Optimization of roller burnishing process parameters using lion optimization algorithm

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Abstract. The aim of this work is to optimize the roller burnishing process parameters for minimizing the surface roughness using response surface methodology (RSM) and lion optimization algorithm. A RSM based box-behnken design is utilized for experimentations. The empirical model of surface roughness is developed for showing the relation between inputs and output of the burnishing process. The analysis of variance (ANOVA) method was used to check the accuracy of the developed mathematical model. With the developed mathematical model, the roller burnishing process parameters were then optimized to minimize the surface roughness by a new type of lion optimization algorithm. Further, validation test has been conducted for the optimal conditions suggested by lion optimization algorithm. The experimental value agreed with those predicted value with 3.225% of relative error percentage.

1. Introduction

Burnishing is a plastic deformation process in which force is applied on to a surface through a hard roller or ball[1]. It is a cold working process that can be used to improve surface finish and surface hardness of workpieces [2]. Burnishing offers many advantages; improved size control, densely compacted and fine surface finishes and also increases in the surface hardness[3]. This kind of burnishing process may find many uses in manufacturing components and machine tools since it is applicable for a wide range of industrial finishing operations. Roller burnishing generally uses tools with a hydrostatically supported ball as the rolling element[4]. This is mounted in a suitable holder and supported by a hydraulic piston, which, in turn, may be moved axially in a sleeve mounted on the tool shank and which ensures a constant rolling force corresponding to the hydraulic pressure. This process belongs to a group of manufacturing technologies, which are used for the mechanical strain hardening of the surface layer[5]. Esme [6] investigated the multi-response optimization of burnishing process for an optimal parametric combination to yield favourable surface roughness and micro hardness using the Grey relational analysis and Taguchi method. The objective functions have been selected in relation of burnishing parameters; burnishing force, number of passes, feed rate and burnishing speed.
The results showed that the application feasibility of the Grey relation analysis in combination with Taguchi technique for continuous improvement in product quality in manufacturing industry. Sagbas[7] used an optimization strategy of desirability function approach together with response surface methodology in ball burnishing process of 7178 aluminium alloy. The process model variables are burnishing force, number of passes, feed rate and burnishing speed were considered. Babu et al[3] studied the effects of various burnishing parameters on the surface characteristics, surface microstructure, micro hardness in roller burnishing of EN Series steels (EN 8, EN 24 and EN 31), Aluminum alloy (AA6061) and Alpha-beta brass. The following burnishing parameters were considered as burnishing speed, burnishing force, burnishing feed and number of passes. Taguchi technique is employed in the present investigation to identify the most influencing parameters on surface roughness. The optimum levels were found for minimum roughness values by theoretical Taguchi method. Basak and Goktas[8] conducted the burnishing experiments on Aluminum alloy (Al 7075 T6) by considering the different burnishing parameters (number of revolution, feed, number of passes, and pressure force) Using the experimental results a fuzzy logic model has been used to achieve the best parameters for the burnishing process. The surface roughness is directly affected negatively if the applied force is increased was found. The root mean square errors are obtained around in 2.55% and 0.62% for surface roughness and surface hardness respectively. It was found that the fuzzy logic is a suitable technique that may be efficiently used to optimize the burnishing process. Tayeb and Brevern[9] investigated the impact of burnishing speed, burnishing force and burnishing tool dimension on the surface qualities and tribological properties on Aluminium 6061 under different parameters and different burnishing orientations. Gharbi et al[10] identified the effect of burnishing parameters (i.e., burnishing speed, burnishing force, and feed rate) on surface roughness, surface hardness, and microstructure of burnished surfaces in burnishing of AISI 1010 steel using the Taguchi technique and response surface methodology. It was found that the burnishing force has the most influential effect on the surface roughness and hardness, followed by the burnishing speed, and least influence by the feed rate. In addition, microstructural examinations of the burnished surface indicate that burning force more than 400 N causes flaking of the burnished surfaces. The optimal burnishing parameters obtained through Taguchi method. Using the optimal parameters, the mean surface roughness has been improved from Ra = 2.48 to 1.75 micron, while the hardness increases from 59 to 65.5 HRB. John and Vinayagam[11] dealt with optimization of burnishing process in CNC machining centre using response surface methodology. The ball burnishing tool is used in a CNC machining centre for finishing after an end milling process. The tool and work piece materials are Tungsten carbide and Tool steel. The input parameters are burnishing force, feed, speed and number of passes. The output parameters are surface roughness and surface hardness. The output parameters are modelled and optimized using response surface methodology. When the burnishing force is increased above the yield stress of the material, the deformation takes place at the surface. Hence the surface roughness is minimized. When the number of passes is increased, the surface roughness is gradually increased because more contact force is generated on the surface which produces more heat and softens the top layer of the work piece. Hence, the surface roughness is increased and surface hardness is decreased. At lower feed rates, the more contact time exists between tool and work piece. Hence, the surface roughness is minimized at lower feed compared to higher feed rate. At medium speed, more contact force is generated on the surface compared to at the other speeds. Hence, the surface roughness is minimized at average speed. Taweel and Axir [12] employed the Taguchi technique to identify the effect of burnishing parameters, i.e., burnishing speed, burnishing feed, burnishing force and number of passes, on surface roughness, surface micro-hardness, improvement ratio of surface roughness, and improvement ratio of surface micro hardness. The results of analysis showed that the burnishing force with a contribution percent of 39.87% for surface roughness and 42.85% for surface micro-hardness had the dominant effect on both surface roughness and micro-hardness followed by burnishing feed, burnishing speed and then by number of passes. The published literature indicates that few studies have been reported for the optimization of process parameters in roller burnishing of brass. Therefore, the present paper aims at the optimization of best input process parameters for high
performance burnishing process to yield the good quality surface roughness. A RSM-based box-behnken design matrix[13] has been used for conducting the experiments. The experiments was carried out using three different burnishing process parameters (Burnishing speed, feed rate and burnishing depth) to develop a mathematical model on the outcome of surface roughness. Then, a lion optimization algorithm was utilized to optimize roller burnishing process parameters.

2. Experimental work
The experimental work was carried out on an all gear lathe machine with a maximum speed of 2000 RPM and a 8kW drive motor. A special custom-made burnishing tool was used for roller burnishing. When the roller was pressed against the surface of the metallic specimen, a precalibrated spring became compressed. This spring was used mainly to reduce the possible sticking of the tool onto the surface of the specimen. The shank of the burnishing tool was designed in such a manner that it could be simply mounted or fixed onto the tool holder of a machine tool. The roller burnishing experimental setup as shown in Figure 1.

![Figure 1. Experimental setup](image)

| Table 1. Parameters and Levels for BBD |
|---------------------------------------|
| Process parameters | Reference symbol | Units | Low(-1) | Centre(0) | High(+1) |
|---------------------|------------------|-------|---------|-----------|----------|
| Burnishing speed    | $X_1$            | rpm   | 350     | 450       | 550      |
| Burnishing feed rate| $X_2$            | mm/rev| 0.06    | 0.09      | 0.12     |
| Burnishing Depth    | $X_3$            | mm    | 0.1     | 0.15      | 0.2      |

The brass as a workpiece material was selected and widely used in manufacturing industry. The general composition of brass is: 0.831% S, 2.21% Pb, 36.37% Zn, 0.216% P, 0.293% Fe, 0.442% Al, <59.23% Cu, and 0.237% Ni. The bars are received from Narendra steels, Mumbai, as 50 mm diameter and depicted in Figure 2. The external roller burnishing tests were performed under
unlubricated (dry) conditions. Experiments were designed based on RSM based box-behnken design method at different parametric settings and illustrated in Table 1. The upper limit of a factor was coded as (+1), and the lower limit was coded as (−1). The selected process parameters burnishing speed (350 to 550 rpm), burnishing feed rate (0.06 to 0.12 mm/rev) and burnishing depth (0.1 to 0.2 mm) were considered based on the available machine capacity. A precise surface roughness tester (Mitutoyo- Surftest SJ-210 - Series 178) was used to measure surface roughness of the burnished workpiece at five distinct locations. Totally, seventeen experimental runs are carried out according to the design matrix in a random order to avoid any systematic error creeping into the system.

**Figure 2.** Sample of burnished workpieces

| Exp. No | Burnishing speed rpm | Burnishing feed rate mm/rev | Burnishing Depth mm | Exp. Surface Roughness Micron | Pred. Surface Roughness Micron |
|---------|----------------------|-----------------------------|---------------------|-------------------------------|-------------------------------|
| 1       | 450                  | 0.06                        | 0.20                | 0.284                         | 0.283                         |
| 2       | 350                  | 0.09                        | 0.10                | 0.505                         | 0.510                         |
| 3       | 450                  | 0.09                        | 0.15                | 0.505                         | 0.510                         |
| 4       | 450                  | 0.09                        | 0.15                | 0.515                         | 0.514                         |
| 5       | 450                  | 0.09                        | 0.15                | 0.510                         | 0.511                         |
| 6       | 550                  | 0.06                        | 0.15                | 0.291                         | 0.291                         |
| 7       | 550                  | 0.09                        | 0.20                | 0.505                         | 0.505                         |
| 8       | 450                  | 0.09                        | 0.15                | 0.502                         | 0.504                         |
| 9       | 350                  | 0.09                        | 0.20                | 0.529                         | 0.530                         |
| 10      | 450                  | 0.12                        | 0.20                | 0.730                         | 0.730                         |
| 11      | 450                  | 0.06                        | 0.10                | 0.252                         | 0.258                         |
| 12      | 350                  | 0.06                        | 0.15                | 0.313                         | 0.321                         |
| 13      | 550                  | 0.12                        | 0.15                | 0.855                         | 0.854                         |
| 14      | 550                  | 0.09                        | 0.10                | 0.553                         | 0.551                         |
| 15      | 350                  | 0.12                        | 0.15                | 0.769                         | 0.768                         |
| 16      | 450                  | 0.12                        | 0.10                | 0.791                         | 0.792                         |
| 17      | 450                  | 0.09                        | 0.15                | 0.505                         | 0.505                         |

3. Model development and ANOVA analysis

Table 2. summarizes various process parameter combinations for 17 experiments with measured surface roughness value. A nonlinear regression analysis was conducted using the experimental data
collected as per BBD to establish input-output relationships of an roller burnishing process by the Design Expert software. The application of RSM is yielded the following second-order polynomial equation, which are empirical relations between surface roughness, and the process test variables ($X_1$ – burnishing speed, $X_2$ - burnishing feed, and $X_3$ – burnishing depth) in un-coded units as follows:

\[
\text{SurfaceRoughness}=0.28705-0.00277359X_1+2.58253X_2+4.50086X_3+0.00890689X_1X_2-0.00360645X_1X_3-15.46230X_2X_3+0.00000291389X_1^2+22.69179X_2^2-5.40438X_3^2
\] (1)

As shown in Table 2, the experimental surface roughness values fitted well with the predicted surface roughness values which were calculated using the regression model (equation 1). It demonstrated the feasibility to apply BBD to setting up the experimental optimization design for measuring the surface roughness values and establishing the regression equation model. The adequacy of the models so developed was tested using the analysis of variance technique (ANOVA)[14]. The ANOVA for the second-order equation is presented in Table 3 at 95% confidence level.

\[
\begin{array}{|c|c|c|c|c|}
\hline
\text{Source} & \text{Sum of Squares} & \text{df} & \text{Mean Square} & \text{F Value} & \text{p-value (Prob > F)} \\
\hline
\text{Model} & 0.516434 & 9 & 0.057382 & 890.1053 & < 0.0001 \\
\text{$X_1$} & 0.00096 & 1 & 0.00096 & 14.89588 & 0.0062 \\
\text{$X_2$} & 0.5027 & 1 & 0.5027 & 7797.912 & < 0.0001 \\
\text{$X_3$} & 0.000364 & 1 & 0.000364 & 5.651209 & 0.0491 \\
\text{$X_1X_2$} & 0.002856 & 1 & 0.002856 & 44.30205 & 0.0003 \\
\text{$X_1X_3$} & 0.001301 & 1 & 0.001301 & 20.17571 & 0.0028 \\
\text{$X_2X_3$} & 0.002152 & 1 & 0.002152 & 33.37796 & 0.0007 \\
\text{$X_1^2$} & 0.003575 & 1 & 0.003575 & 55.45645 & 0.0001 \\
\text{$X_2^2$} & 0.001756 & 1 & 0.001756 & 27.24131 & 0.0012 \\
\text{$X_3^2$} & 0.000769 & 1 & 0.000769 & 11.92279 & 0.0106 \\
\hline
\text{Residual} & 0.000451 & 7 & 6.45E-05 & & \\
\text{Lack of Fit} & 0.000359 & 3 & 0.00012 & 5.172013 & 0.0732 \\
\text{Pure Error} & 9.25E-05 & 4 & 2.31E-05 & & \\
\hline
\text{Cor Total} & 0.516885 & 16 & & & \\
\hline
\text{Std. Dev.} & 0.008029 & & R-Squared & 0.999 & \\
\text{Mean} & 0.524272 & & Adj R-Squared & 0.998 & \\
\text{C.V. %} & 1.53147 & & Pred R-Squared & 0.988 & \\
\text{PRESS} & 0.005885 & & Adeq Precision & 97.128 & \\
\hline
\end{array}
\]

The ANOVA of the quadratic regression model indicated that the model was highly significant, as the $F$ value for the model was 890.1053. There was only a 0.01% chance that the “model $F$ value” this large could occur because of noise. The $p$ value $\text{Prob}>F$ value of the model was <0.0001, which also
confirmed that the model was highly significant. A lack of fit value of 5.172013 implies that the lack of fit is not significant relative to the pure error, when $p$ value is 0.0732>0.05 also supports the fitness of the model. The $R^2$ is a gage of the amount of deviation around the mean explained by the model and adjusted $R^2$ is the R-squared adjusted for the number of terms in the model proportionate to the number of points in the design matrix. Predicted $R^2$ is a gage of the amount of degree of diversity in new data explained by the model. It displays that the quadratic model with maximum adjusted $R^2$ and predicted $R^2$ values and minimum PRESS value (0.00588 is the best model) recommend as a suitable case. A normal probability plot of the residuals is depicted in Fig. 5, which reveals that the residuals generally fall on a least-square line which is used to estimate the cumulative distribution function for the population. As evident from the figure, the errors are normally distributed and there are almost no serious violations of the assumptions that underlie the analysis. Thus, for advance analysis, this model was suggested.

**Figure 3.** Normal probability plot

4. **Optimization by lion optimization algorithm**

The step by step evaluation for lion optimization algorithm [15] as follows:
1. Generate random sample of lions $N_{pop}$ ($N_{pop}$ is number of initial population).
2. Initiate prides and nomad lions
   i. Randomly select $\%N$ (percent of lions that are nomad) of initial population as nomad lion. Partition remained lions into $P$ ($P$ is number of prides) prides randomly, and formed each prides territory.
   ii. In each pride $\%S$ (Sex rate) of entire population are known as females and the rest as males. This rate in nomad lions is inversed.
3. For each pride do
   i. Some randomly selected female lion go hunting.

![Normal Probability Plot](image-url)
ii. Each of remained female lion in pride go toward one of the best selected position from territory.
iii. In pride, for each resident male; %R(Roaming percent) of territory randomly are selected and checked. %Ma(Mating probability) of females in pride mate with one or several resident male.(New cubs become mature).
iv. Weakest male drive out from pride and become nomad.

4. For nomad do
i. Nomad lion(both male and female) moving randomly in search space. %Ma(Mating probability) of nomad female mate with one of the best nomad male.(New cubs become mature).

5. For each pride do
i. Some female with I rate ((Immigrate rate)) immigrate from pride and become nomad.

6. Do
i. First, based on their fitness value each gender of the nomad lions are sorted. After that, the best females among them are selected and distributed to prides filling empty places of migrated females.
ii. With respect to the maximum permitted number of each gender, nomad lions with the least fitness value will be removed.

If termination criterion is not satisfied, then go to step 3.

At first, mathematical model of surface roughness is developed and considered as fitness function with subject to the constraints of upper and lower bounds of burnishing process parameters to minimize the surface roughness. The lion optimization algorithm is implemented and executed in
The matlab environment in several times to yield the best optimal process parameters by tuning the algorithm parameters. The convergence plot of surface roughness value over max number of generations using lion optimization algorithm is shown in Figure 4, which illustrates the algorithm, converges up to 200 generations. And, the best optimal is achieved at 40th iteration. Table.4 summarizes the comparison between the initial condition and optimal condition achieved by LO algorithm. The relative percentage of improvement is achieved 20.51%, and it is clear that the predictive capability of the lion optimization algorithm. After the selection of AWJ optimal process parameters, further experiments were carried out to verify the corresponding surface roughness predicted by algorithm. Table.5 shows that the percentage of error between the predicted and experimented values. From this analysis, it is observed that the calculated error (i.e. 3.225) is very small which confirms the excellent reproducibility of the experimental conditions.

**Table 4.** Comparison between the initial condition and optimal condition achieved by LO algorithm

| Model Summary          | Initial condition | Optimal condition | % of improvement |
|-----------------------|-------------------|-------------------|------------------|
| Process parameters    |                   |                   |                  |
| Burnishing speed (rpm)| 350               | 458.11            |                  |
| Burnishing feed rate (mm/rev)| 0.06       | 0.06              |                  |
| Burnishing depth (mm) | 0.15              | 0.1               |                  |
| Response              | 0.313             | 0.2488            | 20.51            |

**Table 5.** Experimental validation of optimal parameter settings

|                          | Burnishing speed (rpm) | Burnishing feed rate (mm/rev) | Burnishing Depth (mm) | Surface roughness (Micron) |
|--------------------------|------------------------|-------------------------------|-----------------------|-----------------------------|
| Predicted by algorithm   | 458.11                 | 0.06                          | 0.1                   | 0.248                       |
| Experimental             | 458.11                 | 0.06                          | 0.1                   | 0.256                       |
| % Error                  | 3.225                  |                               |                       |                             |

5. Conclusions

The experimental work on burnishing of brass was performed successfully. Then, the Lion optimization algorithm was implemented to yield the best optimal values. The following conclusions are drawn as follows:

1. The Box-Behnken design approach is used for experimental design. The selected process parameters burnishing speed (350 to 550 rpm), burnishing feed rate (0.06 to 0.12 mm/rev) and burnishing depth (0.1 to 0.2 mm) were considered based on the available machine capacity to perform the experiments.
2. The predicted values match the experimental values reasonably well, with R² of 0.999 for surface roughness. Thus the developed model is more suitable for further analysis.
3. The group behaviour of lions is an effective model for constructing the lion optimization algorithm.
4. The optimal performance characteristics are observed to have minimum surface roughness (0.248 microns) when the process parameters are burnishing speed (458.11rpm), burnishing feed rate (0.01mm/rev) and burnishing depth (0.1 mm).

5. A significant improvement in surface roughness characteristics is observed at the optimum parameter settings in comparison to the initial settings.

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