Development of mathematical models and optimization of the process parameters of laser surface hardened EN25 steel using elitist non-dominated sorting genetic algorithm

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Abstract. The ultimate goal of all production entities is to select the process parameters that would be of maximum strength, minimum wear and friction. The friction and wear are serious problems in most of the industries which are influenced by the working set of parameters, oxidation characteristics and mechanism involved in formation of wear. The experimental input parameters such as sliding distance, applied load, and temperature are utilized in finding out the optimized solution for achieving the desired output responses such as coefficient of friction, wear rate, and volume loss. The optimization is performed with the help of a novel method, Eltit Non-dominated Sorting Genetic Algorithm (NSGA-II) based on an evolutionary algorithm. The regression equations obtained using Response Surface Methodology (RSM) are used in determining the optimum process parameters. Further, the results achieved through desirability approach in RSM are compared with that of the optimized solution obtained through NSGA-II. The results conclude that proposed evolutionary technique is much effective and faster than the desirability approach.

Keywords. Laser surface hardening, optimization, NSGA-II, coefficient of friction, wear rate.

1. Introduction
The low alloy steel of EN25 grade is mainly preferred for its excellent strength and good mechanical properties than conventional carbon steels. They tend to have wide applications in the areas of connecting rods, gear shafts and hot forging dies [1]. The surface layers of EN25 low alloy steels are necessary to exhibit excellent wear resistance and high hardness in order to be used for critical applications. This can be achieved with the help of surface heat treatment by utilizing high concentration energy sources such as laser surface treatment, etc [2]. Although, the traditional hardening methods are found to have several advantages, laser surface hardening helps in reducing wear rate, friction and enhances strength, surface hardness with minimum level of distortion [3, 4]. The wear rate being a major problem in industries, it has to be minimized to the maximum extent [5]. The process parameters considered in controlling the wear rate are sliding distance, applied load, and temperature [6, 7]. The optimized set of solutions have to be obtained for predicting the process parameter level in which the desired output response can be obtained. The optimization can be carried
out using statistical and evolutionary techniques. The experimental wear analysis on laser surface hardened EN25 steel has been carried out by Dinesh Babu et al. [8]. They have conducted the experimental trials based on Design of Experiment (DOE). The influences of process parameters on laser surface hardened EN25 steel have been obtained using Response Surface Methodology (RSM).

In order to provide better optimal solution and to utilize an evolutionary algorithm [9], we have utilized Elitist Non-dominated Sorting Genetic Algorithm (NSGA-II). In this research, the main motive is to determine the optimal solution for reducing wear rate and friction using NSGA-II and to compare the results obtained in both statistical and evolutionary methods [10]. The better solution achieved for the selected material can be used in automobiles and aircraft for high temperature sliding contact applications.

2. Proposed methodology

In order to obtain the desired output response with any research work, the optimization of process parameters of that experimental analysis is extremely important. The optimum solutions may be minimum or maximum liable to particular function with respect to their input parameters. The set of parameters and different levels chosen are shown in Table 1. The two techniques that are used in obtaining maximum optimized solution of the process parameters are shown below. Earlier, many other researchers have done the comparative studies using RSM and ANN approaches [11].

Response Surface Methodology (RSM) is an approach which is mainly preferred for developing mathematical models and providing optimal solutions. This approach is said to provide a collection of statistical and mathematical techniques which supports in developing an effective mathematical model [12]. The main purpose of RSM is to optimize an output response which is influenced by several independent input process parameters. This technique holds a desirability approach, which is widely preferred for its simplicity, availability and flexibility in giving importance level for individual responses [13].

| Sl. No | Parameter                | Levels       |
|-------|--------------------------|--------------|
| 1     | Applied Load             | 10 N, 25 N, 40 N |
| 2     | Temperature              | 200 °C, 400 °C, 600 °C |
| 3     | Sliding distance         | 1000 m, 2000 m, 3000 m |

![Figure 1. Iteration procedure of NSGA-II algorithm](image)

Elitist Non-dominated Sorting Genetic Algorithm (NSGA-II) algorithm was proposed by Deb [14] which uses an elite-preserving mechanism, by preserving the previously found solutions. One other
reason is for the quick non dominated sorting algorithm followed by NSGA II. It does not require any tunable parameter. This feature makes the algorithm independent of the user. First, a random parent population Po is created, which is then sorted based on the non-domination level. The computational complexity is reduced with the help of a book-keeping procedure. A fitness value is assigned to each of the solutions equal to its non-dominated level. The techniques such as binary tournament selection, recombination and mutation operators were used for creating a child population Qo of size N. The iteration procedure of NSGA-II algorithm is shown in Figure 1. The steps are performed for a specified number of generations.

3. Criteria for optimization
The design of experiment was established using Design Expert software with the optimization criteria, minimum and maximum limits for all the input parameters and output responses as given in Table 2. The sliding distance, applied load, and temperature are the input parameters and coefficient of friction, wear rate, and volume loss are the output responses considered for the laser surface hardening of EN25 graded steel.

| Type            | Factor              | Goal             | Min. Limit | Max. Limit | Importance Level |
|-----------------|---------------------|------------------|------------|------------|------------------|
| Input parameter | Applied load        | is in range      | 10         | 40         | 3                |
|                 | Temperature         | is in range      | 200        | 600        | 3                |
|                 | Sliding distance    | is in range      | 1000       | 3000       | 3                |
| Output response | Wear rate           | minimize         | 0.43       | 2.536      | 3                |
|                 | Volume loss         | minimize         | 1.19       | 5.689      | 3                |
|                 | Coefficient of friction | minimize       | 0.27       | 0.51       | 3                |

4. Methodology

The mathematical models for laser surface hardened EN25 graded steel involving the process parameters and output responses are established by utilizing Design Expert software. The optimization is carried out in desirability approach with the application of Response Surface Methodology (RSM). The empirical relationships developed using RSM are then applied in NSGA-II based on evolutionary
algorithm for attaining the global search procedure within given input limits. After the implementation of NSGA-II, the results are compared with those obtained through RSM. Finally, the optimal solution which yields better result is validated and implemented. The flow chart of the steps involved in the NSGA-II based optimization is shown in Figure 2.

4.1 Development of mathematical models using RSM
The empirical relationships of output responses developed for laser hardened steel are given in the Eq. (1) - (3). These relationships are utilized in NSGA-II methodology for running the evolutionary algorithm in Visual Studio 6.0 software. The number of iterations have to be chosen based on the accuracy and precision required for the optimized model to be developed. Here, A - applied load, B – temperature, C - sliding distance, COF – coefficient of friction, \( W_r \) – wear rate, \( V_{loss} \) – volume loss.

\[
W_r = 1.797 + 0.0134 \times (A) - 7.951 \times 10^{-3} \times (B) - 6.829 \times 10^{-5} \times (C) + 1.275 \times 10^{-5} \times (A \times B) + 1.883 \times 10^{-6} \times (A \times C) + 2.8 \times 10^{-7} \times (B \times C) + 4.41 \times 10^{-4} \times (A^2) + 9.9125 \times 10^{-6} \times (B^2) + 6.5 \times 10^{-9} \times (C^2)
\]

(1)

\[
V_{loss} = 4.896 - 0.076 \times (A) - 0.01541 \times (B) - 6.34 \times 10^{-4} \times (C) + 4.242 \times 10^{-5} \times (A \times B) + 7.25 \times 10^{-6} \times (A \times C) + 3.5125 \times 10^{-7} \times (B \times C) + 3.104 \times 10^{-3} \times (A^2) + 1.8722 \times 10^{-5} \times (B^2) + 1.60375 \times 10^{-7} \times (C^2)
\]

(2)

\[
COF = 0.369 + 3.5 \times 10^{-3} \times (A) - 5.837 \times 10^{-4} \times (B) + 2.16 \times 10^{-5} \times (C) - 2.5 \times 10^{-6} \times (A \times B) + 1.1667 \times 10^{-6} \times (A \times C) - 3.5 \times 10^{-8} \times (B \times C) - 6.667 \times 10^{-9} \times (A^2) + 9.75 \times 10^{-7} \times (B^2) - 6 \times 10^{-9} \times (C^2)
\]

(3)

5. Results and discussion
5.1 Optimization using desirability approach (RSM)
The RSM based optimization involves desirability approach to determine the optimum process parameters in analytical and graphical methods. The optimized solution could be arrived based on the chosen criteria and importance level. The objective is to minimize the output responses such as wear rate, volume loss and coefficient of friction. This can be achieved with the help of Design Expert software and the solutions obtained with desirability for each process parameter level are as shown in Table 3. Out of the 24 solutions obtained, the most significant solution can be taken with desirability 0.990. The various desirability values obtained for all the process parameter levels are shown in Figure 3. The desirability plot with the optimized solution for each process parameter is shown in Figure 4. Further, the optimized solutions are investigated through graphical method in RSM. This method tends to generate an overlay plot which suggests the optimized parameters and their responses. The yellow colored region in the overlay plot is considered as the optimized region for laser surface hardened EN25 graded steel. The overlay plot is shown in Figure 5.
### Table 3. Optimized solutions using RSM

| Sl. No | Applied Load | Temperature | Sliding distance | Wear rate | Volume loss | Coefficient of friction | Desirability |
|-------|--------------|-------------|------------------|-----------|-------------|------------------------|--------------|
| 1     | 10.00        | 355.08      | 1000.13          | 0.504265  | 1.21002     | 0.325599               | 0.990        |
| 2     | 10.00        | 354.34      | 1008.58          | 0.505195  | 1.21005     | 0.325641               | 0.990        |
| 3     | 10.00        | 353.55      | 1018.62          | 0.506211  | 1.21001     | 0.325688               | 0.990        |
| 4     | 10.01        | 360.76      | 1000.00          | 0.501869  | 1.20309     | 0.325046               | 0.989        |
| 5     | 10.00        | 349.02      | 1083.59          | 0.512858  | 1.21008     | 0.326053               | 0.989        |
| 6     | 10.00        | 337.57      | 1000.17          | 0.516114  | 1.23915     | 0.325046               | 0.989        |
| 7     | 10.18        | 356.33      | 1131.99          | 0.508869  | 1.21001     | 0.326322               | 0.989        |
| 8     | 10.00        | 346.47      | 1157.89          | 0.517443  | 1.21001     | 0.326550               | 0.989        |
| 9     | 10.00        | 346.59      | 1196.70          | 0.519004  | 1.19918     | 0.326938               | 0.988        |
| 10    | 10.00        | 358.72      | 1250.65          | 0.519012  | 1.18672     | 0.327590               | 0.987        |
| 11    | 10.00        | 346.73      | 1251.28          | 0.524811  | 1.20273     | 0.327170               | 0.986        |
| 12    | 10.00        | 358.21      | 1304.72          | 0.525348  | 1.19325     | 0.327627               | 0.985        |
| 13    | 10.00        | 359.20      | 1306.38          | 0.522622  | 1.18479     | 0.327910               | 0.985        |
| 14    | 10.00        | 353.93      | 1375.59          | 0.529319  | 1.19049     | 0.328025               | 0.984        |
| 15    | 10.00        | 398.74      | 1471.91          | 0.501169  | 1.18733     | 0.329582               | 0.983        |
| 16    | 10.00        | 368.65      | 1471.91          | 0.532233  | 1.17855     | 0.329040               | 0.982        |
| 17    | 10.00        | 347.54      | 1590.98          | 0.546895  | 1.20706     | 0.328560               | 0.980        |
| 18    | 10.00        | 427.28      | 1600.01          | 0.519559  | 1.21110     | 0.334193               | 0.974        |
| 19    | 10.00        | 367.51      | 2521.27          | 0.615699  | 1.39774     | 0.325218               | 0.961        |
| 20    | 10.00        | 370.85      | 2579.73          | 0.620842  | 1.42013     | 0.324630               | 0.959        |
| 21    | 10.00        | 369.52      | 2943.59          | 0.653995  | 1.58480     | 0.320002               | 0.949        |
| 22    | 10.00        | 326.88      | 2999.99          | 0.662637  | 1.65225     | 0.320619               | 0.941        |

**Figure 4.** Desirability plot showing the optimized solution for each process parameter
5.2 Optimization using evolutionary algorithm (NSGA-II)

The NSGA-II based optimization has been executed with the help of Visual Studio C++ 6.0. The mathematical relationships established using RSM are fed into the software which results in an optimum solution. The objective of the GA program was to minimize the output responses such as wear rate, volume loss and coefficient of friction. The optimized values of the input process parameters are observed after conducting ‘n’ no of iterations as required. The optimization has been carried out to find the value of input process parameters such that the wear and friction are minimized. The problem specifications are entered while executing the program. The NSGA-II methodology uses the following parameters: variable type = real variable, no. of real variables = 2, no. of constraints = 0, population size = 100, no. of generations = 100, crossover probability = 0.6, mutation probability = 0.3, distribution index for real-coded crossover = 10, distribution index for real-coded mutation = 100. The random seed is considered as 0.8956.

After the successful execution of GA program, the output files are created in their respective destination folders. The optimized solutions obtained through desirability approach and elitist non-dominated sorting genetic algorithm are compared and shown in Table 4. It has been found that the wear rate and friction tend to get reduced, when the NSGA-II based optimization is adopted. This approach is found to be much effective and faster than the desirability approach. The variation of each objective function with respect to the number of generations is plotted in Figure 6. This plot between the number of generations and objective functions show that the wear rate, volume loss and coefficient of friction tend to decrease as the number of generation increases.

Table 4. Optimized solutions obtained through statistical and evolutionary techniques

| Sl. No | Methodology          | Input parameters | Output responses |
|--------|----------------------|------------------|------------------|
|        |                      | Applied load (N) | Temperature (°C) | Sliding distance (m) | W_r (x10^3 mm^3/m) | V_loss (mm^3) | COF    |
| 1      | Desirability approach| 10.00            | 355.08           | 1000.13              | 0.504265          | 1.21002      | 0.325599 |
| 2      | NSGA-II              | 10.098           | 356.12           | 1003.25              | 0.481             | 1.196        | 0.289   |
Figure 6. Variation of objective function versus number of generations for laser surface hardened EN25 graded steel (a) Objective function – Wear rate (b) Objective function – Volume loss (c) Objective function – Coefficient of friction

6. Validation of results

Table 5. Validation of the NSGA-II based models

| Exp no. | Applied load (N) | Temperature (°C) | Sliding distance (m) | Output responses | \( W_r \) (\( \times 10^3 \) mm\(^3\)/m) | \( V_{loss} \) (mm\(^3\)) | COF |
|---------|------------------|-----------------|---------------------|-----------------|---------------------------------|-----------------|------|
| 1       | 10.091           | 355.98          | 1002.36             | Actual          | 0.478                           | 1.115           | 0.217 |
|         |                  |                 |                     | Predicted       | 0.481                           | 1.126           | 0.221 |
|         |                  |                 |                     | Error %         | 0.623                           | 0.976           | 1.809 |
| 2       | 10.098           | 356.12          | 1003.25             | Actual          | 0.481                           | 1.196           | 0.289 |
|         |                  |                 |                     | Predicted       | 0.489                           | 1.21             | 0.292 |
|         |                  |                 |                     | Error %         | 1.635                           | 1.157           | 0.254 |
| 3       | 10.095           | 356.04          | 1002.95             | Actual          | 0.480                           | 1.175           | 0.254 |
|         |                  |                 |                     | Predicted       | 0.489                           | 1.184           | 0.258 |
|         |                  |                 |                     | Error %         | 1.840                           | 0.76            | 1.55  |
Based on the comparison between optimized solutions obtained through RSM and NSGA-II, it has been confirmed that the NSGA-II based results are better. The results are validated by performing three experiments for verifying the obtained models through NSGA-II. The validation as shown in Table 5 confirms the agreement between the predicted and actual responses.

7. Conclusion
This research work deals with the use of Design of Experiment (DOE) for conducting successful experiments. We have used two different approaches RSM and NSGA-II for predicting and comparing the wear properties of the laser surface hardened EN25 graded steel. Thus, the following outcomes can be noted.

- An improved model is proposed by using NSGA-II, which considers the minimisation of the wear properties of the hardened steel. It is clear that NSGA-II methodology uses a faster non-dominated sorting approach and an elitist strategy with no niching parameter.
- The NSGA-II algorithm performs a faster work and yields better result for obtaining good wear resistance than observed with the desirability approach in RSM. The prediction of optimized wear properties of EN25 graded steel are found to be robust and exact in NSGA-II when compared with that of the response surface model.
- A good agreement is authentically established among the actual and mathematical results. The GA based model shows high appropriateness, which would help in future to determine values with minimum amount of error.
- NSGA-II yields the result faster than the RSM tool. The output responses tend to improve when the NSGA-II is adopted. Though, all the parameters doesn’t seem to improve, there is an improvement in the entire model. In order to optimize and obtain improvement in all the responses, some other evolutionary techniques may be adopted.

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