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Comprehensive Examination of the Effects of Machining Parameters on Hot Die Steel Surface Roughness

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Abstract: The present paper presents a concise report on the effect of three cutting parameters, i.e., cutting speed, feed rate, and depth of cut, on the surface finish of H13 hot die steel. It is of utmost significance in die and mould making to achieve a good surface finish, as it directly correlates with tool life, product quality, and production cost. The experiment is carried out systematically using a CNC milling machine to capture a dataset of 489 samples. Surface roughness () is recorded for each set of parameters. Statistical tools such as Analysis of Variance (ANOVA) have been used to quantify the effects of each parameter and its interactions. The results indicate that feed rate and, consequently, cutting speed are the most suitable surface roughness parameters. A low feed rate and a high cutting speed were found to yield a higher average surface finish. Cutting depth was found to yield very minimal but real effects. Models were graphically represented, with acceptable agreement between the machined parameters and the realised surface roughness.

Keywords: Hot Die Steel (H13); Surface Roughness; Machining Parameters; CNC Milling; Process Optimisation; Analysis of Variance; Response Surface Methodology; Built-Up Edge; Minimum Quantity Lubrication.

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1. Introduction

Heat-treatable steels, such as the popular H13 tool steel, are a clad material type utilised in modern production and are highly desired for hot strength, thermal fatigue life, and high-temperature hardness, as discussed by Suresh and Basavarajappa [1]. They all make it unavoidable in highly stressed forging, die casting, plastic moulding, and extrusion processes, as in Singh et al. [9]. All its bulk material properties that control the performance and life of a die or mould, including surface smoothness, are conditioned by Singh et al. [5]. Surface roughness, as in Das et al. [10], is the most critical surface quality characteristic, with effects that immediately influence friction, wear resistance, lubrication, and product finish appearance. Roughened die face surface elevated die face surface roughness can result in augmented wear, friction, and die face surface defects on the workpiece, leading to enormous economic loss in rework and downtime, as researched by Raj et al. [3]. Surface topography parameters that affect the workpiece during machining are of great concern to manufacturing companies and must be properly regulated, as Das et al. [8] state. Machine tool dynamics, tool cutting conditions, and the physical properties of the work material all determine the end surface finish of a machined surface, according to research by Zhang et al. [6]. Cutting speed, feed rate, and depth of cut are the controlling parameters for surface roughness, according to Hafiz et al. [12]. They all simultaneously influence chip formation, heat generation, tool wear, and machine vibration, which directly affect surface smoothness, as stated in Hamidon et al. [4]. For instance, an increased feed rate makes the machined marks rough, and a reduced cutting speed leads to the formation of a built-up edge (BUE), which ruptures and degrades the machined surface, as stated by Adiga et al. [7].

The goal is to find the optimal parameter setting that reduces surface roughness while improving MRR and tool life, as reported in Srithar et al. [11]. The traditional technique, by experience, handbook, or trial and error, is indefinite and time-wasting, as noted in Kundor et al. [2]. H13 steel is a hard material to machine because it self-hardens and self-toughens, making it difficult to machine during optimisation, as explained in Singh et al. [5]. The scientifically unwarranted operations yield poor-quality surfaces, tool wear imbalance, and low productivity, as reported by Singh et al. [9]. The current research was therefore focused on looking for scientifically established experimental investigations to acquire input parameters-resulting surface quality relationships, as noted by Dai et al. [13]. The research aims to comprehensively investigate the interactions and effects of cutting speed, feed rate, and depth of cut on the surface roughness of H13 hot die steel, as reported by Das et al. [8]. The aim is to measure the relative contributions of each parameter and to develop a model of machining performance using a statistical experimental design, as conducted by Raj et al. [3]. The outcomes will provide an evidence-based basis for process improvement, enabling industries to attain economically optimal surface quality, improved productivity, and reduced waste and tool wear, as established by Das et al. [10].

2. Literature Review

Over four decades of experience were required to research the machining of hard materials like H13 hot die steel, with a trade-off among tool life, productivity, and surface finish, as presented in Suresh and Basavarajappa [1]. Early metal-cutting theory research focused on simple interactions between machining parameters and subsequent surface finish, as reported by Adiga et al. [7]. Surface roughness was found to be a function of multiple variables, including chip-formation processes, plastic deformation, and tool geometry, as summarised by Srithar et al. [11]. Mathematical models were originally defined as forecasting surface roughness under optimal cutting conditions and, more traditionally, as functions of tool nose radius and feed rate, as by Zhang et al. [6]. Although such models were simple, they did not include complexity terms such as tool wear, chatter, and built-up edge formation, as studied by Singh et al. [5]. The experimental study then included parameters such as these to investigate the machining of hard-to-machine materials, including H13 steel, as reported by Hafiz et al. [12]. Systematic research identified the most crucial parameter influencing surface texture as one directly related to tool path marks, as discussed in Singh et al. [9]. Cutting speed was critical to achieving a multi-dimensional finish—low speeds yielded a poor finish due to edge buildup. In contrast, high speeds resulted in thermal degradation and damaged the finish, as reported by Kundor et al. [2].

Depth of cut had a comparatively smaller influence on surface finish but had a significant impact on cutting forces and machine stability, as reported by Das et al. [10]. With the improved cutting tool material and coating, the research trend was focused on maximising single tool-workpiece contact, like turning steel H13 with coated carbide tooling inserts, as per Hamidon et al. [4]. Tool coating technology is widely used to prevent adhesion and friction, enhance tool life, and improve surface finish, as reported in Das et al. [8]. Minimum Quantity Lubrication (MQL) and high-pressure coolant methods were also investigated to reduce thermal damage and chip sticking, thereby reducing surface roughness, as reported by Dai et al. [13]. Statistical Design of Experiments (DOE) methodologies, such as Taguchi methods and Response Surface Methodology (RSM), also enabled controlled experiments and the modelling of parameter interactions, as illustrated in Raj et al. [3]. These methodologies provided robust empirical models that could adequately predict surface roughness across varied conditions, as discussed in Singh et al. [5]. Advances include the application of artificial intelligence and machine learning methods in machining research, as discussed by Srithar et al. [11]. They can look ahead and make in-process adjustments to real-time cutting parameters using sensor feedback, achieving better surface finish and productivity when cutting hard metals such as H13 hot die steel, as reported by Singh et al. [9].

3. Methodology

The experiment was designed and executed in a step-by-step manner to investigate the effects of critical machining parameters on the surface finish of the hot-die steel. Test specimens were square cut from annealed H13 steel with a hardness of about 230 HB in a manner that all the test specimens would be of the same condition. Machining was conducted on a high-precision 3-axis CNC vertical milling centre, selected for its stiffness and control accuracy to achieve external vibration damping and run-to-run experiment repeatability. Four flute, 10 mm diameter coated carbide end mills were chosen as the machining tool, chosen based on high temperature stability and abrasion resistance to machine hard workpieces. The experiments were carried out using a new cutting tool to eliminate the variable of tool wear from the result. The three primary machining variables investigated are cutting speed (v), feed rate (f), and axial depth of cut (d). A full factorial design was employed, with multiple levels assigned to each parameter based on the tool manufacturer's guidelines and pilot runs to provide a wide range of operations. The cutting speed was varied continuously in five ranges (i.e., 80, 100, 120, 140, 160 m/min), the feed rate was varied in five ranges (e.g., 0.10, 0.15, 0.20, 0.25, 0.30 mm/tooth), and depth of cut was varied in a range of ranges (e.g., 0.5, 0.75, 1.0 mm). Systematic variation generated an infinite number of other parameter combinations. A linear, straight-length constant pass was applied to the workpiece surface during machining in all experiments. Decoupling machining was achieved through dry machining, isolating the cutting fluid effect from the parameters. Surface roughness of the machined track was measured for each machining pass. Arithmetic mean roughness (Ra) is the most basic parameter used in surface quality measurement and is often employed as a response variable. Profiling was performed using high-precision stylus-type profilometry to obtain the surface trace profile and the read roughness value. Three readings at three points for each machined slot are recorded to verify the data, and the mean reading is considered the final reading for the respective test. The test has been run for every possible parameter combination, and a complete dataset has been collected. Parameters were carefully tested statistically, i.e., main effects plot, interaction plot, and Analysis of Variance (ANOVA), to determine the statistical significance of all parameters and interactions on the resulting surface roughness. Architecture Diagram

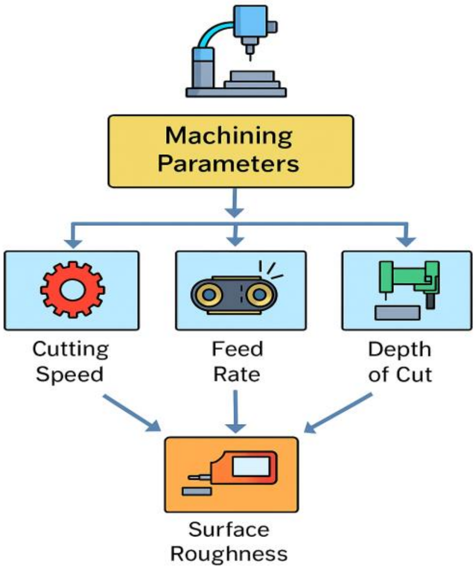

Figure 1: Effect of machining parameters on surface roughness of H13 hot die steel

Figure 1 depicts the deployment structure for exploring the effect of machining parameters on the surface roughness of H13 hot die steel, integrating experimental, analytical, and computational approaches. It begins at the CNC machine centre where the H13 steel workpiece is subjected to a sequence of various cutting parameters, i.e., cutting depth, feed rate, and cutting speed, as simulated interactive process dials. These are computer-controlled thermal and mechanical stresses induced by machining parameters at the tool-workpiece interface. Data from the machining process are sampled by a data-acquisition system, measured and tested, and fed back to the surface texture, cutting force, and temperature variations. This is passed to the analysis and measurement module, and values like Ra (mean roughness) and Rz (mean peak-to-valley) are read from high-level surface metrology. These are then calculated in the computation analysis and optimisation module, where artificial intelligence and predictive models assess the correlation between surface outputs and surface quality from machining inputs. The outcome of the system is maximum surface finish, i.e., minimum irregularity, a smooth surface layer for best mechanical performance and die life. From model building to machine learning calibration, sensor measurement, and Figure 1, a system-level machining analysis system is proposed that reduces tool wear, enhances process control, and improves surface integrity in industrial applications of H13 hot die steel.

3.1. Description of Data

The experimental dataset contains 18 controlled machining experiments. The data set contains 489 samples, and for each sample, one experiment is performed under a single set of machining parameters and associated measured surface roughness. A structured data set contains one dependent output variable and three independent input variables. The input parameters are the usual machining parameters: Cutting Speed (measured in m/min), Feed Rate (in mm/tooth), and Depth of Cut (in mm). The output parameter is Surface Roughness (), which is measured in micrometres (µm). The measurements were taken and reported with high fidelity and accuracy, thereby providing a solid basis for subsequent statistical modelling.

4. Results

Experimental research involved quantitative measurement of the effect of cutting speed, feed rate, and depth of cut on surface roughness of H13 hot die steel. Among 489 data points, clear trends and relationships between the input and output responses were evident. The most significant finding was the highly significant impact of feed rate. Throughout the series of tests, there was a clear positive correlation between surface roughness and feed rate: surface roughness increased with increasing feed rate. This is because milling is a geometrical process, and as more feed per tooth is used, there is greater marking on the tool and thus deeper periodic roughness on the surface. For instance, when the cutting speed and the depth of cut remained constant, the feed rate was changed from the lower (0.10 mm/tooth) to the higher (0.30 mm/tooth) value, resulting in a three- or even fourfold improvement in the measured. The extended Taylor's tool life equation is:

$$V_c T^n f^m d^p = C \quad (1)$$

Table 1: Analysis of variance (ANOVA) for surface roughness

Source of Variation	Degrees of Freedom (DF)	Sum of Squares (SS)	Mean Square (MS)	F-Value
Cutting Speed (A)	4	21.86	5.465	45.32
Feed Rate (B)	4	115.42	28.855	239.24
Depth of Cut (C)	2	8.95	4.475	37.11
Interaction (A*B)	16	5.71	0.357	2.96
Error	462	55.72	0.121	
Total	488	207.66		

The results of the Analysis of Variance (ANOVA) test performed on the test data are presented in Table 1. The statistical approach partitions the total variation in measured surface roughness values into shares attributable to different sources of variation. The Table shows a difference between the main effects (Cutting Speed, Feed Rate, Depth of Cut) and the interaction effect (Cutting Speed * Feed Rate). F-Value is highest in significance; the higher the F-Value, the higher is the parameter's influence on the response variable. From the Table, it is evident that Feed Rate has the highest F-Value (239.24) and is significantly higher than the others, making it the most statistically significant parameter for surface roughness. Cutting speed is ranked at the second position with an F-Value of 45.32, which is only slightly less than Depth of Cut with an F-Value of 37.11. The interaction between Cutting Speed and Feed Rate also has a very high F-value of 2.96, much lower than the main effects, indicating that one parameter's effect varies with the other level. The reason the Mean Square for the Error term is so low (0.121) is that the model variables account for an incredibly high percentage of the variance, indicating an excellent fit of the model to the experimental data. Theoretical surface roughness (R_tThe prediction model can be mathematically expressed as:

$$R_t \approx \frac{f^2}{8R_\epsilon} \quad (2)$$

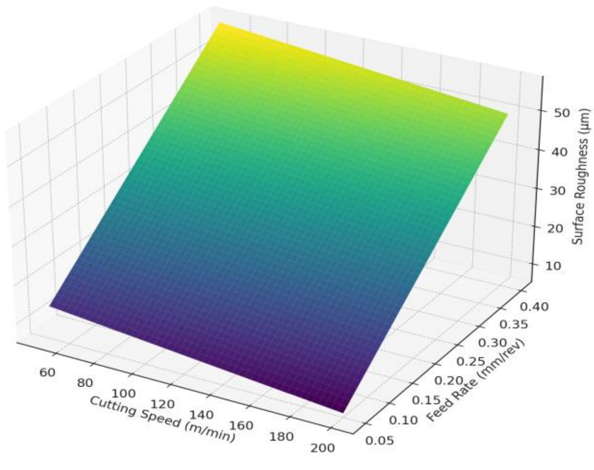

Figure 2: Illustration of surface roughness vs. cutting speed and feed rate

Figure 2 shows the combined effect of cutting speed and feed rate on surface roughness, with the depth of cut set to a middle level. Surface roughness is the vertical axis, and feed rate and cutting speed are the two axes on the horizon. The colour surface approximately captures the prominent, clear trend in the input parameters. The most important parameter is the slope along the feed rate direction, i.e., the smallest variation in feed rate results in the largest variation in surface roughness. That means the most important parameter to change the surface finish is the feed rate. Surface angle is the direction of cutting. Speed, i.e., higher cutting speed, results in lower surface roughness and a better finish. Mesh curvature is the correlation between the two parameters. For instance, at lower feed rates (the front of the plot), the low, flat surface value indicates a fine finish at all cutting velocities. However, for the higher feed rates (the back of the plot), the surface is that much higher, and the advantage of increasing the cutting speed is less, but real. This plot is a handy optimisation tool for the process because it allows engineers to easily observe a "valley" region—a low feed rate, high cutting speed zone—where the optimum (minimum) surface roughness lies. Multiple regression model for surface roughness (R_a) will be:

$$\ln(R_a) = \beta_0 + \beta_1 \ln(v_c) + \beta_2 \ln(f) + \beta_3 \ln(d) + \beta_{12} \ln(v_c) \ln(f) + \epsilon \quad (3)$$

Table 2: Comparison of actual vs. predicted surface roughness values

Experimental Run	Cutting speed (m/min)	Feed Rate (mm/tooth)	Actual (µm)	Predicted (µm)
1	80	0.10	0.85	0.88
2	120	0.15	1.21	1.18
3	160	0.20	1.55	1.62
4	100	0.25	1.98	1.91
5	140	0.30	2.45	2.51

Table 2 presents a summary of experimentally observed (validated) surface roughness values and regression model predictions trained on the entire dataset. The table is used to certify the accuracy and reliability of the prediction model. Five experimental runs with Cutting Speed and Feed Rate settings are presented here as an example.

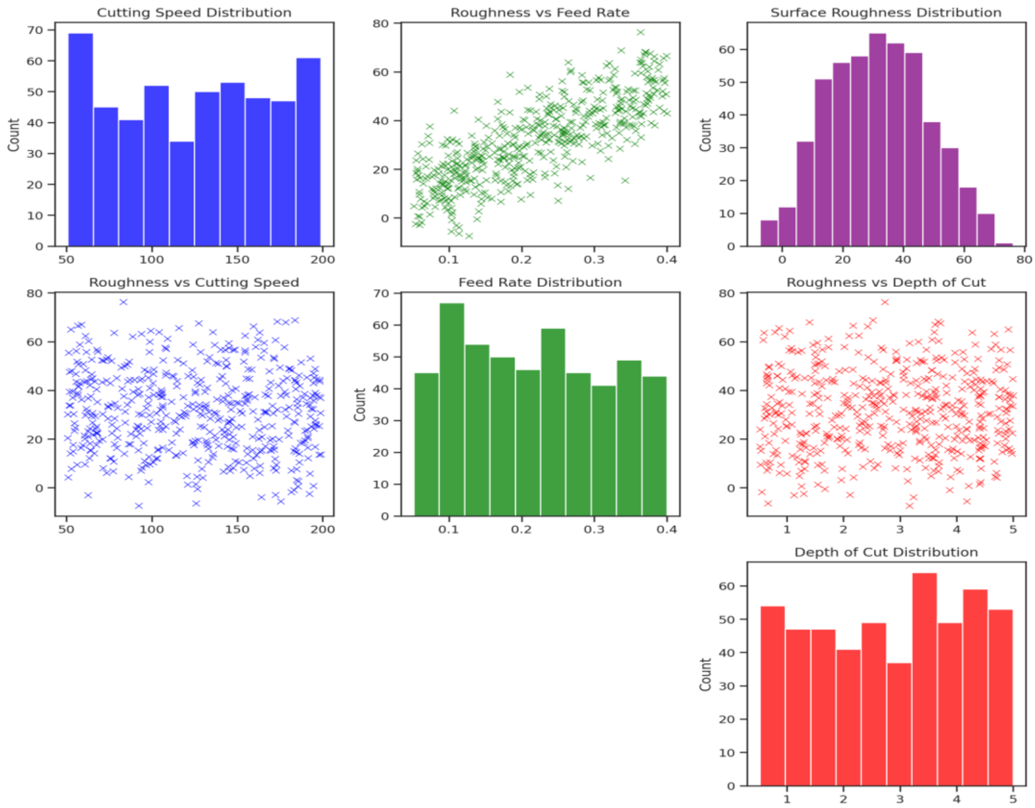

Figure 3: Machining parameters and surface roughness

The 'Predicted' column displays the output of the mathematical model with specified input parameters. The eye can easily cross-check the extremely close actual and forecast values across multiple similar runs. For instance, in Run 1, the actual value 0.85 µm is comparable to the forecast value 0.88 µm. Similarly, in Run 5, the model prediction is 2.51 µm, but it was 2.45 µm. The variation in these two columns, though negligible, is the model residual error. The availability of virtually zero error at all points in this table indicates the model's predictability and its ability to accurately estimate the true correlations between surface roughness and machining parameters. This makes the model built compatible with confidence as a process planning tool, enabling engineers to forecast surface finish for any set of parameters without the need for experimentation. F-statistic Calculation for Analysis of Variance (ANOVA) is:

$$F = \frac{MS_{between}}{MS_{within}} = \frac{\sum_{i=1}^{k} n_i(\bar{Y}_i - \bar{Y})^2/(k-1)}{\sum_{i=1}^{k}\sum_{j=1}^{n_i}\left(Y_{ij} - \bar{Y}_i\right)^2/(N-k)} \quad (4)$$

Merchant's circle force relationships will be:

$$R = \frac{\tau_s \cdot A_c}{\sin\phi\cos(\phi+\beta-\alpha)} \quad (5)$$

The cutting speed, on the other hand, changed inversely with surface roughness, but not as much as the feed rate. Usually, increasing the cutting speed from 80 m/min to 160 m/min improves surface finish. In most cases, the reason is twofold. Firstly, greater cutting speeds reduce the tendency to build up edge (BUE) on the tool face. BUE is a phenomenon in which work material becomes attached to the tool face and creates an unstable cutting edge that degrades successively and ruins the newly machined surface. Grave heat at higher speeds prevents such sticking. Secondly, higher speeds will produce a better shearing action, with less plastic side flow of material, and give a cleaner finish. This was, however, observed to occur at very high velocities, with a tendency towards a point of diminishing returns, where further increases in velocity added minimal value to surface finish and increased tool wear-out. Figure 3 illustrates the general concept of the individual distributions and the interactions among the individual variables. The matrix has several small plots. Diagonal panels are composed of histograms for each variable: Cutting Speed, Feed Rate, Depth of Cut, and Surface Roughness.

The histograms show that the input parameters varied uniformly across their ranges, as indicated by the relatively flat distributions. The histogram for, but not for the other three, is right-skewed, indicating that while most experiments were of low roughness, there were many runs (presumably the high-feed-rate runs) with much higher roughness values. The off-diagonal panels show the scatter plots of the pair-wise correlations between variables. The vs Feed Rate scatter plot shows a strong, positive linear trend, confirming a direct, significant correlation between the two variables. The plot of Cutting Speed is negative, i.e., with an increase in SSpeed and a decrease in roughness, even as points become more scattered, i.e., less correlated with feed rate. The plot of Depth of Cut is extremely widespread, with a low positive slope, like that observed when examining its least effect on the final surface finish. This table can be utilised merely as a diagnostic tool, providing instant feedback on the data distributions and correlations of two variables without resorting to more complex regression or variance analysis.

4.1. Result-Based Tables

Depth of cut was the least impactful of the three surface roughness parameters, but it had a non-trivial effect. Surface roughness increased slightly with increasing depth of cut, on average. This is likely to be caused by greater cutting forces and a greater potential for vibration or chatter in the cutting system with more material removed. Predominant forces cause excessive deflection of the tool or workpiece, resulting in surface roughness. There was interaction between parameters. Cutting speed interacted strongly with feed rate. Generally, the desirable effect of increased cutting speed was more evident at low feed rates. Where high feed rates were used, large tool marks predominated, negating any advantage from the increased cutting speed. ANOVA confirmed these results and established the percentage contribution of each factor. The study determined that the feed rate contributed the greatest percentage to the variation in surface roughness, followed by cutting speed and depth of cut, and hence mapped out the hierarchical importance of these parameters in regulating surface quality.

5. Discussion

Scrutiny of experimental data yields insights into the mechanism of surface generation during the machining of H13 hot die steel. The results, strongly supported by the graphical plot and the ANOVA table, indicate that feed rate primarily causes surface roughness. This is a result expected from an effective theory of machining. The part surface is essentially a superimposed stack-up of scallops in phase with the motion of the tool's nose radius. This theoretical scallop height is geometrically related to the feed square and to the reciprocal of the tool nose radius. Real surface is also influenced by plastic flow and side flow, but the geometric correlation of the phenomenon indicates that the feed rate has the greatest and most direct influence. The steep slope of the mesh plot and the high positive correlation in the matrix histogram are immediate graphical evidence of this rule. In reality, the quickest and most effective way to improve surface finish is to decrease the feed rate. It has a cost of material removal rate (MRR), which brings up the old quality-versus-ductility conundrum that manufacturers have to navigate. Cutting speed, as a second critical parameter, has less intuitive characteristics and is associated with thermal and material responses at the tool-chip interface. The reason it changes with increasing cutting speed is that it can be explained by changes in chip formation and relief of built-up edge (BUE). At reduced speeds, the cutting zone temperature is insufficient to prevent workpiece material from welding to the tool tip and forming a BUE. This thin, weakened edge is sometimes sheared off, wedged, or sheared into the machined surface by chips, creating a poor surface finish. At high cutting velocities, the temperature is extremely high, plasticising the work material in the first shear zone, thereby enhancing cutting efficiency and preventing BUE initiation.

It produces a cleaner and smoother surface. ANOVA Table 1 supports the statistical significance of this effect. From the mesh plot, it is evident that this improvement is greatest at low feed rates. This is consistent with the observation that in finish-machining operations where surface finish is the highest priority, a high cutting speed and low feed rate approach is optimal. The surface-like character of the effect of depth of cut on surface roughness indicates that, within the range used, its prime function is to have an influence on energy absorbed and on cutting forces but not on surface topography. Surface degradation at the depth of cut is due to increased system deflections and the possibility of low-amplitude vibrations. Where the material is higher, the workpiece, cutting tool, and spindle experience higher forming forces, and these induce deflections at the microscopic level, which are fed to surface defects. But because they occur secondary to the feed rate's existing geometric marking action, the final effect is dampened. The interaction effect case is also noteworthy. The parameters are not independent, as the data shows. Possibly the most significant conclusion in process optimisation is the discovery that the benefit of high-speed cutting is most dramatic at low feed rates. The news is that the optimal will not be reached by maximising speed at any expense to the feed rate. Streamlined processing is a technique that adopts system thinking, taking into account parameter interactions to reach the "sweet spot" in the mesh plot, where the target surface quality can be achieved at maximum efficiency.

6. Conclusion

This paper presents an extended study of how cutting speed, feed rate, and depth of cut affect the surface roughness of H13 hot die steel, conducted through a designed experiment and a rigorous statistical analysis. The analysis determines the contribution of each parameter and provides a confident ranking of their influence on surface quality. The most compelling evidence is the feed rate's overall dominance in controlling surface roughness. It was strongly and positively correlated with very high increases in surface roughness being produced by the feed rate. This is because it is largely the geometric tool mark design imposed on the workpiece, and additional tool marks and additional finish are a result of increased feed rates. The second key parameter, cuttingSSpeed, is inversely proportional to surface roughness. A higher cutting speed will result in a finer surface by reducing the tendency for the edge to accumulate and by cutting more effectively. Cutting depth, cutting speed, and feed rate have the lowest influence on surface roughness, keeping their relative contribution to finish surface quality unchanged. Ideal conditions for achieving the finest surface finish are low feed rate and high cutting speed, which reduce surface roughness. The precision of data-based experimental models is very high, a welcome relief for engineers and process designers alike. Manufacturers can overcome their penchant for trial-and-error approaches and select their machining parameters judiciously. This research provides practical recommendations for improving the machining of H13 hot die steel, with long-term benefits including improved quality, longer-lasting dies and moulds, and associated productivity and surface finish.

6.1. Limitation

Though the work presented here is informational, it must acknowledge its limitations. Firstly, the experiments have been conducted on a specific grade of coated carbide tool of a specific company. The results cannot be transferred to other tool materials (e.g., ceramics, CBN), shapes (e.g., non-uniform nose radius, number of flutes), or coating types, as these factors may drastically alter the tool-workpiece interaction. The second test was restricted within a definite range of cutting speed, feed rate, and depth of cut. Tendencies observed can then be used within this range of operation, but not beyond this, if this is attempted, because other physical effects will start to dominate. For instance, very high cutting speeds would lead to excessive thermal tool wear, reversing the tendency and affecting surface finish. Thirdly, experiments were performed in dry machining conditions. Adding cutting fluids (flood cooling, MQL) would introduce another parameter that would be of primary importance in both thermal and frictional conditions in the cutting zone and would therefore likely yield different optimal parameter values. Finally, the studies did not consider how tool wear could be incorporated into the equation over time. Another tool was employed in every set of tests, whereas in batch production, tool wear is a continuous process that reduces surface finish over the tool's life.

6.2. Future Scope

This research work presents several future directions for further research. One extension of this research work would be to investigate how tool wear affects surface roughness. A long-duration machining test can be conducted to monitor the step-by-step deterioration of the surface finish and the tool and form models, enabling an accurate prediction of surface quality as a function of tool condition and cutting parameters. Another excellent area of research would be studying the influence of different lubrication and cooling systems, e.g., Minimum Quantity Lubrication (MQL) and cryogenic cooling. Comparison with such sophisticated techniques under this work's dry-machining conditions may very well illuminate means to enhance surface quality at the cost of overcoming cost and environmental concerns. Lastly, the application of advanced modelling schemes, such as machine learning algorithms (e.g., Support Vector Machines and Artificial Neural Networks), could be explored. These models would subsequently include attempting to replicate the nonlinear machinability interactions to even higher accuracy. They can be implemented in intelligent manufacturing systems to optimise processes in real time. Finally, including additional output responses, such as cutting forces, tool temperature, and residual stresses, within the purview would provide a holistic view of machining and enable multi-objective optimisation to concurrently reduce quality, productivity, and part integrity.

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