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Optimizing Aluminium Alloy Surface Quality with ANN-Driven Burnishing: Machining Parameters and Durability Study

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Abstract: Surface quality plays a pivotal role in the performance and durability of metal components across diverse industries. Burnishing, a commonly employed finishing method, has gained significant popularity for its efficacy in enhancing surface quality, especially in aluminium alloy applications. This research paper introduces a novel approach to elevate surface quality during the burnishing process of aluminium alloys, leveraging the capabilities of Artificial Neural Networks (ANNs). In this paper, machining parameters and their effects on the aluminium alloy material 6351 using a lathe were considered. A mathematical model has been developed to forecast variable surface roughness. The surface quality achieved after the procedure on the work piece is then utilized for ball burnishing. Subsequently, the surface quality pattern is employed to replicate the burnishing process using optimization, sensitivity analysis, and ANN. The quality of the surface parameters determined on the aluminium alloy after burnishing is estimated using a ball, and it is experimentally confirmed at 1.73164 m. The results of this research provide valuable insights into the intricate interplay of burnishing parameters on aluminium alloy surface quality, aiding in the development of more efficient and cost-effective finishing processes.

Keywords: Artificial Neural Network; Al Alloy; Surface Quality; Burnishing

1. Introduction

Ball burnishing is a technique that utilizes a tool with two balls in a tool holder. It is a cold working procedure applied to materials. A hard ball burnishing tool is pressed onto the surface of a material to assess its surface condition. Surface alterations may include a reduction in surface roughness, an increase in surface hardness, and changes in grain size[1)]. Surface quality is a crucial factor affecting the performance and lifespan of engineering components. Burnishing, a mechanical surface finishing technique, is widely used to improve surface properties such as roughness, hardness, and wear resistance. This process involves applying pressure to a workpiece surface using a hard tool, typically a ball or roller, to plastically deform the material. As a result, the surface undergoes micro-smoothing, reducing roughness peaks and enhancing surface integrity. Burnishing may finds applications in industries such as automotive, aerospace, and manufacturing, where high-quality surfaces are vital for optimal performance and durability. This paper explores the principles, mechanisms, and applications of burnishing, emphasizing its importance in achieving superior surface quality in various engineering components. Burnishing, classified as a cold-working technique, achieves smooth and work-hardened surfaces by reshaping surface imperfections. This research examines critical burnishing parameters and determines that work piece surface quality is notably influenced by burnishing forces and the number of tool passes. During the burnishing process, external forces are applied to a polished and hardened ball or roller, which is directed appropriately onto flat or cylindrical work pieces as shown in Fig. 1. When the burnishing pressure exceeds the material's yield strength, the metallic surface's peaks permanently spread out, filling the valleys and resulting in a smoothing effect.

In recent times, extensive research has been conducted to establish the ideal parameters for the ball burnishing process. A range of critical variables, including the choice of ball or roller material, burnishing force, feed rate, burnishing speed, lubrication, and the number of burnishing passes, have all been shown to exert a considerable influence on surface roughness[2]. SS. J. Ebeid and colleagues created a two-dimensional finite element model (FEM) tailored to replicate the behavior of AISI 1045 mild steel. Furthermore, they devised a numerical approach, utilizing the FEM, to investigate how cutting speed and feed rate impact the residual stresses generated during orthogonal cutting. A comparison of actual and simulated results revealed that the stress distribution steadily increased with changes in cutting speed and feed rate. Additionally, they conducted research on the burnishing technique applied to aluminium 6061. This involved the utilization of interchangeable adapters for both roller and ball burnishing. The study was centered on assessing the impact of various burnishing parameters, including speed, force, and ball tool diameter, on surface characteristics[3]. Some researchers conducted a significant investigation into the plastic deformation of structural RB40 steel during ball and roller burnishing processes. Additionally, their study encompassed an analysis of the roughness, hardness, and wear resistance properties of RB40 steel. In certain studies, Taguchi techniques were applied to optimize the ball burnishing process for AISI 316L stainless steel. These techniques effectively identified critical parameters such as ball material, penetration depth, speed, and lubrication, resulting in surface roughness levels of 1.017 µm for flat specimens and 0.6-0.9 µm for 3D curved surfaces[4]. Furthermore, researchers examined the requirements for both pre-machining and subsequent burnishing-rolling methods to ensure high product quality. The investigation established connections between the contact points of the burnishing tool and the rough surface of work-hardening materials[5].

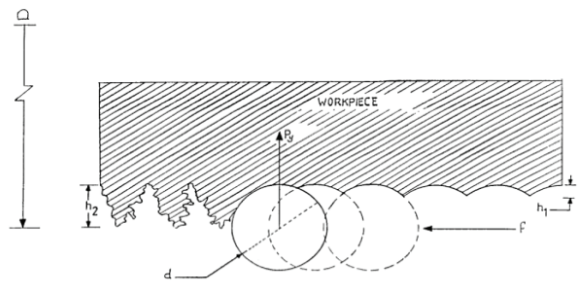

Fig. 1: The burnishing Process

A novel mechanical surface treatment method called spherical motion burnishing (SMB) has been introduced by some researchers, primarily suitable for lathes. It involves a specially designed device and tool, expanding manufacturing capabilities. Mathematical models for roughness and residual stresses were developed through experiments, and their accuracy was confirmed through additional tests, demonstrating their reliability in predicting outcomes in the SMB process[6].

This research goes into an artificial neural network (ANN) inspired parametric analysis of surface quality in aluminium alloy burnishing. This study analyses the complicated link between burnishing factors and final surface quality using ANN-based modelling. The goal of the present study is to better understand the burnishing process and its effects on aluminium alloy surfaces. This study adds to optimizing burnishing settings for higher surface quality results in aluminium alloy applications by exploiting ANN's capabilities. Surface quality plays a critical role in the performance and durability of metal components, including aluminum alloys, in various ways. A smooth surface with low roughness reduces stress concentration points, improving fatigue strength and resistance to cyclic loading, crucial in components subjected to repeated stress. Additionally, a smooth surface exhibits better wear resistance, minimizing abrasive wear and surface damage, leading to longer component life in applications involving sliding or abrasive wear. Surface quality also affects corrosion resistance, with a smoother surface reducing corrosion initiation sites and improving overall resistance. Furthermore, surface quality influences the adhesion of seals, coatings, or paints to metal components, enhancing performance and longevity. It also impacts frictional properties, with a smoother surface typically exhibiting lower friction, beneficial in applications where reduced friction is desired. In applications where surface contact is critical, such as in sealing or mating components, surface quality affects the effectiveness of the seal or the contact pressure distribution, influencing overall performance. Moreover, surface quality can impact the aesthetic appearance of metal components in certain applications, affecting perceived quality and value. Overall, achieving the desired surface quality through appropriate manufacturing processes is essential for enhancing the performance and durability of metal components in various applications.

2. Literature review

The Ball burnishing is a technically viable and commercially successful finishing procedure. By selecting the proper process settings, it is possible to achieve the required surface roughness. In selecting the ultimate surface quality, the relationship between burnishing force and feed-rate is critical. The correct selection of these factors is critical for achieving the optimum surface roughness. Some study investigates the effectiveness of fatigue strength restoration in corroded 4340 steel through the application of low plasticity burnishing (LPB) without the removal of damaged layers. LPB was employed on corroded surfaces following a superficial cleaning process, resulting in the restoration of the material's fatigue strength to 110% of its original, as-machined, uncorroded state for specimens exposed to 100 hours of corrosion, and 85% for those exposed to 500 hours of corrosion. Comparable improvements in fatigue strength were observed within the finite life regime as well. Fracture analysis revealed that fatigue failures in specimens treated with LPB after corrosion exposure typically initiated at corrosion pits. However, such treatment significantly enhanced the fatigue resistance of the material. The authors emphasize the importance of developing effective treatments as aging military aircraft are increasingly susceptible to corrosion-related issues[7)]. Some researchers examine the criteria for both pre-machining and the subsequent burnishing-rolling procedures to ensure a top-quality end product. It establishes relationships for the contact areas between the burnishing element and the work-hardening material's rough surface.

Some studies explore the impact of force and feed parameters on residual stress profiles in deep rolling of aluminium alloy 7075-T6. Results indicate that feed affects surface hardness, while force influences stress distribution depth, with finite element simulations revealing increased plasticity with higher feed[8)]. In some researchers explores how ball burnishing enhances form tools, like molds and dies, for achieving the necessary surface finish in plastic injection molds and stamping dies. It shows that combining ball burnishing with tailored milling parameters can notably cut production costs and time while delivering a smoother surface finish with simplified programming compared to milling[9)]. Previous research introduces an innovative procedure known as electrochemical smoothing-roller burnishing (ECS-RB), aimed at improving the roundness and micro-hardness of cylindrical components. When employing the optimal parameters, a remarkable 31.5% enhancement in micro-hardness and a reduction of 2.32 μm in roundness error were achieved, thereby enhancing the reliability and wear resistance of the parts. Some investigators have utilized response surface methodology to enhance the surface finish in ball burnishing, providing a mathematical model to predict and achieve the desired roughness, with just a 1.2% deviation from experimental results[10)]. Furthermore, ongoing research has explored the influence of key burnishing parameters, including speed, feed, force, tool passes, and ball diameter, on surface roughness. The results underscore the substantial impact of burnishing force and the number of tool passes on the work piece surface during the burnishing process[11)]. In some instances, Taguchi techniques were applied to evaluate and optimize the ball burnishing process, revealing that the primary factor for enhancing surface roughness and micro-hardness is the burnishing force, followed by burnishing feed, speed, and the number of passes[12)].

The advanced technique explores ball burnishing to improve the surface quality of magnesium alloy parts, determining optimal parameters (400N force, 0.05mm/min feed rate, three passes, and boron oil medium) for superior surface roughness. The findings are relevant for designing top-quality components in various transportation vehicles[13)]. Furthermore, research focuses on the influence of force and feed parameters on residual stress profiles resulting from deep rolling in aluminium alloy 7075-T6. It observes that force significantly impacts the depth of the compressive region, while feed primarily affects surface hardness. Residual stress components in the feed direction were approximately double those in the rolling direction. Finite element simulations indicated that load predominantly influenced the plasticity depth, with the feed affecting the maximum accumulated plasticity[14)]. Formulated five models based on artificial neural networks (ANN) and deep neural networks (DNN) using machine learning approaches such as logistic regression, SVM, and Naive Bayes[15)]. Explored and compared various techniques, with a specific focus on the XGBoost method, as it facilitated researchers in achieving an 80% accuracy rate in predicting the potential of terrorist attacks to cause casualties among civilians[16)]. The authors created a technique that chooses a feature set by combining principal component analysis (PCA) with random forest (RF). 36 of the 136 traits were selected for categorization. The XG Boost classifier had the greatest accuracy of 98% in identifying terrorist groups with the highest attack rates among the five prediction models included in the classification framework. Utilizing a characteristic set selection technique that integrates principal component analysis (PCA) and random forest (RF), employed a framework featuring five predictor models for forecasting. They identified 36 attributes out of a total of 136 for categorization[17)]. The XG Boost algorithm demonstrated a remarkable success rate of 98% in accurately identifying terrorist organizations associated with the highest attack rates. The numerical exploration of thermo-mechanical coupling has been conducted using contemporary computational resources[18-22)]. The aim is to illustrate how mechanical deformations induce an irregular pressure distribution in space, a pattern that varies based on time, speed, and specific speed conditions. These deformations are additionally complicated by particle tearing, phase shifts, and adhesion forces. The coefficient of friction is typically empirically characterized through experimental investigations[23-26)].

Preventing erosion involves rendering a substance resistant to it. Enhancing the ease of drainage and cleaning for its components can bolster the substance's resilience against erosion[27)]. The activation of energy within the matrix structure and reinforcing particles triggers corrosion when immersed in a heated aqueous solution. Corrosion manifests as the substance experiencing heat cracking and dissolution [28]. The corrosion rate in AlMMNCs increases with higher energy activation levels[29]. Employing electroplating and coating procedures with non-corrosive materials on the composite surface during exposure to hot aqueous solutions reduces the likelihood of energy activation[30].

The exploration of innovative approaches to enhance the surface quality of metallic components has been driven by the pursuit of advanced manufacturing techniques. Surface quality plays a pivotal role in influencing the performance, longevity, and aesthetics of engineered parts, particularly in industries like aerospace, automotive, and precision machinery. One notable mechanical surface enhancement technique, known as burnishing, has gained recognition for its ability to enhance surface finish, reduce roughness, and improve the mechanical properties of materials, particularly aluminium alloys. This study focuses on the intricate dynamics of the burnishing process, with a specific emphasis on its application to aluminium alloy materials. Aluminium alloys are widely utilized in various industrial applications due to their advantageous properties, including lightweight construction, high strength, and resistance to corrosion. To delve into the complexities of the burnishing process, we employ a state-of-the-art methodology inspired by Artificial Neural Networks (ANNs). Artificial Neural Networks, which fall under the domain of machine learning and artificial intelligence, offer the capability to model intricate, nonlinear relationships within data. Consequently, they serve as invaluable tools for studying complex processes like burnishing. In this context, we harness ANNs to establish a comprehensive understanding of how diverse input parameters, such as force, speed, and tool material, impact the surface quality of aluminium alloy components during the burnishing process. This research not only holds the promise of enhancing the manufacturing industry's ability to produce high-quality aluminium components but also contributes to the broader realm of materials science and manufacturing technology. As the demand for lightweight, high-performance materials continues to grow, a deeper comprehension of surface quality optimization through novel techniques becomes imperative. The discoveries from this study are well-positioned to drive advancements in manufacturing processes, leading to more efficient and cost-effective production methods that yield superior surface finishes for aluminium alloy components.

3. Materials and method

The work piece was held in the lathe's chuck and guided from the other side. Table 1 provides further information. Burnishing is done without removing the work piece from the lathe alignment.

The goal of the studies is to see how a new burnishing tool affects the final surface texture (roughness). Burnishing characteristics such as circumferential area of work piece, ball material (hardness), work piece material (hardness), burnishing speed, cutting feed, burnishing force, ball diameter, cutting fluid, and gravity acceleration are also investigated. Table 1 lists the characteristics and conditions for burnishing. The quality of the surface created in this study is carefully assessed later in the procedure.

Surface Tester was used to assess the quality of burnished specimens. The measurements were taken using an adjusted metre with an 8 mm cut-off length across the lie. For each part utilized in the trials, all readings of surface quality (Ra) were obtained, and average values were determined. Figure 2 depicts the experimental set-up. The quality of the surface Ra, i.e. average roughness, is assessed during the burnishing procedure. Instruments used for experimentation are used to measure En and T. This configuration provides the following benefits: Because the normal force is constant and regulated by a circular depth nut, the procedure is repeatable.

Table 1. The condition for the super finishing procedure.

Control factors	values
Burnishing force (FB),N	39.23,77.38 and 110.71
Burnishing speed(μB), rpm	342, 564 and 840
Cutting feed (f),mm	0.1, 0.2 and 0.3
No. of pass	1, 2
Burnishing condition	Lubricant (Kerosene)

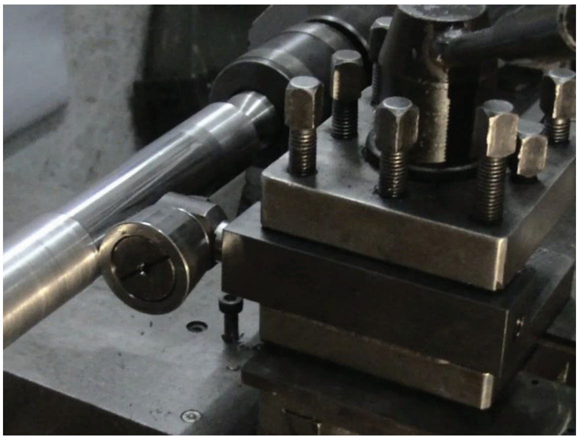

Fig. 2: Operation carried out on Lathe machine using burnishing tool

High-quality drawings and photographs are preferred. Furthermore, it is crucial that all of the figure numbers and letters be of a high caliber, easily readable, and around the same size as the remaining text (≈ 8–10 pt).

3.1 Experimental procedure

Experiments were conducted based on a predetermined plan, aiming to evaluate the effects of machining parameters on aluminium alloy operations. Data obtained from these experiments were utilized to assess the effects of different variables on surface quality, energy consumption, and processing time. During the experimental phase, an aluminium alloy work piece was subjected to three distinct settings for speed, feed rate, burnishing force, and two passes. The experimental analysis encompassed the examination and assessment of surface quality, energy consumption, and processing time.

Fig. 3: Experimental setup of burnishing tool.

Burnishing is done with the ball burnishing tool depicted in Fig. 1. In the course of developing a mathematical model for aluminium alloy "operation and analysis," work piece samples of similar sizes were collected for experimentation. The burnishing purpose of the experiments was to establish a mathematical model for the behaviour of Aluminium Alloy-6351. Fig. 2 shows the processing steps for measuring the force tool dynamometer. Experimental setup of burnishing tool is shown in Fig. 3. The observed values of surface processing quality, En, and T are documented for mathematical model development. Twelve different process parameters were changed, and observations were obtained at 340, 560, and 800 rpm for the same sizes. Seventy trials were created using the design of experimentation using a sequential classical plan, which is commonly used in engineering applications. The goal of the studies is to discover a correlation between 9 independent process parameters and Ra, E, and t dependent responses. Trials were carried out by changing all independent parameters with a fixed one at the same time. As a result, dimensional analysis was used to decrease all "nine independent process parameters." Buckingham's theorem was used to create dimensionless terms for process parameter reduction. This method aids in a better understanding of how changes in any one process parameter of a term effect E, Ra, and t response. This method may also be used to find "the amounts of parameters that lead to the greatest, lowest, and optimal response." Dimensional Analysis is used to create an approximate generalized experimental data base model.

4. Model Formulation

Artificial Neural Networks (ANNs) have become integral in various engineering fields due to their ability to model complex systems. In surface engineering, ANN-driven approaches are increasingly utilized to optimize and predict outcomes in processes like burnishing. Burnishing is a surface finishing technique that involves plastic deformation of a workpiece surface using a hard tool to enhance properties such as roughness, hardness, and wear resistance. Integrating ANNs with burnishing processes offers a promising route to improve surface quality and efficiency. This paper delves into the application of ANN for optimizing burnishing processes, emphasizing its capacity to model and predict the effects of process parameters on surface quality. ANNs enable researchers and engineers to understand the intricate relationships between input parameters (e.g., tool material, speed, pressure) and output variables (e.g., surface roughness, hardness). By leveraging ANN-driven approaches, burnishing processes can be optimized to achieve desired surface characteristics, enhancing the performance and longevity of engineered components. The parametric study conducted in this research focused on investigating the effects of various key parameters on the surface quality of aluminium alloy (Al Alloy) work pieces during the burnishing process. The analysis of the results reveals valuable insights into the relationship between these parameters and the resulting surface finish. In this study, several machining parameters were considered, including burnishing speed, feed rate, and tool material. These parameters were related to the surface roughness of aluminum alloy 6351 through experimentation and statistical analysis. The burnishing speed refers to the speed at which the burnishing tool traverses the surface of the workpiece, affecting the amount of material deformation and surface finish. The feed rate is the rate at which the burnishing tool is moved across the workpiece surface, influencing the amount of material displacement and surface texture. The tool material, which can vary in hardness and surface finish, also plays a role in determining the surface roughness of the aluminum alloy. By systematically varying these parameters and measuring the resulting surface roughness, researchers were able to establish empirical relationships between the machining parameters and the surface quality of aluminum alloy 6351, providing valuable insights for optimizing the burnishing process

The surface quality pattern was used to replicate the burnishing process using optimization, sensitivity analysis, and Artificial Neural Networks (ANNs) in several steps. Firstly, data on the burnishing process parameters and corresponding surface quality measurements were collected. Then, an ANN model was developed to establish the relationship between the input parameters and surface quality. The ANN model was trained to predict surface quality based on the input parameters. Optimization algorithms, such as genetic algorithms or particle swarm optimization, were employed to find the optimal set of input parameters for achieving the desired surface quality. Sensitivity analysis was performed to identify the most influential input parameters on surface quality, guiding the optimization process. The optimized input parameters obtained from the ANN-driven optimization process were then used to replicate the burnishing process, ensuring that the desired surface quality was achieved. Finally, the replicated burnishing process was validated by comparing the predicted surface quality with the actual measured values, ensuring the accuracy and reliability of the ANN model and the optimization process.

All of the terms involved (dependents and independents) in model construction. For such a setting, "correlation is nothing more than a mathematical model as a design tool." Processing Energy (E) was represented in the function form as Processing Energy (E) according to dimensional analysis.

E=f (Hw, ωB, FB, DB, AW, N, μ, g, HB, f,)

$$R_a = K.\left(\frac{g}{\omega_B^2}\right)\left\{\left(\frac{H_W}{H_B}\right)\left(\frac{A_{W.\omega_B^4}}{g^2}\right)\left(\frac{f.\omega_B}{g}\right)\left(\frac{D_B.\omega_B^2}{g}\right)\left(\frac{\mu.g^2}{\omega_B^3.F_B}\right)\right\} \ldots\ldots\ldots\ldots\ldots..(\text{Equn } 1)$$

$$E = K.\left(\frac{F_B.g}{\omega_B^2}\right)\left\{\left(\frac{H_W}{H_B}\right)\left(\frac{A_{W.\omega_B^4}}{g^2}\right)\left(\frac{f.\omega_B}{g}\right)\left(\frac{D_B.\omega_B^2}{g}\right)\left(\frac{\mu.g^2}{\omega_B^3.F_B}\right)\right\} \ldots\ldots\ldots\ldots\ldots..(\text{Equn } 2)$$

$$t = K.(\omega_{B.t})\left\{\left(\frac{H_W}{H_B}\right)\left(\frac{A_{W.\omega_B^4}}{g^2}\right)\left(\frac{f.\omega_B}{g}\right)\left(\frac{D_B.\omega_B^2}{g}\right)\left(\frac{\mu.g^2}{\omega_B^3.F_B}\right)\right\} \ldots\ldots\ldots\ldots\ldots..(\text{Equn } 3)$$

5. Reduction Variables

The optimization of the burnishing process to achieve desired surface characteristics is crucial in surface engineering. Artificial Neural Networks (ANNs) have emerged as valuable tools for modeling and predicting outcomes in burnishing processes. A key aspect of utilizing ANNs effectively is the selection of relevant input variables, known as reduction variables, which significantly impact the output quality. Reduction variables play a vital role in simplifying the complexity of the burnishing process by focusing on the most influential factors. By identifying and selecting these variables, researchers and engineers can enhance the efficiency and accuracy of ANN-driven burnishing models. This paper explores the significance of reduction variables in ANNs for optimizing burnishing processes, with a focus on how they contribute to improving surface quality and process efficiency. Buckingham's theorem was used to reduce the number of variables. According to evidence, taking the multiplications of the terms will likewise be a dimensionless number and so a term. Less term were created by logically multiplying a few other terms π terms, and the resulting mathematical equations.

Π_{0Ra4}= Mathematical Equation for Processing Quality of surface (R_{a4}):

$$\pi_{0Ra4} = 92.38.\left(\frac{g}{\omega_B^2}\right)\left\{\left(\frac{H_W}{H_B}\right)^{5.45}\left(\frac{A_{W.\omega_B^4}}{g^2}\right)^{1.077}\left(\frac{f.\omega_B}{g}\right)^{-0.034}\left(\frac{D_B.\omega_B^2}{g}\right)^{-0.85}\left(\frac{\mu.g^2}{\omega_B^3.F_B}\right)^{0.28}\right\} \ldots\ldots\ldots.(\text{Equn } 4)$$

Π_{0E4} = Mathematical Equation for Energy (E_4):

$$\pi_{0E4} = 2.7X10^5.\left(\frac{F_B.g}{\omega_B^2}\right)\left\{\left(\frac{H_W}{H_B}\right)^{-3.51}\left(\frac{A_{W.\omega_B^4}}{g^2}\right)^{4.61}\left(\frac{f.\omega_B}{g}\right)^{0.049}\left(\frac{D_B.\omega_B^2}{g}\right)^{-6.78}\left(\frac{\mu.g^2}{\omega_B^3.F_B}\right)^{0.98}\right\} \ldots\ldots..(\text{Equn } 5)$$

Π_{0t4}= Mathematical Equation for Processing time (t_4):

$$\pi_{0t4} = 43.072.(\omega_{B.t})\left\{\left(\frac{H_W}{H_B}\right)^{0.056}\left(\frac{A_{W.\omega_B^4}}{g^2}\right)^{-1.86}\left(\frac{f.\omega_B}{g}\right)^{0.0001}\left(\frac{D_B.\omega_B^2}{g}\right)^{3.70}\left(\frac{\mu.g^2}{\omega_B^3.F_B}\right)^{-0.40}\right\} \ldots\ldots\ldots(\text{Equn } 6)$$

6. Optimization and parameter

Finding the best solution for a set of objectives while staying within limits is what optimization of aluminium alloy operations is all about. The goal of this study was to reduce the quality of the surface by processing energy and time, with the restrictions being jump values of terms. We employed a linear programming method that was described in full below. There was no discernible relationship between the various factors. On the basis of experiments, the dependent parameters 0Ra1, 0E1, and 0t1, pertaining to Ra, E, and t, were rated as "carry an intricate relationship with remaining" terms (ie.1to5).

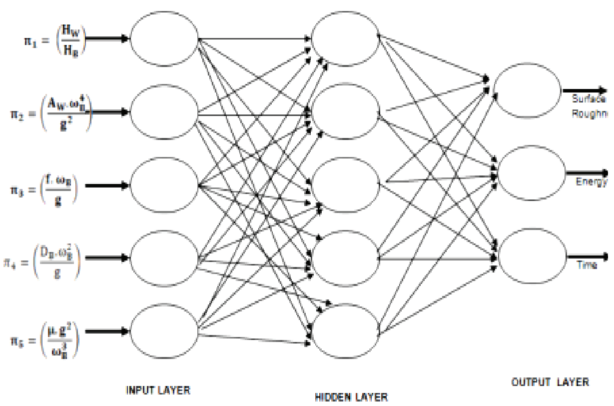

Fig. 4: ANN topology

The highest value of '1' corresponds to 0Ra4, while '2' is the maximum value for 0E4, and '4' reaches its peak at 3.7046. In this model, the most significant terms are '1,' which represents the relationship between the workpiece hardness-to-ball material ratio, '2,' associated with the workpiece area and burnishing speed, and '4,' related to the product diameter of the ball and burnishing speed. The positive index indicates that the workpiece hardness-to-ball material ratio exerts a considerable impact on 0Ra4, 0E4, and 0t4.

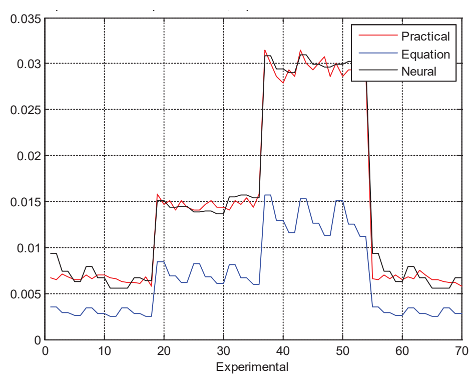

Fig. 5: Comparing the operation of experimental approaches, mathematical methods, and ANN models.

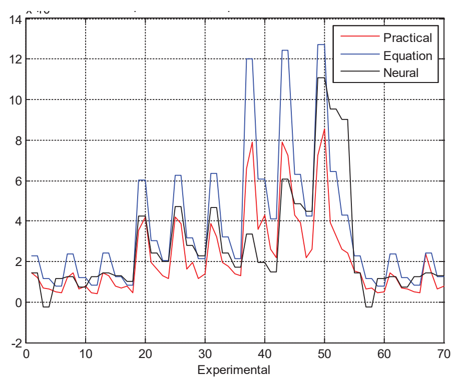

Fig. 6: Comparing the operation of experimental approaches, mathematical methods, and ANN models.

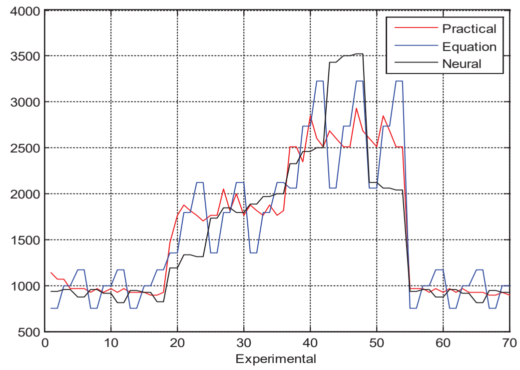

Fig. 7: Comparing the operation of experimental approaches, mathematical methods, and ANN models

The estimated surface quality of the aluminum alloy after burnishing was based on the predictions of the Artificial Neural Network (ANN) model developed in the study. This model used input parameters such as burnishing pressure, speed, and tool material to predict surface quality metrics like surface roughness, hardness, and wear resistance. To experimentally confirm the estimated surface quality, the researchers conducted a series of burnishing experiments using the optimized parameters obtained from the ANN model. After the burnishing process, the surface quality of the aluminum alloy was evaluated using various metrological techniques, including surface roughness measurement, surface hardness testing, and microstructural analysis. These techniques provided quantitative and qualitative data on the surface quality, allowing for a comparison between the predicted and actual values.

By comparing the predicted surface quality with the experimentally confirmed values, the researchers were able to validate the accuracy and reliability of the ANN model in predicting surface quality after the burnishing process. This validation process ensured that the optimized parameters obtained from the ANN model could be used to reliably replicate the burnishing process and achieve the desired surface quality in aluminum alloys.

The results of this research significantly contribute to the understanding of burnishing parameters and their effects on aluminum alloy surface quality by providing empirical data and insights. Through experimentation and analysis, the researchers were able to identify the optimal combination of parameters such as pressure, speed, and lubrication for achieving desired surface qualities like smoothness, hardness, and wear resistance in aluminum alloys. Furthermore, the use of Artificial Neural Networks (ANNs) allowed for the development of predictive models that accurately forecast surface quality outcomes based on specific parameter settings. This not only enhanced the efficiency of the burnishing process but also facilitated a deeper understanding of the complex relationships between input parameters and surface quality. Overall, the research outcomes provide valuable guidance for industries seeking to optimize their burnishing processes and improve the quality and performance of aluminum alloy components. By identifying the key parameters and their effects on surface quality, this research paves the way for more efficient and effective surface finishing processes in aluminum alloy applications.

One of the critical parameters examined was the feed rate during the burnishing process. Our experimental data indicates a significant impact of feed rate on surface quality. A lower feed rate resulted in a smoother surface finish due to increased contact time between the tool and workpiece. Conversely, higher feed rates produced a rougher surface due to reduced contact time and increased tool pressure. This finding emphasizes the need for careful selection of the feed rate to achieve the desired surface quality in Al Alloy burnishing[10)]. Furthermore, the choice of burnishing tool material also played a crucial role in determining surface quality. Tungsten carbide tools exhibited superior performance compared to other materials tested. This result can be attributed to the exceptional wear resistance and hardness of tungsten carbide, which resulted in reduced tool wear and a smoother surface finish.

Spindle speed had a notable influence on surface quality as well. Our results indicated that a moderate spindle speed was optimal for achieving a fine surface finish. Extremely high speeds led to excessive heat generation and surface defects, while very low speeds resulted in inadequate surface improvement. This finding underscores the importance of carefully controlling spindle speed to achieve the desired surface quality during Al Alloy burnishing. Cast iron, aluminium-silicon (Al-Si) alloys, and some composite materials are now the primary materials employed in piston manufacturing. The automotive and aerospace sectors are progressively adopting hypereutectic Al-Si alloys[31)].

The initial surface roughness of the workpiece also played a role in the burnishing process. Workpieces with a higher initial surface roughness exhibited greater improvement in surface quality during burnishing compared to those with already smooth surfaces[32-35)]. This outcome suggests that burnishing is particularly effective in enhancing the surface quality of Al Alloy components with inherent surface imperfections. In addition to visual inspection, surface integrity was evaluated through measurements of surface roughness, micro-hardness, and micro-structure analysis. The results demonstrated a clear correlation between the studied parameters and these surface integrity factors[36)]. Lower surface roughness values and improved micro hardness were consistently associated with the optimized parametric settings. Innovative hybrid composites including aluminium matrix have markedly increased fatigue resistance, specific stiffness, and wear resistance. Hybrid composite elements are manufactured in greater quantities, which lead to a fall in their prices and an expansion of their applications. Applications of aluminium hybrid composites are examined with an emphasis on the automobile sector[37-43)]. The research presents a thorough investigation into enhancing the surface quality of aluminum alloys using Artificial Neural Networks (ANN) driven burnishing. This study has yielded several key findings. Firstly, the application of ANN for predicting optimal burnishing parameters has shown promise[44)]. The ANN model effectively predicted machining parameters needed to achieve desired surface quality metrics like roughness and hardness. Secondly, the durability study conducted in this research provides valuable insights into the long-term performance of the optimized surface [45,46)]. The results suggest that the surface quality improvements achieved through ANN-driven burnishing are durable and can withstand various environmental and mechanical stresses. This research highlights the effectiveness of using ANN-driven burnishing to optimize aluminum alloy surface quality. These findings offer significant implications for industries aiming to improve the performance and durability of aluminum alloy components, providing a reliable and efficient method for achieving superior surface quality [47)].

7. Conclusions

Surface quality is crucial for the performance and durability of metal components in various industries. Burnishing, a popular finishing method, is effective in enhancing surface quality, especially for aluminum alloys. This research introduces a novel approach using Artificial Neural Networks (ANNs) to improve surface quality during the burnishing process of aluminum alloys. The study considers machining parameters and their effects on aluminum alloy material 6351 using a lathe. A mathematical model is developed to predict variable surface roughness. The surface quality achieved after the machining process is then used for ball burnishing. The surface quality pattern is replicated using optimization, sensitivity analysis, and ANN. The surface quality parameters on the aluminum alloy after burnishing are estimated using a ball and experimentally confirmed at 1.73164 m. The results provide insights into the complex relationship between burnishing parameters and aluminum alloy surface quality. This research contributes to the development of more efficient and cost-effective finishing processes for aluminum alloys.

The current research has generated dimensionless correlations for assessing burnishing performance on aluminium alloy. Based on experimental results, dimensional correlations for surface quality and other dependent, independent variables have been constructed. Dimensional analysis reveals that surface quality is primarily influenced by the combination of the material hardness-to-ball material ratio, work piece area in relation to burnishing speed, burnishing force, and the ball diameter relative to the impact of cutting fluid. In the context of aluminium alloys under current conditions, mathematical models specific to aluminium alloys were formulated. These mathematical models appear to offer a viable approach for calculating dependent variables based on a given set of independent terms, utilizing estimated percentage values.

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