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# ANALYSIS, MODELLING AND OPTIMIZATION OF CHIP COMPRESSION RATIO IN MEDIUM TURNING OF C45E STEEL

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**Abstract**. *Given the multiple significance of chip compression ratio (CCR) for machinability assessment, this study focuses on the analysis of CCR in medium longitudinal turning of C45E steel. The standard $2^3$ full factorial design was used to arrange three main cutting parameters, i.e., depth of cut, feed rate and cutting speed, at two levels. Based on experimental data, a quasi-linear CCR prediction model was developed for better understanding of the main and interaction effects of the considered cutting parameters. The obtained results suggest the dominant main effect of depth of cut and the interaction effect of cutting speed and feed rate. In addition to modelling, a Pareto multi-objective optimization problem was formulated and solved using a multi-objective genetic algorithm (MOGA). CCR and material removal rate were set as objective functions, and surface roughness and chip slenderness ratio as functional constraints. The analysis of Pareto sets revealed that the turning parameters of the highest significance are depth of cut and cutting speed. A perfect linear relationship between material removal rate and CCR was also identified.*

**Key words**: *Turning, Chip compression ratio, C45E, Modelling and optimization, MOGA*

## 1. INTRODUCTION

Turning technology still has wide application in today's industry due to favourable cutting mechanics for a wide variety of metal materials and the fact that it is a receptive technology which can ensure high productivity and quality, along with acceptable costs [1]. Input parameters of the turning production system, alone or in interaction, affect multiple cutting phenomena during the actual cutting process, which are consequently reflected on different process performance measures, such as quality of machined surface, machining time and costs, and power consumption. In this regard, it is very important to analyse the influence of these inputs on different process outputs, model them and ultimately determine more favourable cutting regimes through optimization. Commonly considered performance measures in machining include [2]: cutting forces, power, tool

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wear and tool life, chip flow angle, chip curling and chip-breaking, built-up edge, cutting temperature, workpiece surface finish and surface integrity, burr formation, part distortion and accuracy, tool deflection, dynamic stability limits and thermal damage of the tool/workpiece. Therefore, numerous investigations and studies have analysed the influence of inputs on surface roughness [1, 3], surface integrity [4], burr formation [5], dimensional accuracy [6, 7], cutting forces [8,9], part distortion [10], deflection of the cutting tool [11], tool wear [12, 13], tool life [14, 15], cutting temperature [16], cutting power [17], energy consumption [18], and chip formation [19-22].

Chip compression ratio (CCR) indicates the amount of plastic deformation that the material experiences during the chip formation process [19] and the frictional behaviour at the chip-tool interaction points [12]. There are several recent studies focused on the analysis of CCR in turning. In the majority of these studies, the influence of cutting parameters on CCR was analysed [21, 23, 24]. Other authors focused on the analysis of the influence of cooling/lubricating conditions [25], cutting tool coating [26], tool rake angle [27], and rake surface texture geometry [28] on CCR. There is only one recent study dealing with cutting parameters optimization for minimal CCR in turning [23].

The analysis of CCR in medium turning of unalloyed medium carbon steel C45E is in the focus of the present study. To this aim, a $2^3$ factorial design was performed to define eight turning regimes with two levels of feed rate, cutting speed and depth of cut. The change in CCR was analysed using 3D surface plots for better understanding of the combined effects of input parameters. Unlike previous studies that focused solely on CCR modelling, this paper integrates CCR analysis with multi-objective optimization considering two constraints. An attempt was made to determine the set of alternative cutting regimes for simultaneous minimization of CCR and maximization of productivity. To this aim, Pareto multi-objective optimization problem was formulated, and its two variants, with and without active constraints (required surface roughness and favourable chip slenderness ratio), were solved using a multi-objective genetic algorithm (MOGA).

## 2. EXPERIMENTAL SETUP

For the purposes of CCR prediction model development and analysis, an experimental investigation was performed. In order to determine model coefficients, three input parameters, i.e., feed rate ($f$), cutting speed ($v$) and depth of cut ($a_p$), were considered and varied at two levels in accordance with the classical $2^3$ factorial design (Fig. 1). Cutting parameter ranges were selected considering machine tool characteristics, recommendations for the selected cutting insert and workpiece material characteristics.

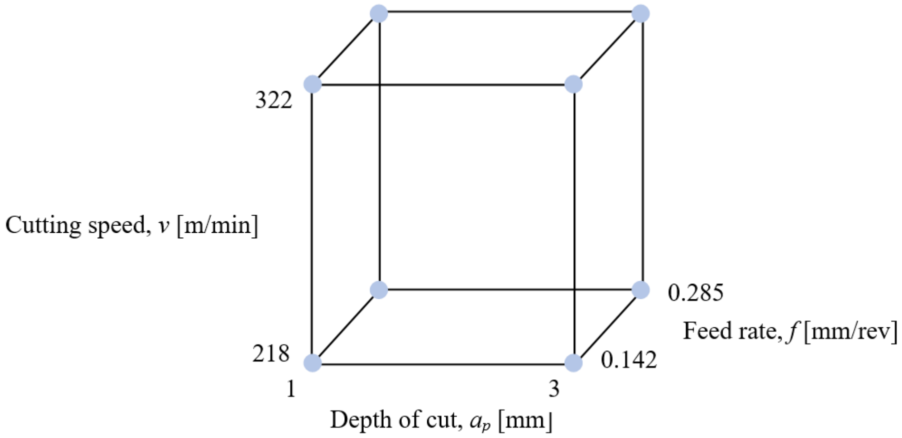


**Fig. 1** Investigated experimental space in the experiment

Unalloyed medium carbon steel C45E (Ck45 DIN 17200) was used as workpiece material. The experimental unit was in the form of a bar with a diameter of 63 mm. The cutting experiment was performed using a CORUN PCLNR 3225P 12 holder and a CNMG120404-MA insert manufactured by Mitsubishi with the grade of UE6110 (coated carbide). The cutting tool geometry was as follows: rake angle of $\gamma_o$ = 16° and nose radius $r_\varepsilon$ = 0.4 mm. The tool cutting edge angle was held constant during experimentation ($\kappa$ = 95°). Longitudinal turning tests were performed without coolant, in line with recent trends [29], on a universal lathe machine POTISJE PA-C 30.

In order to calculate the chip compression ratio, apart from knowing the undeformed (uncut) chip thickness, which is estimated based on feed rate and tool cutting edge angle, it is necessary to experimentally measure actual chip thickness for each run. To this aim, chip thickness measurement was performed with a Mitutoyo digital micrometer (range of 0-25 mm and resolution of 1 μm). Chip shapes obtained under investigated cutting conditions are shown in Fig. 2.


**Fig. 2** Chip shapes formed under various cutting conditions

## 3. RESULTS AND DISCUSSION

With the application of design of experiments (DOE) theory for analysis of $2^k$ experimental designs [30], the effects, sums of squares and percentage contribution of each model term were estimated (Table 1).

**Table 1** Effect estimate summary for experimental data

| Factor | Effect estimate | Sum of squares | Percent contribution |
|---|---|---|---|
| $f$ | -0.066 | 0.0088 | 1.31 |
| $v$ | 0.153 | 0.0467 | 6.94 |
| $a_p$ | 0.356 | 0.2540 | 37.78 |
| $f \cdot v$ | 0.389 | 0.3036 | 45.15 |
| $f \cdot a_p$ | -0.008 | 0.0001 | 0.02 |
| $v \cdot a_p$ | 0.171 | 0.0586 | 8.71 |

Based on the data from Table 1, it can be apparently seen that depth of cut ($a_p$) is the factor with the greatest effect on the chip compression ratio. Since the coefficient (effect estimate) is positive, this relationship is directly proportional. The effects of cutting speed and feed rate are less pronounced, with the direct and inverse proportionality with the chip compression ratio, respectively. However, the two-way interaction of cutting speed and feed rate, accounting for 45 percent of the total variability, has the strongest effect on the resulting chip compression ratio. The importance of the significant interaction effect with cutting speed is consistent with previous conclusions. Namely, it has been previously discussed that feed rate, tool cutting edge angle, and cutting edge inclination angle may differently influence CCR at different cutting speeds [31].

Based on these experimental results, the regression model for predicting the chip compression ratio has the following form:

$$CCR = 1.845 - 0.033 \cdot x_1 + 0.076 \cdot x_2 + 0.178 \cdot x_3 + \\ 0.195 \cdot x_1 \cdot x_2 - 0.004 \cdot x_1 \cdot x_3 + 0.086 \cdot x_2 \cdot x_3 \qquad (1)$$

where the coded variables $x_1$, $x_2$ and $x_3$ represent feed rate ($f$), cutting speed ($v$) and depth of cut ($a_p$), respectively.

The coefficient of the determination of the developed model showed that more than 99% of variability in chip compression ratio can be explained by all included model terms. The derived empirical model can be visualized by creating 3D surface plots, allowing the individual (main) and two-way interactions to be presented in a more detailed and comprehensive way [32]. From the performed analysis one can conclude that in order to minimize CCR it would be beneficial to use the combination of a high feed rate, low cutting speed and low depth of cut. Lower CCR values would yield lower cutting forces that are required for the shearing action of chips from the workpiece and improve the breakability of chips during machining [33]. However, CCR is only one aspect of machinability, and for a more adequate determination of machining conditions, it is necessary to look at other process performances, such as tool life, surface quality, productivity, chip slenderness ratio, etc. As noted by Kumar et al. [34] it is very important to reduce CCR without affecting productivity.

Bearing in mind the foregoing considerations, an attempt was made to determine the optimum cutting parameter values for simultaneous minimization of CCR and maximization of productivity, expressed in terms of volumetric material removal rate ($q$). Given that chip slenderness ratio ($\xi$) (ratio of depth of cut to feed rate) is a vital parameter in theoretical and applicable machining [35], a functional constraint related to the allowable chip slenderness ratio values was added [36]. In addition, the maximal allowable surface roughness (N7, $R_{amax}$ = 1.6 μm) constraint was considered, and it was determined using the previously developed quasi-linear empirical model [1]. Therefore, the following multi-objective constrained optimization problem was formulated:

$$\begin{gathered} Minimize: CCR \\ Maximize: q = f \cdot v \cdot a_p \\ Subject\ to: 4 \leq \xi \leq 16 \\ R_a \leq R_{amax} = 1.6\ [\mu m] \\ 0.142 \leq f \leq 0.285\ [mm/rev], 218 \leq v \leq 322\ [m/min], 1 \leq a_p \leq 3 [mm] \end{gathered} \tag{2}$$

The formulated constrained multi-objective optimization problem can be solved using several approaches and techniques [37]. Some methods, such as Pareto and scalarization methods [38], find solutions representing the best compromise in conflicting objectives, while other, such as multi-criteria decision-making (MCDM) methods [39], assess and rank the discrete alternatives to each other according to multiple criteria, taking both the objectives and other decision factors into consideration. In the present study an a posteriori approach based on Pareto optimality concepts, i.e., Pareto dominance and Pareto optimality, was adopted. A multi-objective genetic algorithm (MOGA), which uses a population of solutions in each iteration, was used to determine Pareto fronts and Pareto optimal sets. The algorithm is capable of exploring efficiently the diverse regions of the solution space and is very popular choice for solving multi-objective machining optimization problems [40]. The metaheuristic algorithm was run with the following parameters: population size: 50, selection: tournament, reproduction: crossover fraction of 0.8, mutation: adaptive feasible, type of crossover: intermediate with ratio of 1, stopping criteria: 1000 generations.

In the present study two Pareto optimal sets were determined, the first set as the result of solving constrained multi-objective optimization problem as given in Eq. (2), and the second set as the result of solving the relaxed optimization problem excluding the constraints related to surface roughness and chip slenderness ratio.

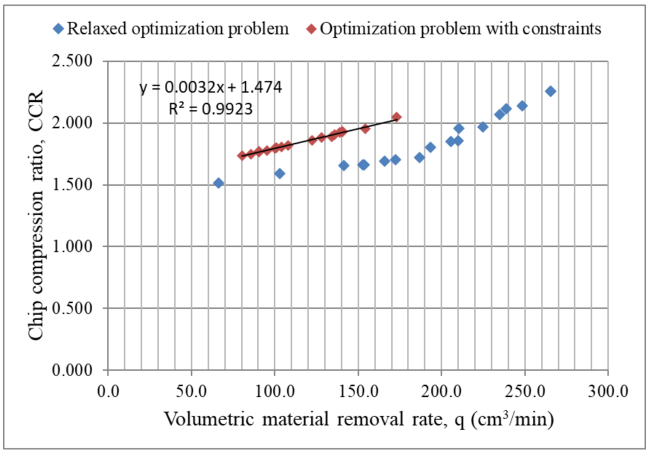


**Fig. 3** Pareto front of multi-objective optimization solutions

As can be observed from Fig. 3, CCR and material removal rate are contradictory objectives, i.e., there are no cutting regimes which would simultaneously maximize material removal rate and minimize CCR. Therefore, some trade-off solutions need to be adopted. As might be expected, due to neglecting constraints the diversity of determined solutions, in terms of distribution and spread, is better in the case of solving relaxed optimization problem. On the other hand, solving constrained multi-objective optimization problem reveals that there are cutting parameters combination that would yield material removal rate in the range from 80 to 173 cm$^3$/min and CCR in the range from 1.74 to 2.05, while at the same time satisfying surface roughness and chip slenderness ratio constrains. It is interesting to note that in this case there exists a perfect linear relationship between material removal rate and CCR.

The optimal set of cutting regimes for both optimization problems is given in Table 4.

**Table 4** Set of Pareto solutions obtained by MOGA

| Solution | Relaxed optimization problem | | | | | Optimization problem with constraints | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | $f$ (mm/rev) | $v$ (m/min) | $a_p$ (mm) | $q$ (cm$^3$/min) | CCR | $f$ (mm/rev) | $v$ (m/min) | $a_p$ (mm) | $q$ (cm$^3$/min) | CCR |
| 1 | 0.285 | 233 | 1.00 | 66.4 | 1.516 | 0.214 | 257 | 2.80 | 154.2 | 1.952 |
| 2 | 0.285 | 310 | 3.00 | 265.4 | 2.258 | 0.214 | 282 | 2.30 | 139.0 | 1.922 |
| 3 | 0.285 | 310 | 3.00 | 265.4 | 2.258 | 0.214 | 272 | 1.74 | 101.1 | 1.800 |
| 4 | 0.285 | 251 | 2.93 | 210.0 | 1.855 | 0.214 | 292 | 2.24 | 140.3 | 1.930 |
| 5 | 0.285 | 234 | 2.49 | 165.6 | 1.689 | 0.214 | 277 | 1.44 | 85.5 | 1.750 |
| 6 | 0.285 | 235 | 2.58 | 172.4 | 1.705 | 0.214 | 283 | 1.49 | 90.6 | 1.763 |
| 7 | 0.285 | 233 | 2.81 | 186.9 | 1.721 | 0.214 | 250 | 1.94 | 103.9 | 1.807 |
| 8 | 0.285 | 236 | 2.10 | 141.4 | 1.655 | 0.214 | 257 | 2.22 | 122.2 | 1.861 |
| 9 | 0.285 | 293 | 2.98 | 248.5 | 2.137 | 0.214 | 270 | 1.39 | 80.4 | 1.737 |
| 10 | 0.285 | 269 | 2.93 | 224.7 | 1.970 | 0.214 | 250 | 2.51 | 134.1 | 1.889 |
| 11 | 0.285 | 247 | 2.75 | 193.3 | 1.802 | 0.214 | 267 | 2.25 | 128.2 | 1.883 |
| 12 | 0.282 | 251 | 2.90 | 205.8 | 1.850 | 0.214 | 267 | 2.38 | 136.1 | 1.907 |
| 13 | 0.285 | 286 | 2.88 | 234.7 | 2.071 | 0.214 | 281 | 2.34 | 140.6 | 1.927 |
| 14 | 0.285 | 294 | 2.85 | 238.8 | 2.114 | 0.214 | 298 | 2.71 | 173.1 | 2.046 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| 15 | 0.285 | 274 | 2.69 | 210.3 | 1.959 | 0.214 | 245 | 2.06 | 108.0 | 1.817 |
| 16 | 0.285 | 237 | 1.53 | 103.0 | 1.592 | 0.214 | 287 | 1.56 | 95.5 | 1.778 |
| 17 | 0.285 | 233 | 2.30 | 152.8 | 1.663 | 0.214 | 274 | 1.71 | 100.1 | 1.797 |
| 18 | 0.285 | 233 | 2.31 | 153.8 | 1.665 | 0.214 | 268 | 1.58 | 90.6 | 1.769 |

Analysis of the results from Table 4 reveals that the cutting parameters of the highest significance are depth of cut and cutting speed. It can be observed that for constant maximal feed rate ($f$ = 0.285 mm/rev), combinations of depth of cut and cutting speed ensure minimal CCR and maximal material removal rate. Similarly, in the case of active constraints, combinations of depth of cut and cutting speed in a somewhat narrower range ensure minimal CCR and maximal material removal rate, but for the minimal feed rate ($f$ = 0.214 mm/rev). Finally, it should be noted that each Pareto solution is an acceptable optimization solution and the choice of a particular one can be driven by the specific requirements.

## 4. CONCLUSION

The present study analysed the effects of feed rate, cutting speed and depth of cut on CCR in medium turning of unalloyed medium carbon steel C45E. In addition, a Pareto optimization problem considering CCR and material removal rate as objective functions and surface roughness and chip slenderness ratio as functional constraints was formulated and solved using the multi-objective genetic algorithm. Analysis of the obtained results leads to the following conclusions:

- For the covered experimental hyper-space, depth of cut is the most influential parameter affecting CCR, followed by cutting speed and feed rate.
- There is a significant interaction effect of cutting speed and feed rate on CCR. In other words, feed rate may be in direct or indirect relationship with CCR, depending on the specific value of cutting speed. The same applies to the variable effect of cutting speed.
- Material removal rate and CCR are contradictory objectives, i.e., higher CCR levels are needed to increase the material removal rate.
- Some trade-off solutions between higher material removal rates and lower CCR require specific combinations of cutting speed and depth of cut while using the lowest feed rate.
- In compliance with the conditions for securing favourable chip slenderness ratio and ISO surface roughness grade N7, an increase in the material removal rate linearly increases CCR.

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