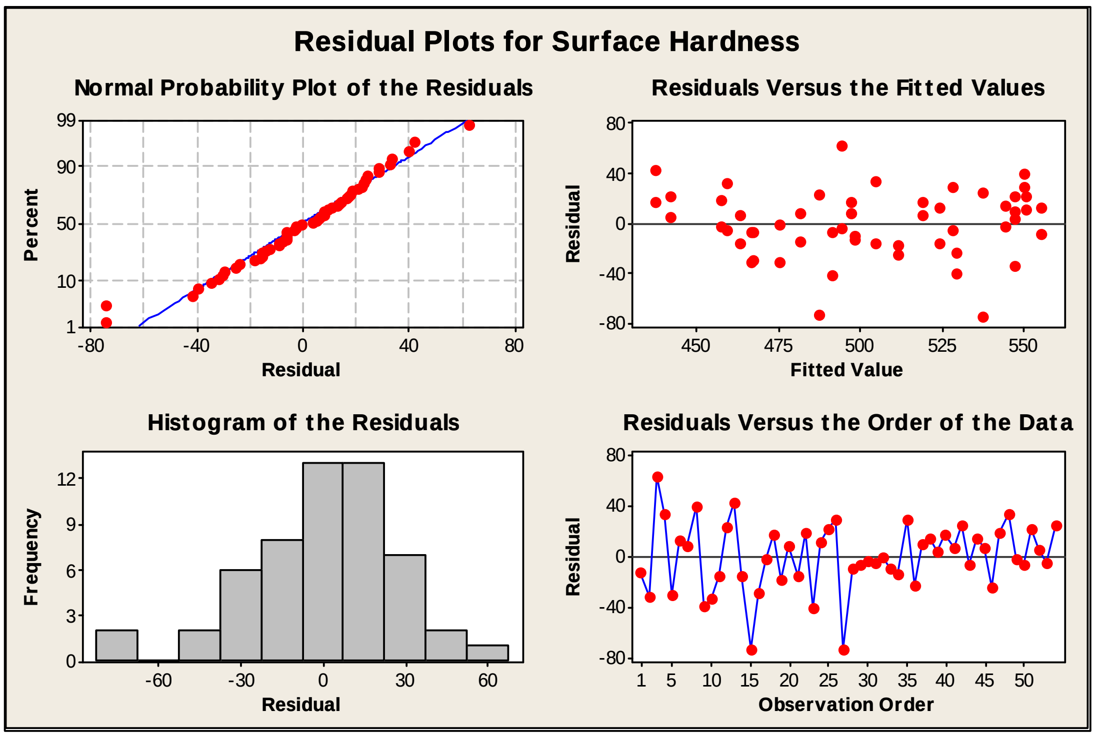

Fig. 1. Residual Plots for Surface Hardness

The ANOVA table revealed that the factors green density (*C*) & material (*D*) and the interaction soaking time x temperature (*AxB*) had significant effect surface hardness (p value ≤ 0.05). The Fig. 1 showed that the residuals were approximately normally distributed and there was no systematic pattern or trend in the residual versus fitted values or residuals versus order of the data.

The ANOVA table for the response case depth is given in Table 5 and the corresponding residual plots is given in Fig. 2. The Table 5 revealed that the factors soaking time (*A*), temperature (*B*) & green density (*C*) and the interaction soaking time x temperature (*AxB*) had significant effect on the response case depth. The figure 2 showed that the residuals were approximately normally distributed and there was no systematic pattern or trend in the residual versus fitted values or residuals versus the order of the data.

Table 5
ANOVA table for Case Depth

Source	DF	SS	MS	F	p
Soaking Time	2	0.59009	0.295	215.74	0.000
Temperature	2	0.126759	0.06338	46.34	0.000
Green Density	2	0.30287	0.1514	110.73	0.000
Material	2	0.000093	0.000046	0.03	0.967
Soaking Time x Temperature	4	0.0788	0.0197	14.4	0.000
Soaking Time x Green Density	4	0.001019	0	0.19	0.944
Error	37	0.050602	0.001368		
Total	53	1.150231			

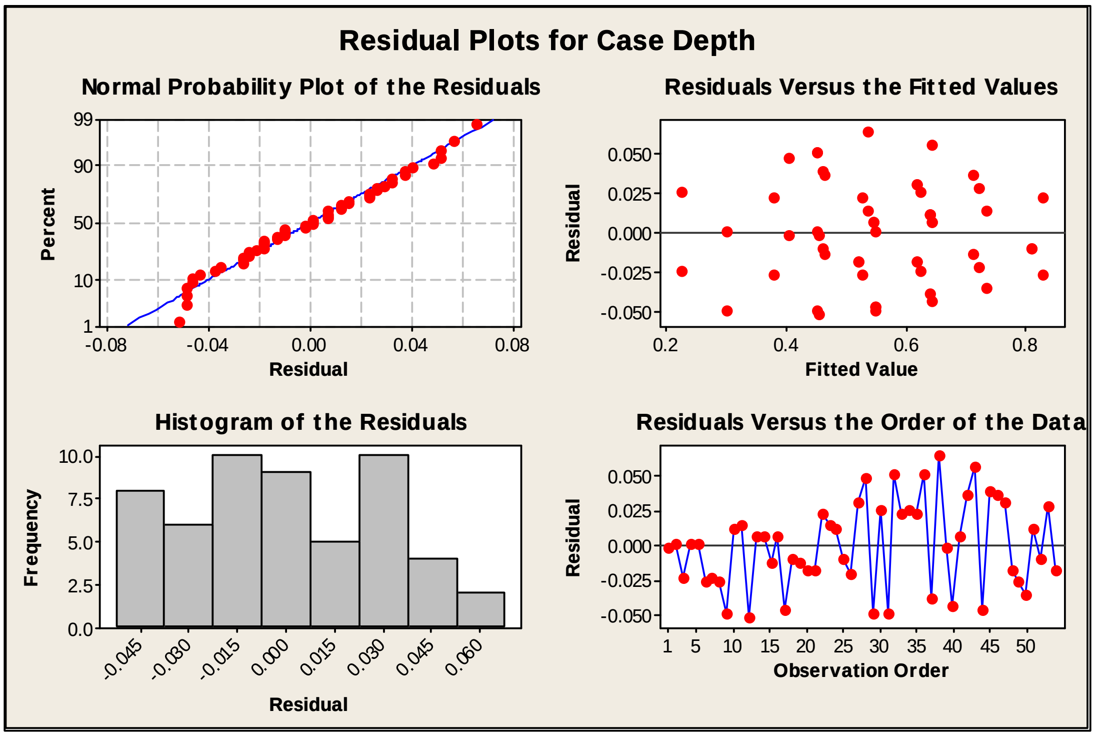

Fig. 2. Residual plots for Case Depth

After identifying the significant factors and interactions, the expected values of the response variables were computed for all the possible 81 combination of factor levels (81 combinations are possible with 4 factors each having 3 levels). The expected response for all these combination can be estimated as the sum of overall mean and the contributing effects of significant factors and interactions (Peace, 1993).

These expected values were then converted into desirability values using Eq. (1). The value of α and β were varied from 0. 1 to 1.0 and it was found that at 0.1, the total desirability was highest for the optimum combination. So α and β were chosen as 0.1. Finally the total desirability for each of the 81 combinations was calculated using Eq. (4). The results obtained are given in Table 6. From Table 6, the optimum combination with highest desirability value of 0.9931 was identified as $A_1B_3C_3D_3$ (combination 27 in Table 6). The estimated surface hardness and case depth values for the optimum combination were 509.6111 and 0.4463 which were very close to the respective targets of 500 and 0.45.

Table 6
Estimated responses for all possible 81 combinations

SL No	Soaking Time	Temperature	Green Density	Material	Surface Hardness	Case Depth	Desirability
1	Low	Low	Low	Type I	495.1667	0.213	0.9421
2	Low	Low	Low	Type II	445.6667	0.2102	0.8917
3	Low	Low	Low	Type III	444.5	0.2102	0.8896
4	Low	Low	Medium	Type I	521.7223	0.1157	0.8429
5	Low	Low	Medium	Type II	472.2222	0.113	0.8302
6	Low	Low	Medium	Type III	471.0556	0.113	0.8292
7	Low	Low	High	Type I	542.2778	0.0296	0
8	Low	Low	High	Type II	492.7778	0.0269	0
9	Low	Low	High	Type III	491.6111	0.0269	0
10	Low	Medium	Low	Type I	548.5001	0.538	0.9408
11	Low	Medium	Low	Type II	499	0.5352	0.9855
12	Low	Medium	Low	Type III	497.8334	0.5352	0.9848
13	Low	Medium	Medium	Type I	575.0556	0.4407	0.8689
14	Low	Medium	Medium	Type II	525.5555	0.438	0.9792
15	Low	Medium	Medium	Type III	524.3889	0.438	0.9803
16	Low	Medium	High	Type I	595.6111	0.3546	0
17	Low	Medium	High	Type II	546.1111	0.3519	0.9423
18	Low	Medium	High	Type III	544.9445	0.3519	0.9439
19	Low	High	Low	Type I	513.1667	0.6324	0.9552
20	Low	High	Low	Type II	463.6667	0.6296	0.9359
21	Low	High	Low	Type III	462.5	0.6296	0.9346
22	Low	High	Medium	Type I	539.7223	0.5352	0.9529
23	Low	High	Medium	Type II	490.2222	0.5324	0.9803
24	Low	High	Medium	Type III	489.0556	0.5324	0.9794
25	Low	High	High	Type I	560.2778	0.4491	0.9323
26	Low	High	High	Type II	510.7778	0.4463	0.9923
27	Low	High	High	Type III	509.6111	0.4463	0.9931
28	Medium	Low	Low	Type I	505.3334	0.4769	0.9926
29	Medium	Low	Low	Type II	455.8333	0.4741	0.9572
30	Medium	Low	Low	Type III	454.6667	0.4741	0.9556
31	Medium	Low	Medium	Type I	531.8889	0.3796	0.964
32	Medium	Low	Medium	Type II	482.3889	0.3769	0.9761
33	Medium	Low	Medium	Type III	481.2222	0.3769	0.9752
34	Medium	Low	High	Type I	552.4445	0.2935	0.9204
35	Medium	Low	High	Type II	502.9444	0.2907	0.9683
36	Medium	Low	High	Type III	501.7778	0.2907	0.969
37	Medium	Medium	Low	Type I	488.1667	0.6602	0.9475
38	Medium	Medium	Low	Type II	438.6667	0.6574	0.889
39	Medium	Medium	Low	Type III	437.5	0.6574	0.8861
40	Medium	Medium	Medium	Type I	514.7223	0.563	0.9708
41	Medium	Medium	Medium	Type II	465.2222	0.5602	0.9537
42	Medium	Medium	Medium	Type III	464.0556	0.5602	0.9524
43	Medium	Medium	High	Type I	535.2778	0.4769	0.9675
44	Medium	Medium	High	Type II	485.7778	0.4741	0.9867
45	Medium	Medium	High	Type III	484.6111	0.4741	0.9859
46	Medium	High	Low	Type I	508.6667	0.863	0
47	Medium	High	Low	Type II	459.1667	0.8602	0
48	Medium	High	Low	Type III	458	0.8602	0
49	Medium	High	Medium	Type I	535.2223	0.7657	0.8648
50	Medium	High	Medium	Type II	485.7222	0.763	0.885
51	Medium	High	Medium	Type III	484.5556	0.763	0.8842
52	Medium	High	High	Type I	555.7778	0.6796	0.8931
53	Medium	High	High	Type II	506.2778	0.6769	0.9452
54	Medium	High	High	Type III	505.1111	0.6769	0.946
55	High	Low	Low	Type I	529.3334	0.6935	0.921
56	High	Low	Low	Type II	479.8333	0.6907	0.9298
57	High	Low	Low	Type III	478.6667	0.6907	0.9289
58	High	Low	Medium	Type I	555.8889	0.5963	0.9166
59	High	Low	Medium	Type II	506.3889	0.5935	0.9699
60	High	Low	Medium	Type III	505.2222	0.5935	0.9707
61	High	Low	High	Type I	576.4445	0.5102	0.8478
62	High	Low	High	Type II	526.9445	0.5074	0.9709
63	High	Low	High	Type III	525.7778	0.5074	0.972
64	High	Medium	Low	Type I	519.1667	0.8019	0
65	High	Medium	Low	Type II	469.6667	0.7991	0.7257
66	High	Medium	Low	Type III	468.5	0.7991	0.7249
67	High	Medium	Medium	Type I	545.7223	0.7046	0.8982
68	High	Medium	Medium	Type II	496.2222	0.7019	0.9361
69	High	Medium	Medium	Type III	495.0556	0.7019	0.9354
70	High	Medium	High	Type I	566.2778	0.6185	0.886
71	High	Medium	High	Type II	516.7778	0.6157	0.9571
72	High	Medium	High	Type III	515.6111	0.6157	0.958
73	High	High	Low	Type I	494.5	0.988	0
74	High	High	Low	Type II	445	0.9852	0
75	High	High	Low	Type III	443.8333	0.9852	0
76	High	High	Medium	Type I	521.0555	0.8907	0
77	High	High	Medium	Type II	471.5555	0.888	0
78	High	High	Medium	Type III	470.3889	0.888	0
79	High	High	High	Type I	541.6111	0.8046	0
80	High	High	High	Type II	492.1111	0.8019	0
81	High	High	High	Type III	490.9444	0.8019	0

The optimum combination obtained through desirability function method was compared with the best combination obtained through optimising one response at a time. The comparison results are shown in Table 7. The Table 7 showed that optimising surface hardness alone would give a surface hardness almost on target but would result in a case depth of 0.535 much higher than the target value of 0.45 and optimising case depth alone would give a case depth more or less on target but would result in a surface hardness of 560.28 far away from the surface hardness target of 500. Meanwhile the simultaneous optimisation of surface hardness and case depth using desirability function would give a compromise solution of surface hardness equal to 509.61 and case depth equal to 0.4463 reasonably close to the respective targets of 500 and 0.45. Hence it was decided to implement the optimum combination arrived through desirability function approach.

Table 7
Optimum Combination

Response	Optimum Combination	Surface Finish	Case Depth
Surface Hardness	$A_1B_2C_1D_2$	499.00	0.535
Case Depth	$A_1B_3C_3D_1$	560.28	0.4490
Desirability Function	$A_1B_3C_3D_3$	509.61	0.4463

5. Implementation of Solution

A pilot lot of 12 bushes were carbonitrided with the optimum combination of factors and the response variables surface hardness and case depth were measured. The results obtained were compared with the 95% confidence interval on expected result. The confidence interval was calculated using the formula (Taguchi et al, 1993)

$$100\,(1-\alpha)\ \%\ \mathrm{CI} = \mu_{\exp t} \pm \sqrt{F_{\alpha,1,\nu} V_e \left(\frac{1}{n_e}\right)} \tag{5}$$

where ν is degrees of freedom of error, V_e: mean square (MS) of error and n_e: total number of experiments / (1 + sum of degrees of freedom for significant factors and interactions). The data on the pilot implementation of the solution is given in Table 8. The Table 8 showed that the values of response variables were within the confidence interval. Hence it was decided to go ahead with the full-scale implementation of optimum combination.

Table 8
Pilot implementation results

SL No	Surface Hardness	Case Depth
1	507	0.47
2	510	0.45
3	505	0.48
4	509	0.43
5	511	0.46
6	510	0.44
7	506	0.44
8	512	0.42
9	509	0.48
10	508	0.44
11	505	0.45
12	512	0.43
95% CI	509.61 ± 37.21	0.4463 ± 0.047

Since the target values of the response variables would vary from customer to customer based on the application of bushes, a program was written in Visual Basic for Application to calculate the total desirability of all the possible 81 factor level combinations and identify the combination with highest desirability with customer specified targets. This helped the management to set the significant factors of carbonitriding process in such a way to produce bushes with customer specified requirements on case depth and surface hardness.

6. Conclusion

The paper presented a case study on optimising the heat-treated properties of carbonitrided bushes using design of experiments. Since optimising the response variables individually would adversely impact the performance of other response, the response variables surface hardness and case depth were simultaneously optimised using desirability function. Moreover the study became a useful and effective input to design the production process to manufacture bushes with customer specified heat-treated properties.

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