21st International Conference Man and Working Environment
SEMSIE
Safety Engineering & Management - Science, Industry, Education

ORIGINAL SCIENTIFIC PAPER

DOI: 10.46793/SEMSIE25.245T

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ANALYSIS OF CO_2 EMISSIONS IN LONGITUDINAL MEDIUM TURNING OF 42CrMo4 STEEL

Abstract: *In the context of sustainable, eco-friendly machining, in addition to standard process performances, through which the suitability of selected parameters is assessed, analysis of the process environmental and sustainable performances is often considered. With this in mind the present study aims at analysing CO_2 emissions per volume of material removed in dry longitudinal single-pass medium turning of low-alloyed steel 42CrMo4 using a coated carbide cutting tool. Full factorial design was applied to arrange the main cutting parameters, i.e. depth of cut, feed rate and cutting speed, at three levels. For each experimental trial CO_2 emissions data were obtained using a tool and cutting data recommendation system of the cutting tool manufacturer (Walter GPS). The analysis of results involved the analysis of main, interaction and quadratic effects, determination of statistically significant effects and development of non-linear model for the prediction of CO_2 emissions per volume of material removed. In addition, the optimized cutting conditions for minimization of CO_2 emissions were determined.*

Keywords: turning, CO_2 emissions, full factorial design, 42CrMo4 steel, prediction

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INTRODUCTION

Sustainable, green and environmentally friendly manufacturing industry is a goal set by many production companies, regulatory authorities and regulations. Actually, it has been a major role player in the Industry 4.0 transformation (Gupta, 2020). The scientific society and manufacturing practice are constantly investigating the possibilities of incorporating circular economy models, improving energy efficiency and minimizing/eliminating any kind of waste to create a more environmentally friendly manufacturing industry (Barać et al., 2024; Stojković et al., 2022). To this end, investigation and application of machining technologies, as one of the most widely used manufacturing processes, in addition to the analysis of important process performances, technological and economic criteria, in recent times also considers different sustainable, green and environmental performances. Related to turning technology, several previous research studies have addressed these important aspects.

Somashekaraiah et al. (2016) formulated a green cutting fluid and compared its performance with the performance of common commercial cutting fluids used in machining. The formulation was found to be cost effective and stable, offering better machining capabilities. The best sustainable practices in machining regarding water consumption and cutting fluid usage were reviewed and analysed by Pervaiz et al. (2018). Kumar et al. (2022) made a review regarding the use of eco-friendly cutting fluids for sustainable machining.

Bousnina and Hamza (2020) performed an experimental investigation on the turning of 304L stainless steel with the aim to optimize cutting parameters to increase energy efficiency and minimize energy consumption. With the use of Taguchi method and ANOVA, Kumar et al. (2021) determined the optimal values of cutting parameters in finish turning of EN 353 alloy for maximization of energy efficiency. The optimization results were compared to those obtained with the use of RSM prediction model developed in terms of depth of cut, feed rate, cutting speed and tool nose radius. Park et al. (2016) performed bi-objective optimization of consumed cutting energy and energy efficiency in turning of hardened workpiece material. Response surface methodology (RSM) was used to model the relationships between parameters and considered process responses. A non-dominated sorting genetic algorithm was applied to determine a set of Pareto solutions, while the TOPSIS method was used to select the best compromise solution. Hassine et al. (2015) developed a multi-objective optimization model for sustainable rough turning operations. The model considered three objective functions (production time, production cost and energy consumption), five process constraints and two independent variables (cutting speed and feed rate). The authors applied a metaheuristic algorithm, i.e. particle swarm optimization, to determine optimal cutting conditions. Bhanot et al. (2016) presented an overview of models and criteria that can be used for assessing the sustainability of the turning process. In addition, a social sustainability assessment framework was developed. Rajemi et al. (2010) proposed a model for determining economic tool life in order to minimize the energy footprint, i.e. energy cost and environmental footprint.

Ic et al. (2018) applied RSM to optimize process parameters (cutting speed, depth of cut and cutting tool material) in turning of three aluminium alloys to minimize carbon emissions and maximize machining quality. The multi-objective optimization results obtained using goal programming and the desirability function approach were compared. Yin et al. (2019) considered cost and carbon emissions in the turning process using a metric called profit per unit carbon emissions. The authors determined the set of machining parameters to maximize profit per unit carbon emissions using a genetic algorithm for two case studies and discussed the impacts of cutting parameters on carbon emissions. Cakir (2021) proposed a novel approach for carbon emissions minimization in turning. An experimental study in turning of DIN 1.2367 steel material showed that using harder cutting tools, lower feed rates, and higher depths of cut values at optimum cutting speed can result in lower carbon emissions. Jiang et al. (2021) developed a model for calculating carbon emissions in turning by considering energy consumption, resource depletion and waste generation. In addition to experimental validation, the authors analysed the effects of process parameters on carbon emissions.

Fernando et al. (2022) performed a life cycle assessment (LCA) to analyse the environmental performance in turning of AISI P20 under dry and wet cutting conditions. The authors observed that electrical energy was the most significant contributor, while the effect of cutting fluid was negligible. In addition, with the application of grey-based Taguchi method optimized cutting conditions were determined. Mia et al. (2019) performed LCA and multi-objective optimization of eco-friendly cryogenic N_2 assisted turning of Ti-6Al-4V. The authors concluded that there is a clear relation between cooling strategy and environmental aspects that directly affect the machining process.

As could be observed from literature review there is a greater number of empirical modelling and optimization studies related to LCA, carbon emissions, energy efficiency and use of sustainable cutting fluids in turning. This reflects the continual endeavour of researchers to explore sustainable, green and environmentally friendly strategies in the application of turning technology. With this in mind, the present study focuses on the analysis of CO_2 emissions per volume of material removed in medium turning of low-alloyed steel 42CrMo4. Analysis of the results involved determination of statistically significant effects, analysis of parameter effects, development of non-linear prediction model and identification of a stationary point that yields minimal CO_2 emissions per volume of material removed.

EXPERIMENTAL DATA

The start diameter for longitudinal single-pass turning was 60 mm, while the machined length was 50 mm. The workpiece material was low-alloyed steel 42CrMo4. The machine tool was the CNC lathe with the motor power of P_m = 25 kW, the maximum spindle speed of n_{max} = 3000 rpm and the maximum torque of M_{cmax} = 1100 Nm.

Walter was selected as the cutting tool manufacturer. The cutting tool was the Walter PCLNR3225P12 toolholder (cutting edge angle of κ = 95°, rake angle of γ_{oh} = -6°) with a Walter CNMG120408-MP5 WPP20G coated carbide insert for medium machining (cutting edge length of l = 12 mm, nose radius of r_ε = 0.8 mm and rake angle of γ_{oi} = 15°). Cutting parameter ranges and levels were selected considering the availability and capabilities of the tool and the cutting data recommendation system of the cutting tool manufacturer (Walter GPS) and recommended cutting conditions for the insert.

The experimental trials were conducted in accordance with the full factorial design. The main cutting parameters, i.e. depth of cut, feed rate and cutting speed, were arranged at three levels (Table 1).

Table 1. *Cutting parameter levels used in the experiment*

Parameter	Level 1	Level 2	Level 3
Depth of cut a_p [mm]	0.8	2.4	4
Feed rate f [mm/rev]	0.18	0.29	0.4
Cutting speed v [m/min]	240	269	298

Twenty-seven different combinations of factor levels were tried in the “virtual” experiment and CO_2 emissions per component (gCO_2) produced by machining operation and idle machine run were obtained using the tool and cutting data recommendation system of the cutting tool manufacturer (Walter GPS). For every experimental trial, CO_2 emissions per volume of material removed (gCO_2/cm^3) were calculated by dividing total CO_2 emissions per component by the volume of material removed.

RESULTS AND DISCUSSION

Statistical analysis of main, interaction and quadratic effects

Based on the applied design matrix and by using the obtained values of CO_2 emissions per volume of material removed, main, interaction and quadratic effects were estimated using RSM (Table 2).

Table 2. *Summary of estimated main, interaction and quadratic effects*

Term	Coefficient	T	p
Constant	0.87788	11.835	0.000
a_p	-0.97348	-28.350	0.000
f	-0.47180	-13.740	0.000
v	-0.11121	-3.239	0.005
$a_p \times a_p$	0.64307	10.812	0.000
$f \times f$	0.19139	3.218	0.005
$v \times v$	0.02209	0.371	0.715
$a_p \times f$	0.35401	8.418	0.000
$a_p \times v$	0.09182	2.183	0.043
$f \times v$	0.06282	1.494	0.154
$S = 0.146$, $R^2 = 0.986, R^2_{adj} = 0.978, R^2_{pred} = 0.963$			

The analysis of the results indicates that all linear effects of cutting parameters are significant. In addition, small p-values of interaction and quadratic effects suggest the presence of curvature in the response surface. Among these, however, the quadratic effect of the cutting speed and the interaction effect of the feed rate and cutting speed are not statistically significant. Coefficient of determination (R^2) shows that 98.6% of the total variability of CO_2 emissions per volume of material removed is explained by main, interaction and quadratic effects. In addition, based on the predicted coefficient of determination (R^2_{pred}), one can expect that this model would be able to explain 96.3% of the variability in predicting new cutting regimes, with arbitrarily chosen values of depth of cut, feed rate and cutting speed.

ANOVA

In order to validate the appropriateness and predictive capability of the quadratic model, ANOVA was performed, as given in Table 3. ANOVA of the quadratic model indicates that all model terms (linear, interaction and quadratic) are significant as indicated by the Fischer's F-test and zero probability values (p-values = 0.000).

Table 3. *Analysis of variance for the CO_2 emissions per volume of material removed data*

Source of variation	Sum of squares	Degree of freedom	Mean square	F	p
Second order model	25.6435	9	2.8493	134.25	0.000
linear	21.2871	3	7.0957	334.32	0.000
interaction	1.6524	3	0.5508	25.95	0.000
quadratic	2.704	3	0.9013	42.47	0.000
Residual error	0.3608	17	0.02122		
Total	26.0043	26			

Non-linear prediction model

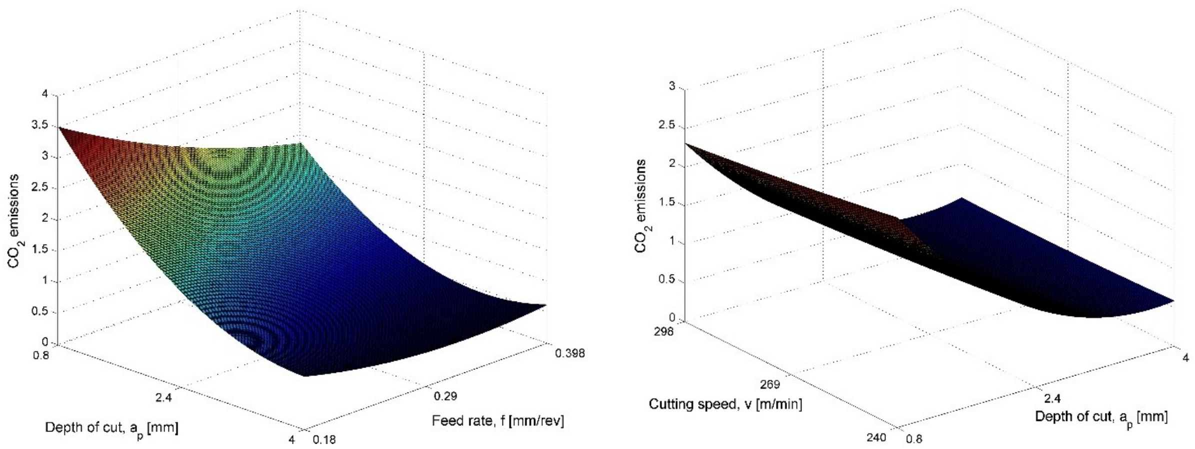
Based on previous analyses, the response variable, i.e. CO_2 emissions per volume of material removed, was modelled with the full quadratic model in order to take into account main, interaction and quadratic effects of the depth of cut, feed rate and cutting speed. The coded form of the CO_2 emissions per volume of material removed data prediction model is as follows:

$$CO_2\ emissions = 0.8778 - 0.9735x_1 - 0.4718x_2 - 0.1112x_3 + 0.6431x_1^2 + 0.1914x_2^2 + 0.0221x_3^2 + 0.354x_1x_1 + 0.0918x_1x_3 + 0.0628x_2x_3 , \quad (1)$$

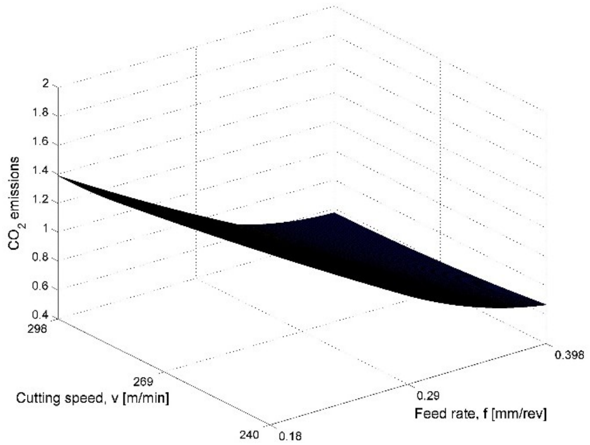
where the coded variables x_1, x_2 and x_3 represent depth of cut (a_p), feed rate (f) and cutting speed (v), respectively.

Analysis of parameter effects

The derived RSM model was further visualized by developing surface plots (Figure 1), allowing the detailed analysis of the main and two-way interaction effects of cutting parameters on the CO_2 emissions per volume of material removed.



a) v = 269 m/min b) f = 0.29 mm/rev



c) a_p = 2.4 mm

Figure 1. *Response surface plots presenting the dependence of CO_2 emissions per volume of material removed with respect to two-factorial interactions*

As shown in Figure 1, increasing the value of any cutting parameter leads to a decrease in CO_2 emissions per volume of material removed. However, the depth of cut has the most significant effect, followed by the feed rate and the cutting speed. The clearly visible patterns of developed surface plots suggest a nonlinear nature of the effects of the depth of cut and feed rate, which is in accordance with the previously performed analysis that showed statistically significant quadratic effects of the depth of cut and feed rate. In the case of cutting speed, the observed dependence is approximately linear.

The existence of interaction effects and qualitative change in the parameter effects can be observed in Figure 1a). Namely, for small depths of cuts, an increase in feed rate non-linearly significantly decreases CO_2 emissions per volume of material removed. For intermediate and high values of the depth of cut, an increase in feed rate also decreases CO_2 emissions per volume of material removed, wherein that decrease is much smaller in a quantitative sense, and it is realized according to a pattern with much less curvature. Moreover, there is a qualitative change in the effect of the feed rate at the highest depth of cut. As could be observed, for the highest depth of cut, an increase in feed rate up to 0.33 mm/rev decreases CO_2 emissions per volume of material removed. However, further increase in feed rate values results in a slight increase in CO_2 emissions per volume of material removed. Finally, it should be noted that, taking into account the previously observed statistical significance of two-factorial interaction effects, related specifically to the effect of the depth of cut, this does not mean that there are no other significant qualitative changes within the covered experimental hyper-space regarding two-factorial interaction effects for other parameter values that are kept constant.

Process optimization

Since the CO_2 emissions per volume of material removed is accurately modelled by the second-order model, it is necessary to determine the optimum settings. Optimization of control parameters in machining is necessary to achieve appropriate efficiency and quality (Kawecka, 2024). In the present study, the optimum setting corresponds to the combination of cutting parameter values that result in minimal CO_2 emissions per volume of material removed. Because of higher dimensionality and possible interaction effects, it is not convenient to locate optimum settings using surface or contour plots, but it is necessary to apply more efficient procedures to determine, if it exists, an optimum point, i.e. a stationary point. The stationary point, representing maximum or minimum response or a saddle point, can be found using matrix algebra. The most straightforward way to determine the nature of the stationary point is the construction of contour plots, or a more formal, or canonical, analysis (Montgomery, 2017).

The stationary point in terms of the natural values of variables was obtained as: depth of cut a_p = 3.27 mm, feed rate f = 0.361 mm/rev and cutting speed v = 282 m/min. Based on these values and using variable transformations, one can estimate the minimum response, i.e., CO_2 emissions per volume of material removed at the stationary point, with the value of 0.433 gCO_2/cm^3. The nature of the response surface can be verified from Figure 2.

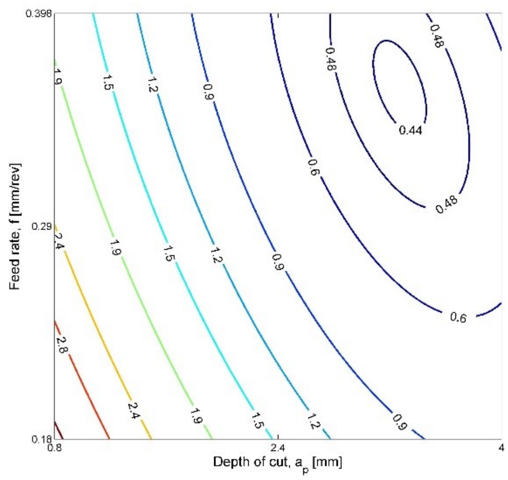


Figure 2. *Contour plot showing the stationary point*

From Figure 2, it could be verified that within the region of exploration, the stationary point is a minimum. Finally, it should be noted that the identified optimum has a response value, i.e. CO_2 emissions per volume of material removed, lower than any of the design points used in the experimental design for model development.

CONCLUSION

The present study dealt with the analysis of CO_2 emissions per volume of material removed in dry longitudinal medium turning of low-alloyed steel 42CrMo4. Based on the conducted analyses and obtained results, the following conclusions can be drawn:

- For the covered experimental hyper-space, CO_2 emissions per volume of material removed are mostly affected by the depth of cut, followed by feed rate and cutting speed.
- All main effects of the depth of cut, feed rate and cutting speed were found to be statistically significant, along with depth of cut interaction effects, as well as quadratic effects of the depth of cut and feed rate.
- Generally, there exists an indirect relationship between CO_2 emissions per volume of material removed and cutting parameters, i.e. increasing either depth of cut, feed rate or cutting speed results in a decrease in CO_2 emissions per volume of material removed.
- By identification of the stationary point, the optimized cutting conditions for minimization of CO_2 emissions were determined as: depth of cut a_p = 3.27 mm, feed rate f = 0.361 mm/rev and cutting speed v = 282 m/min. It may be argued that for a given cutting speed, there exists a particular combination of depth of cut and feed rate that yields minimal CO_2 emissions per volume of material removed.

The RSM model developed in the present study can be used in the formulation of the turning optimization problem while considering other important performances related to quality and cost, as well as process constraints related to technological limitations of machine tools.

ACKNOWLEDGEMENTS

This research was financially supported by the Ministry of Science, Technological Development and Innovation of the Republic of Serbia (Contract No. 451-03-137/2025-03/200109).

This paper was supported by the Ministry of Science, Technological Development and Innovation of the Republic of Serbia [Grant Number: 451-03-137/2025-03/ 200102].

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