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Hybrid WCMFO Algorithm for Microhardness Improvement in Roller Burnishing of Brass (C3604)

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Roller burnishing is a surface improvement technique that creates residual compressive stress in the workpiece surface layers. Compressive surface stress generation may increase surface hardness, which in turn enhances fatigue and corrosion resistance and overall surface quality. In order to optimize the process parameters in roller burnishing of brass, the present work unveils an application of Response Surface Methodology (RSM) and hybrid Water Cycle Moth Flame Algorithm (WCMFO) technique. Three input process parameters viz. burnishing speed, depth of penetration and feed rate have been investigated and modelled for Microhardness (HV) utilizing RSM based central composite design. In present experimentation, quadratic model has been suggested for surface hardness. Following validation of the model's validity, the model was coupled with a new metaheuristic based hybrid WCMFO algorithm to optimize the burnishing parameters for maximum Microhardness. So as to prove the enhancement, the optimal burnishing parameters were tested. A substantial relationship was observed between the predicted micro hardness and the experimental values.

Keywords: Central composite design, Corrosion resistance, Residual compressive stress, RSM, Surface hardness

Introduction

Surface treatment is one of the most critical aspects of rising industrial manufacturing processes.[1] Burnishing is a surface alteration technique that is used in different industries as a final finishing method. Work piece asperity deformations occur due to yield point reach due to significant degree of plastic deformation generation at the tool-workpiece interface.[2] The tools dynamic motion during burnishing helps to spread evenly plastically deformed surface asperities. This contributes to the achievement of the required surface polish and a superior surface texture. There are multiple parameters that can have an influence impact on the surface properties of the workpiece. These are the following: speed of burnishing, number of burnishing passes, feed rate, and material for a workpiece, power, ball material, ball sizes and lubricants.[3]

Several researchers have reported the effects of process variables on burnishing process characteristics and optimized the process parameters using Taguchi and RSM approaches. Patel & Brahmbhatt used Central Composite Design (CCD) of RSM to find a correlation between both input and output variables in Roller burnishing process. Effect of Interference, burnishing speed, number of tool pass and feed was investigated. It was revealed that surface roughness was influenced significantly by interference and feed.[4] Taweel & Axir optimized the parameters using Taguchi method on brass as work material in burnishing process. Surface roughness, burnishing force, and micro-hardness had the greatest impact on both, followed by feed, speed, and passes. Maximum surface micro hardness improvement was seen with the slowest burnishing speed, moderate feed, strongest force, and most passes.[5] Gharbi *et al.* evaluated the ball burnishing behaviour of AISI 1010 steel using Taguchi and RSM and realized that the burnishing force, speed, and feed most affect surface quality.[6] During the process of ball burnishing 7178 aluminium alloy, Sagbas used an optimization technique that was based on desirability function approach in conjunction with RSM methodology. Surface roughness was the performance feature studied in conjunction with burnishing parameters such force, passes, feed rate, and speed.[7] An efficient optimization by Nguyen *et al.* reduced mean roughness depth, energy consumption, and brinell hardness for H13 steel burnished surfaces. Penetration depth, burnishing speed, roller count and feed rate were input parameters. Pareto fronts were

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generated using multi-objective particle swarm optimization, and the optimum solution was decided using the technique for order of preference by resemblance to ideal solution.[8] Cobanoglu & Ozturk examined the impact of feed rate, burnishing speed and burnishing force on microhardness and surface roughness were investigated. The burnishing force was found influencing factor on the surface roughness and microhardness.[9] Using RSM, a parametric study of the ball burnishing behaviour of tool steel (T215Cr12) was done by John & Vinayagam. It concluded that lower feed rates increase tool-workpiece contact time. Therefore, a lower feed rate produces a smoother surface than a greater one. Further, the contact force exerted on the surface is greatest at medium speed compared to the other speeds. As the number of passes increases, the surface roughness increases because additional contact force generates heat and weakens the work piece's top layer. Consequently, surface roughness increases and hardness decreases.[10] As can be seen from the aforementioned summary of the relevant literature, many different modeling and optimization strategies have been used to find the ideal region for burnishing parameters that yields the highest quality with the lowest possible cost. In addition, according to the research that has been conducted, the roller burnishing process might result in an increase in the material's microhardness, if the appropriate process parameters are used. There have been a few researches done to increase the microhardness of brass (C3604), but none have been done to optimize the burnishing process parameters using a hybrid metaheuristic algorithm. Also, it was found that metaheuristic algorithms play an important role to find the best combination of burnishing parameters. However, there is no one metaheuristic algorithm that can successfully address all optimization problems; each approach has its own set of strengths and weaknesses. Metaheuristic algorithms performance is contingent upon their capacity to explore widely and discover deep solutions. In order to increase overall performance, researchers have typically blended two or more metaheuristic algorithms into hybrid ones. As a result, it is possible to generate almost global optimal solutions more quickly than it would be possible to do so using just one algorithm.

Therefore, in this work, RSM and hybrid WCMFO are used together to establish parameter optimization model for roller burnishing of brass material. The RSM model was utilized to determine the relationship between the input variables process parameters and the microhardness of the machined surface. The optimal burnishing conditions are found using a new global hybrid optimization technique called WCMFO algorithm for obtaining improved microhardness. In this, the hybrid metaheuristic WCMFO algorithm is composed of a core algorithm (WCA) that is supported by an auxiliary metaheuristic algorithm (MFO). The core algorithm is an iterative generation process that guides an auxiliary metaheuristic across the search space to explore and exploit it.

Experimental Work

In this study, three parameters were identified, namely A: Burnishing speed (200–700 rev/min), B: Depth of penetration (1–2 mm) and C: Feed rate (0.05–0.11 mm/min), and the range for each process parameter was determined through preliminary experiments. By conducting trial experiments, possible ranges for process parameters for the material were established, allowing problems such as workpiece damage and runout to be avoided. RSM is a valuable technique for modelling and analyzing systems in which a desired response is influenced by multiple factors and their interactions at the same time, with the ultimate goal of RSM being to optimize the response.[11,12] As a result, RSM was utilized in this investigation to establish the optimal experimental design matrix. For experimentation, CCD of the RSM is used and necessitated a total of 20 experiments.

Experiments were conducted on a heavy duty HMT lathe machine, which has a power capability of 2.2 kW and was used for the tests. Roller burnishing tools were designed and fabricated to carry out the burnishing operation in this work, as shown in Fig. 1. A hardened roller of 25 mm diameter, 10 mm in width, was used for burnishing. Burnishing tool shank is intended to be easily placed on the tool holder of a lathe machine. In this present work, C3604 Brass rods (Free machining grade) steel was used as work material. Which was heat treated to hardness of 30 HRC. This type of brass is

Fig. 1 — Fabricated roller burnishing tool

widely used in ship, building, petrochemical & gas, power and valve industries etc. During experimentation, the fabrication of burnishing specimens begins with the rods being turned into circular bars with a diameter of 24 mm. After the turning is complete, the burnishing procedure is carried out using the prescribed burnishing parameters. The experiment was designed and conducted to perform the output parameter by considering microhardness as the main response. Randomized experiments were used to reduce random variance in responses. The burnishing experimental setup is photographed in Fig. 2. Work specimens were made in the manner that is depicted in Fig. 3, and the bars were scaled to the appropriate dimensions. A vickers microhardness machine tester (model HWDN-3) was used to determine the hardness of the burnished surfaces. Microhardness was evaluated throughout the specimen's length and around its circumference. Each sample was observed three times in various locations, and the average of those readings was reported in Table 1. Each measured hardness value was utilized to characterize the effect of burnishing on the surface.

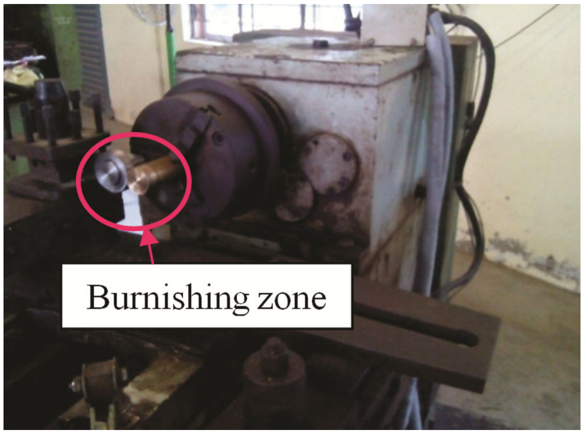

Fig. 2 — Experimentation on roller burnishing process

Fig. 3 —Burnished specimens

Optimization, Results and Discussion

Development of Mathematical Model

Second-order polynomial equations with interaction factors were used to express the empirical relate between the results learned on the basis of the core composite experimental design model and the input process variables. The final predictive mathematical models arrived for microhardness (Uncoded units) as follows:

$$\text{Microhardness (HV)} = +621.78793 + 0.013700 \times A - 463.30303 \times B - 811.70125 \times C + 1.77819E-003 \times AB + 2.75794 \times AC + 5688.97789 \times BC - 3.12415E-004 \times A^2 - 22.80483 \times B^2 - 48507.10588 \times C^2 \quad \ldots (1)$$

Preceding terms with a plus sign imply a synergistic impact, whereas a minus sign denotes an antagonistic one. Determination of different coefficients such as R2, Adj R^2, Pred R^2, Coefficient of Variation (CV%) and adequate precision were determined to ensure the resulting model is adequate and reliable. The obtained details are given in Table 2. When the coefficients are close to the value of 1, the multiple regression models match experimental

Table 1 — Experimental runs and results of average Microhardness

Run	Burnishing speed (rev/min)	Depth of penetration (mm)	Feed rate (mm/min)	Microhardness (HV)
1	450	1.5	0.10	242
2	450	0.7	0.10	208
3	200	1.0	0.08	254
4	870	1.5	0.10	184
5	200	2.0	0.08	174
6	200	1.0	0.11	142
7	700	1.0	0.11	158
8	700	1.0	0.08	220
9	200	2.0	0.11	242
10	700	2.0	0.11	249
11	30	1.5	0.10	168
12	450	1.5	0.10	225
13	450	1.5	0.10	238
14	450	1.5	0.07	214
15	450	2.3	0.10	222
16	450	1.5	0.10	230
17	450	1.5	0.12	187
18	450	1.5	0.10	228
19	450	1.5	0.10	238
20	700	2.0	0.08	150

Table 2 — Validation of quadratic model

Std. Dev.	8.61	R^2	0.9684
Mean	208.64	Adj R^2	0.94
CV %	4.13	Pred R^2	0.8143
PRESS	4357.99	Adeq Precision	18.747

measurements very well. It is also consistent with the multiple regression models and has an excellent relation between selected burnishing process parameters and microhardness. From the Table, the obtained R2 value for Eq. (1) was 0.9684. This suggested that 96.84% of the total variation in microhardness was due to the experimental variable investigated. In addition, it reveals a very significant relationship between three parameters and surface roughness, which is in agreement with the multiple regression models. The Pred R^2 of 0.94 and the Adj R^2 of 0.998 are quite close to one another. The CV is the amount of the deviation from the average value of the output unit. In this study, the small value (i.e. 4.13) of this quantity reveals the accuracy of the model. A high signal-to-noise ratio is achieved when the range of expected values at the design points is less than the average error of prediction. Model discrimination is sufficient if the ratio is larger than 4. In this investigation, the ratio is far more than 4, coming in at 18.747. Because of this, the generated regression model can successfully explore the response space. So, the fitted quadratic model is reliable and can be used to optimize test results. Various indicators can be used to determine the accuracy level of this model after it has been estimated.

Hybrid WCMFO Algorithm

In the year 2018, Khalilpourazari and Khalilpourazary proposed the development of a hybrid WCMFO algorithm. This algorithm draws inspiration from the natural water cycle and moth motion in order to describe its operations.[13] Such, a hybrid algorithm applied in multilevel image segmentation[14–15], fuel cell applications,[16] evapotranspiration[17] and AWJ cutting process.[18] To avoid the population settling on a single optimal solution too quickly, the WCMFO algorithm combines the merits of the Moth-Flame Algorithm (MFO) with the Water-Cycle Algorithm (WCA).[13] To improve the WCA's potential for exploration and exploitation, the WCMFO combines the levy operator, together with the spiralling movement of the MFO, which is accordingly included into the water cycle process.[13] WCA should ideally have a large capacity for problem space exploration. The WCA charts waterways that flow into the sea, and depending on the best option, search agents may swap positions. However, the WCA frequently lacks an effective operator who can carry out exploitation, which is a major source of its problems.[13] MFO, on the other hand, makes excellent use of its potential for spiral movement, but it is unable to adequately explore the solution region. Each moth flies to its own flame and constantly updates its position. Therefore, the MFO does not provide details regarding the optimal approach taken so far. A hybrid algorithm is being developed that combines the advantageous characteristics of the WCA and MFO algorithms. The WCA is the backbone of the new WCMFO algorithm that has been developed.[13] Using the moths' spiral motions, the WCA begins the process of relocating the waterways. In the event of relocation, the straightforward WCA update procedure only accounts for the distance between the stream and the river. Thus, the stream will move between the stream and the river.[13] The MFO algorithm updating technique, on the other hand, allows the moths to move around the flames. The hybrid WCMFO's exploitability is greatly enhanced by the spiraling motion that permits rivers and streams to travel downstream. The WCA is also adjusting its rainmaking procedures to make them more efficient. An essential part of metaheuristic algorithms is their use of randomization. For the WCMFO algorithm, there are two known methods to increase randomness.[13] The first cycle is the rainy cycle, much like in basic WCA. If a river or stream is closer to the sea than the maximum allowable distance, d_{max}, WCMFO will generate new solutions during the cycle. The second is to have stream flow independently in the solution region via a random walk. If there isn't a better choice after updating the rivers, the rivers and sea should stay where they are until the next round of the WCA. To improve the algorithm's randomness, the hybridized version requires the streams to shift their position according to the following equation.[13]

$$x_{i1} = x_i + Levy(\dim) \otimes x_i \qquad \ldots (2)$$

Let x_i denote the current place along the stream, x_{i+1} represents during the course of stream and dim symbolize a determinant factor. The following calculation is then used to determine the levy flight.

$$Levy(x) = \frac{0.01 \times \sigma \times r_1}{|r_2|^{\frac{1}{\beta}}} \qquad \ldots (3)$$

where, each r_1 and r_2 is chosen at random and lies on a scale from zero to one. The parameter can be calculated with the help of the following equation.[13]

$$\sigma = \left(\frac{\Gamma(1+\beta) \times \sin\left(\frac{\pi\beta}{2}\right)}{\Gamma\left(\frac{1+\beta}{2}\right) \times \beta \times 2^{\left(\frac{\beta-1}{2}\right)}} \right)^{\frac{1}{\beta}} \quad \text{... (4)}$$

The following is a pseudo-code presentation of the WCMFO [13]

```
set the parameters of WCMFO such as $N_{pop}$, $N_{sr}$, a, and maximum number of iterations
  for i=1:$N_{pop}$
    Create a random stream
    Calculate the objective function value of the stream
  end for
sort the streams from best to worst based on their objective function value
  Sea← the first stream
  Rivers←$n_{sr}$-1
  Stream←$n_{pop}$-$n_{sr}$
Determine the intensity of flow for rivers and sea
  i=0;
While i< maximum number of iterations
  i=i+1;
  for streams
    Update the position of stream using spiral movement
    Stream_objective=objective function value of the new stream
    if stream_objective < river_objective
      River_position = the new stream
      if stream_objective < sea_objective
        Sea_position = the new stream
      end if
    end if
    if river_objective < sea_objective
      Sea_position =River_position
    end if
  end for
  for rivers
    Update the position of rivers using spiral movement
    river_objective =objective function value of the new river
    if river_objective < sea_objective
      Sea_position =River_position
    end if
  end for
  for streams
    Update the position of the streams using Levy flight
  end for
  for Rivers and streams
    d=calculate the distance between each river or stream and the sea
    if d < $d_{max}$
      raining process (for both rivers and streams)
    end if
  end for
  Linearly decrease the parameter max d
  Linearly decrease the parameter a
end while
```

Hybrid WCMFO Optimization for roller burnishing process

The objective of the burnishing process was to determine the optimal process parameters, including burnishing speed, depth of penetration, and feed rate, with the aim of maximizing the objective function, which is the microhardness. A RSM approach provided an empirical equation, which was subsequently, optimized using a hybrid WCMFO optimization algorithm. Consequently, in order to get the best possible process parameter, the following range based on DOE process was chosen and the optimization problem is then defined as follows:

$$\text{Maximize: HV(A,B,C,D)} \quad \dots (5)$$

Within the parameter feasible ranges:

$$200 \text{ rev/min} \leq A \leq 700 \text{ rev/min} \quad \dots (6)$$

$$1.0 \text{ mm} \leq B \leq 2.0 \text{ mm} \quad \dots (7)$$

$$0.08 \text{ mm/min} \leq C \leq 0.11 \text{ mm/min} \quad \dots (8)$$

The purpose of the optimization procedure in this study was to determine the ideal values of process parameters that would result in the highest possible microhardness of burnished components. The optimization problem is then solved using the hybrid WCMFO method. This is required to ensure the convergence of the objective function. In this optimization, the process parameters were represented by the streams, rivers and sea of raindrops while the surface hardness is represented by the fitness function. By using the combination of Eqs (5–8) and the selected setting values, the optimization was performed. Also, the number of iterations was chosen at 100 because the preliminary test showed that most runs converged between 20 and 40 iterations. There would be no difference in the WCMFO results if the number of iterations was increased. The WCMFO combines the best features of WCA and MFO for the purpose of probing and capitalizing on the solution space. Using moth spiral movements in the MFO, the WCA updating procedure is utilized to enhance the WCMFO. The WCMFO has recognized a spiral pattern in the

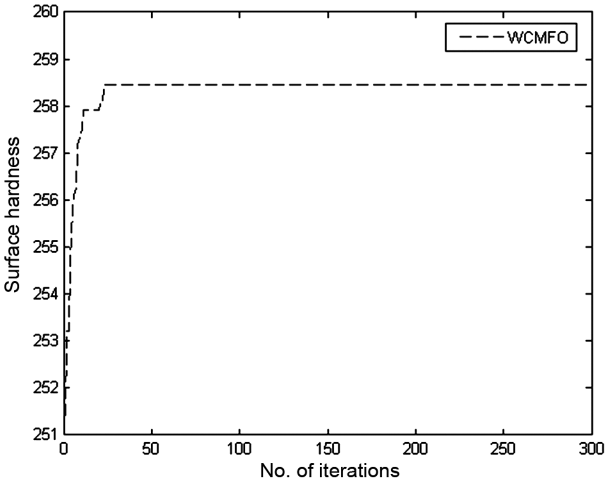

Fig. 4 — Convergence of the WCMFO algorithm for Microhardness

Table 3 — Confirmation experiments

Burnishing speed (rev/min)	Depth of penetration (mm)	Feed rate (mm/min)	Microhardness (HV)	
			WCMFO Predicted	Experimental value
455	1.98	0.11	258.487	257

trajectory of streams, rivers, and the sea which aids in the effective investigation of the solution space for the formulated optimization problem. This is accomplished by allowing random walk (levy flight) for stream updates, which increases randomness in the algorithm and hence improves the WCMFO exploration capability. The hybrid WCMFO algorithm begins by randomly generated rain drops and initialize the parameters (i.e. *a*, N_{sr}, N_{pop}, and maximum iterations).[13] The specific parameters of WCMFO algorithm are number of rivers + sea (*Nsr* :5), Evaporation Condition constant (*dmax*:1.00E-05) and Shaping parameter (*b*:1).[13] The algorithm simulates the precipitation or raining process with starting values for design parameters (matrix of streams) and is the result of a random procedure between Upper (UB) and Lower (LB) Bounds. Each row in the matrix represents a solution for computation of best process parameters. Following precipitation, the objective function values are evaluated using Eq. (5). The best individual is the sea, which has the highest objective value obtained from Eq. (5); others are classified into rivers and streams depending on their objective function values. Then, river and ocean flow intensities are assessed. Here, the volume of water flowing into a river determines how much of that river's water is absorbed by the stream(s) from which it receives its water. In the next step, update all the positions of streams and rivers in consideration of the spiral movements of moths using logarithmic spiral function. These moth's spiral movements are significantly increasing the exploitation ability of algorithm to maximise the objective function (i.e. microhardness). The vertical axis of the convergence graph (Fig. 4) is representing the best solution vectors obtained from the raindrop vector. A total of 300 iterations were allowed for the WCMFO. In this circumstance, as illustrated in figure, the WCMFO algorithm rapidly converges to the global optimum. The optimal solution obtained for the maximum value of microhardness (258.487 HV) is at the 30th iteration of the WCMFO algorithm. The algorithm predicted a burnishing speed of 455 rev/min, depth of penetration of 1.98 mm and feed rate of 0.11 mm/min for the burnishing process. From the observation, the optimization process by using hybrid WCMFO had been successfully performed. The WCMFO optimization technique found this set of settings ideal, and experiments designed to validate the optimum conditions were carried out as a confirmation step. The trials were repeated three times, with the average results shown in Table 3. The algorithm's predicted values of response were compared to the experimental data, and it turned out that the results were consistent. As a result, confirmation experiments provide good reproducibility.

Conclusions

In this research, an effort has been made to identify the ideal process variables for roller burnishing Brass (C3604) material. For that, response surface methodology and WCMFO algorithm techniques were used for modelling and optimization of the process. The application of RSM allowed for the development of a mathematical model, and the model that was developed is acceptable. The adoption of a hybrid WCMFO algorithm-based optimization strategy, in terms of best exploration and exploitation, has been demonstrated to be effective and versatile in locating optimal burnishing conditions given a specified microhardness value. The algorithm results suggest maximum microhardness (258.487 HV), medium burnishing speed (455 rev/min), both the maximum depth of penetration (1.98 mm) and feed rate (0.11 mm/min) as the global optimum parameters. The optimal parameters corresponding to the objective functions can be found on the shop floor using the hybrid WCMFO algorithm, based on production requirements. Once the ideal settings have been identified, the procedure can then be automated to save time. Results have confirmed that new metaheuristic algorithm, called WCMFO as useful for optimizing the burnishing processes.

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