

(REVIEW ARTICLE)



CUTTING PARAMETER OPTIMISATION FOR SURFACE QUALITY AND ENERGY EFFICIENCY IN CNC MACHINING: A SYSTEMATIC LITERATURE REVIEW

MUCHIMBA Mwiminini *, MOYO Nkosilathi, MOYOSVI Walter, MPOFU Blessing Thabo and MUDIWA Noria Tatenda

Department of Industrial and Manufacturing Engineering, National University of Science and Technology (NUST), P.O. Box AC 939, Ascot, Bulawayo, Zimbabwe.

* Corresponding Author

Global Journal of Engineering and Technology Advances, 2026, 29(01), 093–107

Publication history: Received on 26 August 2026; revised on 01 October 2026; accepted on 03 October 2026

Article DOI: <https://doi.org/10.30574/gjeta.2026.29.1.0270>

Copyright © 2026 Author(s) retain the copyright of this article. This article is published under the terms of the Creative Commons Attribution License 4.0

ABSTRACT

The choice of cutting speed, feed rate and depth of cut not only affects the surface finish of the end product of the CNC machine, but also the machine tool's electricity consumption and machining time. Trimming parameter selection is a multi-objective problem because any parameter set that improves one of these responses tends to be detrimental to the other. This paper is a systematic literature review (SLR) based on PRISMA 2020 guidelines that covers and summarizes the research related to cutting-parameter optimisation for surface quality and energy efficiency in CNC turning, milling, drilling, honing and wood machining. The literature was searched in English in Google Scholar, Web of Science and ScienceDirect from January 2016 to June 2026, with backward citation searching for seminal earlier work. The included studies were categorised according to the machining process, cutting parameters, surface and energy responses and the optimisation method, and then synthesised in narrative form. The evidence indicates that feed rate is the most dominant parameter to control surface roughness in most of the studies conducted on turning and milling, depth of cut is the major parameter that affects the power consumption and material removal rate, and cutting speed affects both the surface roughness and the power consumption and tool wear, with better surface finish in a range of cutting speeds specific to the material being turned and better power consumption and tool wear at higher cutting speeds. The optimum (minimal) energy and optimum (minimal) material removal are often different, and minimum power settings are not always minimum energy settings. From single response Taguchi-ANOVA designs, optimisation practice has shifted towards grey relational analysis, TOPSIS, response surface models, artificial neural networks and Pareto based metaheuristics like NSGA-II. There are key challenges in the treatment of tool wear and embodied energy, in-process adaptive optimisation, validation on industrial machines and resource-constrained manufacturing economies. Future work is proposed using a conceptual framework, which connects cutting parameters, responses, optimisation methods and Industry 4.0 feedback.

Keywords: CNC Machining; Cutting Parameters; Surface Roughness; Energy Efficiency; Specific Cutting Energy; Multi-Objective Optimisation; Taguchi Method; Grey Relational Analysis; Systematic Literature Review.

1 INTRODUCTION

Computer-Aided Manufacturing (CAM) and Computer Numerical Control (CNC) systems are computer-controlled systems that use digital product definitions to guide controlled material removal and are capable of precision, repeatability, and automation superior to that of manual machining. CNC machining is hence still the primary method of manufacturing parts with strict dimensional tolerances and desired surface finishes. But cutting conditions, programmed by the process planner, strongly influence the performance of any CNC operation. The material removal conditions (speed, feed rate and depth of cut) determine the machining time, cutting forces, material removal rate (MRR), surface roughness and energy consumption (Chen et al., 2021).

Energy is no longer an overhead, it's a first order process variable. In addition to electrical energy used in the cutting zone of the machine tool, electrical energy is also used by the spindle, feed drives, coolant pumps and auxiliary equipment of the machine tool; a significant proportion of the electrical energy used is not used when the metal is removed from the workpiece (Zhao et al., 2017; Moradnashad and Unver, 2017). As demonstrated in the field reviews, one of the lowest-cost tools to reduce this consumption is to select the best cutting parameters, which does not involve any capital costs (Chen et al., 2021; Soori et al., 2024). Meanwhile, surface roughness is the most commonly used criterion of the quality of a machined surface, and is sensitive to the same parameters that may conflict with the energy response. Camposeco-Negrete (2013), for instance, reported that the rate of energy consumption during turning of AISI 6061-T6 decreased with higher feed rates and surface roughness increased. This has led to the evolution of multi-objective optimisation techniques.

Kant and Sangwan (2014) proposed a predictive model to optimise power consumption and surface roughness simultaneously and concluded that the most important parameter was the feed rate, followed by the depth of cut and cutting speed. In this study, Yan and Li (2013) analyzed the relative importance of energy, production rate and cutting quality for milling by using the WGRA and the RSM. In other cases, such as honing of cast-iron cylinder liners (Tayisepe et al., 2024a), planing of hardwood (Tayisepe et al., 2023) and softwood (Tayisepe et al., 2024b) species, as well as CNC milling of mild steel (Mapindu et al., 2026b), similar trade-offs have been reported since then. Additional weight is given to the problem in the developing manufacturing economies. The grid is highly reliant on the unreliable performance of old coal-fired generation with about 72 % of the maintenance strategy being comprised of corrective maintenance, which leads to forced outages and unstable supply in Zimbabwe (Senda et al., 2026).

Local manufacturers are also being challenged to be more agile and competitive with imports, but it is found that numerically controlled equipment and supporting digital technologies are not uniformly available and are not well integrated (Muhla et al., 2023; Muhla et al., 2025a), survey data show. When these conditions apply, every kWh saved at the machine tool is important and methods of machine tool optimisation that require little capital investment are especially appealing, such as statistically designed experiments. While some reviews discuss the energy consumption of machine tools (Zhao et al., 2017; Sihag and Sangwan, 2020) or energy-efficient parameter selection (Chen et al., 2021), less review combines the evidence specifically on the energy and surface quality of CNC processes and workpieces, and even fewer focus on the application of that evidence in resource-constrained environments.

This paper aims to fill that void by conducting a systematic review of literature. It provides: (i) a systematic overview of the influence of cutting speed, feed rate and depth of cut on surface quality and energy consumption; (ii) a comparison of the methods for cutting speed, feed rate and depth of cut optimisation, ranging from Taguchi designs to Pareto optimisation techniques assisted by machine learning; (iii) an overview of the quality–energy–productivity trade-off in cutting processes depending on the material and process; and (iv) a research agenda with a conceptual framework for energy-aware parameter optimisation.

2 BACKGROUND AND THEORETICAL FOUNDATION

2.1 Cutting parameters and surface generation

Cutting parameters refer to the interaction between the cutting edge and the work piece. The cutting speed (or spindle speed) determines the relative velocity between the cutting tool and the chip interface, and thus the thermal regime, the feed rate determines the uncut chip thickness and the spacing of feed marks, and depth of cut determines the engaged edge length and the material volume removed by a single cut (Li et al., 2017). The geometric relation for a tool with nose radius r_e , which is the classical one, is appropriate to describe the kinematic contribution of feed to roughness:

$$R_a \approx f^2 / (32 r_e) \quad (1)$$

At which point x is the feed per revolution. Due to the square dependency between the height of the feed and the feed-mark, the increase in roughness is not linear with respect to the increase in feed (Abellán-Nebot et al., 2024; Mapindu et al., 2026b). Despite this, measured roughness differs from Eq. (1) due to built up edge, vibration, tool wear, material

side flow and for very small feeds due to ploughing and the minimum chip thickness effect. Lin et al. (2020) demonstrated that prediction accuracy significantly increases when taking into account the machining vibration in addition to the spindle speed, feed and depth of cut, thereby providing evidence that the surface roughness is not a function of any of these parameters alone, but rather a result of multiple parameters working together. Moayyedian et al. (2020) also established the significance of the feed rate, spindle speed, depth of cut and radial immersion in end milling by Taguchi methods and analysis of variance (ANOVA) and found that it varies depending on the operation and the workpiece material.

2.2 Energy consumption of CNC machine tools

The energy absorbed by the CNC machine tool can be divided into MRR component, spindle and feed-drive component, and standby and auxiliary component (Zhao et al., 2017; Li et al., 2017). The system boundary is expanded to include embodied energy of cutting tools and cutting fluids as done by Chen et al. (2021). The specific energy consumption (SEC) is often given by the following unit-process model:

$$SEC = P / MRR = C_0 + C_1 / MRR \quad (2)$$

The machine power, P , and the two machine-specific empirical coefficients, C_0 and C_1 , are defined in this equation. The result (2) is mentioned in many publications: the higher the MRR, the lower the energy consumption per unit volume of material removed as the fixed power of the machine is distributed over a shorter period of time. Therefore, the energy (total) ($E = \int P \, dt$), power and SEC are three different indicators, and optimizing one does not necessarily optimize the others (Li et al., 2017, Cai et al., 2016). Li et al. (2017) suggested the complementary measures of instantaneous energy efficiency, energy utilisation ratio and specific energy efficiency.

2.3 The quality–energy–productivity trade-off

It is not possible to optimize simultaneously the surface quality, energy efficiency and productivity because the three are generally mutually exclusive when selecting the three main parameters of feed, depth of cut and cutting speed. In milling, Zhao et al. (2018) showed this coupling between energy consumption characteristics and surface quality, and Xie, Zhou and Zheng (2018) developed a cooperative optimisation between minimum energy and high surface quality in turning. An appropriate solution is thus a compromise or the set of Pareto-optimal solutions and from amongst them, the process planner chooses based on priorities (Kumar, Bilga and Singh, 2017).

2.4 Design of experiments and optimisation methods

The Taguchi method employs orthogonal arrays to approximate the main effect of each factor while taking only a fraction of the number of runs necessary for full factorial design and transforms replicated responses into a signal-to-noise (S/N) ratio which is used to reward a favourable mean and a low variability (Ross, 1996). Both surface roughness and energy should be minimised and thus the form of the smaller is used:

$$S/N = -10 \log_{10} [(1/n) \sum y_i^2] \quad (3)$$

Where y_i are the n replicate measurements. ANOVA then splits the total variation into factor contributions and error to determine significance and percentage contribution. If the two or more responses are needed to be optimized and their individual optima are contradictory, all the responses need to be normalised first, then, the grey relational coefficients of each trial are calculated and the average values are obtained as grey relational grade (Deng, 1989) to optimize.

$$\xi_i(k) = (\Delta_{\min} + \zeta \Delta_{\max}) / (\Delta_i(k) + \zeta \Delta_{\max}), \quad \Gamma_i = (1/m) \sum_k \xi_i(k) \quad (4)$$

where $\Delta_i(k)$ is the deviation of normalised response k from its ideal value, ζ is the distinguishing coefficient (normally 0.5) and m is the number of responses. This Taguchi–ANOVA–GRA workflow has been applied by the authors' group to CNC milling (Mapindu et al., 2026b), and its transferability beyond metal cutting has been demonstrated for shrinkage and warpage in injection moulding (Mapindu et al., 2026a) and for the strength–print-time conflict in fused deposition modelling (Mapindu et al., 2026c). Related two-level orthogonal designs with regression modelling have been used to optimise vacuum bleaching in edible-oil refining (Jansen et al., 2025), underlining that the statistical logic of parameter optimisation is process-independent even though the physics is not. Where closed-form or statistical models are inadequate, response surface methodology, artificial neural networks (ANN) and metaheuristics such as NSGA-II are used to model non-linear responses and generate Pareto fronts (Yan and Li, 2013; Khan et al., 2019; Xie, Mei and Zhang, 2025).

Within the broader CAD/CAM chain, parameter optimisation at the CAM stage complements design optimisation at the CAD stage. In the design of a passive upper-limb exoskeleton, for instance, alternative geometries and materials were compared through finite-element simulation before prototype manufacture on 3D printers and CNC machines (Tandi et

al., 2025). Treating design choices and process choices as linked optimisation problems is a natural extension of the work reviewed here.

2.5 Development of the research field

The research emphasis has shifted from energy analysis of the machining process to the quality analysis of the surface to that of an integrated optimization of several desired responses. Sihag and Sangwan (2020) compiled a list of 226 research papers on energy consumption in machine-tools and categorized it into four major research streams namely classification, modelling, energy-saving strategies and energy efficiency assessment. The discussion was continued by Binali et al. (2022) for difficult-to-machine composites and superalloys where parametric optimisation is coupled with advanced lubri-cooling strategies. More recent work focussed on cutting-parameter optimisation within a broader sustainable-machining project that incorporates cooling strategies, tool-path planning and digital twins (Soori et al., 2024). The present study builds on these reviews and concentrates upon the optimisation of cutting parameters, treating surface quality and energy as two aspects of the same subject as opposed to productivity, quality and energy.

2.6 Objectives and Research Questions

The aim of the review is to systematically identify, appraise and synthesise research on cutting-parameter optimisation for improving surface quality and energy efficiency in CNC machining. Six objectives (O) were formulated, each paired with a research question (RQ):

Table 1: Review objectives and research questions.

Code	Research question
O1 / RQ1	What is the influence of cutting speed, feed rate and depth of cut on surface quality in CNC machining?
O2 / RQ2	What is the relationship between CNC cutting parameters and machining energy consumption (power, total energy and specific energy)?
O3 / RQ3	Which optimisation techniques have been used for CNC cutting-parameter optimisation, and what are their relative strengths and limitations?
O4 / RQ4	What trade-offs exist between surface quality, energy consumption and machining productivity?
O5 / RQ5	How do reported findings differ across CNC machining processes and workpiece materials?
O6 / RQ6	What limitations and research gaps exist in current research on energy-aware cutting-parameter optimisation?

3 REVIEW METHODOLOGY

3.1 Research design

A systematic literature review was adopted because it provides a transparent and reproducible process for searching, selecting, appraising and synthesising studies against predefined criteria (Snyder, 2019). The review was planned and reported in accordance with the PRISMA 2020 statement (Page et al., 2021).

3.2 Information sources and search strategy

Google Scholar, Web of Science and ScienceDirect were searched for English-language journal articles and peer-reviewed conference papers. Because several influential studies pre-date this window (for example Yan and Li, 2013; Camposeco-Negrete, 2013; Kant and Sangwan, 2014), backward citation searching of included studies and reviews was used to capture seminal earlier work. The Boolean string below was adapted to the syntax of each database and applied to titles, abstracts and keywords:

3.3 Eligibility criteria

Table 2: Inclusion and exclusion criteria.

Criterion	Inclusion	Exclusion
Process	CNC or machine-tool based material removal: turning, milling, drilling, honing, planing/routing	Non-conventional processes (EDM, laser, waterjet) unless used only for comparison
Variables	At least one of cutting speed/spindle speed, feed rate or depth of cut varied	Only tool design, coating or coolant varied at fixed cutting parameters
Responses	At least one surface-quality response and at least one energy or power response (or a review addressing both)	Only surface quality, or only energy, with no link between them
Analysis	Experimental, modelling or optimisation study with reported method	Opinion pieces, patents, trade literature
Publication	Peer-reviewed; English; Jan 2016 – Jun 2026 (earlier seminal work via citation searching)	Non-English; duplicates; full text unavailable

3.4 Study selection

Records were exported to a reference manager, duplicates removed, and titles and abstracts screened against Table 2.

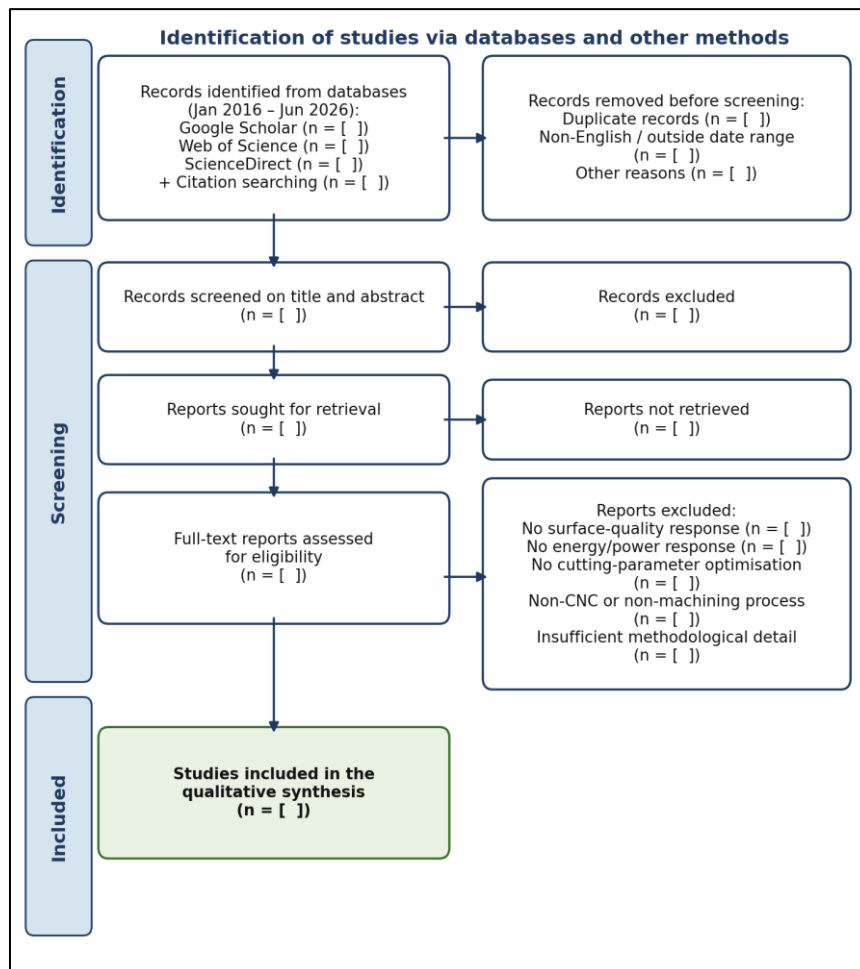


Figure 1: PRISMA 2020 flow diagram of the study selection process. Adapted from the PRISMA 2020 flow diagram template for new systematic reviews (Page et al., 2021).

3.5 Data extraction and quality appraisal

For each study a standard extraction form was completed capturing the following: machining process; workpiece and tool material; cooling condition; parameters and levels; surface, energy and productivity responses; experimental design; optimisation method; optimum reported; and whether a confirmation or validation experiment was conducted.

The methodological quality was evaluated on four aspects, namely, adequate experimental design (replication and randomisation), machine level measurement of energy rather than estimated, statistical testing of the significance of the factors and experimental verification of the expected optimum. The appraisal did not exclude studies, but was used to provide weight to the narrative synthesis.

3.6 Classification and taxonomy

Included studies were classified on five dimensions (Table 3), which also structure the synthesis in Section 5.

Table 3: Classification dimensions used in the review.

Dimension	Categories
Machining process	Turning; milling (face, end, plane, micro-milling); drilling/hole making; honing; wood planing and routing
Cutting parameters	Cutting/spindle speed; feed rate; depth of cut; other (width of cut, number of cutting edges, tool path)
Surface response	Arithmetic mean roughness Ra; areal roughness Sa; cutter/pitch-mark measures
Energy response	Instantaneous power; total energy; specific cutting energy (SEC); energy efficiency ratios
Optimisation method	Taguchi/ANOVA; grey relational analysis; TOPSIS; regression/RSM; ANN; metaheuristics (NSGA-II, PSO, WOA); physics-based models

4 RESULTS AND SYNTHESIS

4.1 Overview of the evidence base

Representative studies from the sets included are summarised in Table 4. The number of studies for milling and turning is higher than for other processes, such as wood machining, while hole making, honing and micro-milling are represented by fewer studies. The most common experimental studies based on Taguchi orthogonal arrays or full factorial designs with ANOVA, multi-response work is increasingly using Taguchi orthogonal arrays combined with GRA, TOPSIS, ANN surrogate models and NSGA-II. The reviewed studies showed that all the three major parameters of cutting speed, feed rate and depth of cut have an effect on CNC machining performance and these effects are not independent; that is the effect of each parameter on surface quality, energy and productivity changes with the process, workpiece material, tool condition and the levels of the other parameters. No one optimum combination of parameters.

Table 4: Summary of representative studies on the joint optimisation of surface quality with energy, productivity or tool wear.

Study	Process / material	Responses	Method	Principal finding
Camposeco-Negrete (2013)	Turning, AISI 6061-T6	Energy, Ra	Taguchi, ANOVA	Higher feed reduced energy but increased Ra
Kant and Sangwan (2014)	Turning	Power, Ra	Predictive model + optimisation	Feed most significant, then depth of cut, then speed
Kumar, Bilga and Singh (2017)	Rough turning	Energy responses, Ra, MRR	Taguchi, weighting methods, TOPSIS	Different weighting schemes gave different optima
Xie, Zhou and Zheng (2018)	Turning	Energy, energy efficiency, Ra, tool life	Cooperative optimisation	Minimum-energy and high-quality settings reconciled through joint formulation
Tayisepi et al. (2024b)	Dry turning, EN19 steel	Energy, Ra	Taguchi full factorial	Energy-efficient and low-roughness cutting conditions identified for dry turning
Hamdi et al. (2024)	CNC turning, polypropylene, MQL	Ra, temperature, SCE	Experimental design	SCE, Ra and temperature examined against cutting parameters and MQL condition

Yan and Li (2013)	Milling	Ra, MRR, cutting energy	Weighted GRA, RSM	Explicit energy–production–rate–quality trade-off
Khan et al. (2019)	Face milling, nanofluid SQCL	Energy, Ra	Taguchi L27, GRA, NSGA-II	Energy reduced by 20.7% versus optimisation on quality and productivity only
Pınarbaşı et al. (2020)	Dry CNC milling, Al-7075	Ra, current, energy	Taguchi, ANOVA	Feed dominated Ra; depth of cut dominated current draw
Jia et al. (2022)	CNC plane milling	Energy, time, Ra	NSGA-II	Efficiency +21.0%, energy –15.3%, Ra improved 5.5%
Feng et al. (2022a)	CNC machining	Energy, time, Ra	Systematic multi-objective method	Energy, time and Ra behave as competing objectives
Erçetin et al. (2023)	Micro-milling, Mg13Sn	Forces, Sa	Taguchi, ANOVA	Higher speed lowered forces and Sa; higher feed raised Sa
Xie, Mei and Zhang (2025)	CNC milling	Power, SCE	WOA-BP ANN, NSGA-II, entropy-TOPSIS	Power –12.33%, SCE –20.01% versus empirical settings
Mapindu et al. (2026b)	CNC milling, mild steel (dry)	Ra, flank wear VB	Taguchi L9, ANOVA, GRA	Feed 82.81% of Ra variation; speed 63.40% of VB; compromise 1000 rpm, 0.10 mm/rev, 0.5 mm
Feng et al. (2022b)	CNC hole machining	Energy	Tool-path parameter optimisation +	Integrating tool path with cutting parameters reduced energy
Tayisepi et al. (2024a)	Honing, cast-iron liner sleeves	Ra, power, energy	Taguchi L16, ANOVA	Speed and tool-path radius dominated Ra; separate optima for Ra, power and energy; validation error <10%
Tayisepi et al. (2023)	Planing, teak, saligna, pine	Total cutting energy, cutter marks	Taguchi L9, ANOVA, regression	Dominant factor and optimum differed by wood species
Çakıroğlu et al. (2022)	CNC machining, walnut and ash wood	Ra, energy, time	ANN	ANN models predicted optimum conditions for quality, energy and time
Bal et al. (2022)	CNC routing, fibreboard	Ra, energy	Experimental	Cutter parameters affected both roughness and energy

4.2 Influence of feed rate (RQ1, RQ2)

The feed rate was always found as the most significant parameter, for surface roughness, in turning and milling. The feed marks get larger with greater feed per tooth, and the roughness increases roughly in proportion to the square of the feed (Eq. 1) for conventional milling; in turning, the roughness goes up roughly in proportion to the square of the feed (Eq. 1). In Al-7075 dry CNC milling, the surface roughness is most affected by feed (Pınarbaşı et al., 2020) and in millerine CNC steel feed is the factor that accounts for most of the variance of the roughness S/N ratio (Mapindu et al., 2026b). In micro-milling, Erçetin et al. (2023) have noted that the roughness is degraded proportionally for each feed. The relationship is not strictly monotonic at the lower end of the range, however: as feed is decreased to lower and lower levels, the resulting improvement is not proportional: rubbing and minimum-chip-thickness effects become important at very low feeds (Abellán-Nebot et al., 2024). The energy effect of feed runs in reverse. Higher feed results in higher MRR and lower machining time, thus lower SEC (Eq. 2) as fixed power of the machine is utilized over a shorter time and total energy. This has been demonstrated directly by Camposeco-Negrete (2013) in turning and was found by Kant and Sangwan (2014) as the most important parameter in power as well as in roughness condition. Feed can also be optimized explicitly, such as optimizing the feed by considering machining allowance and a constraint on spindle power (Wu et al. 2021), and optimizing the feed based on the spindle power prediction with an ANN and a constant-power constraint (Xie et al. 2021) for three-axis rough milling. Feed is thus the focal point for the quality–energy dichotomy.

4.3 Influence of cutting speed (RQ1, RQ2)

The relationship between cutting speed and the responses are more complex and two-sided. In this material range, the higher the speed, the better the surface finish, because the speed will cause the material to be softened in the shear zone for the workpiece, which will reduce the cutting forces and suppress the formation of built-up edge. The authors believed that thermal softening was the reason for the reduction of the cutting forces and areal roughness values in the micro-milling of Mg13Sn alloy as the cutting speed increased. The spindle speed was the most significant factor influencing the surface roughness, alongside tool-path radius, in honing of cast-iron liner sleeves (Tayisepe et al., 2024a). Similarly, in CNC plane milling, spindle speed was observed to exert influence on both energy consumption and surface quality and feed and cutting width were observed to exert influence on material-removal power, according to Jia et al. (2022).

The improvement has restrictions. Fast cutting speeds increase cutting temperature, cause flank wear and may lead to chip adhesion, whereas a worn tool will require more power and will create a rougher surface. For the CNC milling of mild steel, the speed that caused the minimum roughness (2000 rpm) that caused the maximum tool wear (Mapindu et al., 2026b). From an energy perspective, spindle speed will have the same effect on instantaneous power, but could reduce the time required for the process; overall energy will depend on how other factors affect the process, not just on power. To solve this issue, Ma et al. (2017) built a model of the material cutting energy and proposed an energy consumption optimization solution for CNC milling. The cutting speed should, therefore, be optimised, in conjunction with roughness and tool wear, rather than with reference to minimum power, on the basis of total energy or SEC.

4.4 Influence of depth of cut (RQ1, RQ2)

The major impact of depth of cut is on the quantity of material removed per pass and hence on MRR, cutting force and power demand. It is usually not as influential as feed and speed on surface roughness. For CNC milling of Al-7075, by cutting depth, cut roughness had a relatively small effect, and the most significant one was the current draw, as concluded by Pınarbaşı et al. (2020); and for dry honing, the depth of cut had no significant effect on cut roughness ($p = 0.740$), but the significant one was the power and energy as concluded by Tayisepe et al. (2024a). Although depth of cut was not statistically significant for both roughness and tool wear in the CNC milling of mild steel, it was found to be a statistically significant secondary factor for both parameters that improved with the lowest depth (Mapindu et al., 2026b). The effect of the cutting parameters on the roughness variations is quite variable according to the different machining conditions, tool geometry and workpiece material, as Abellán-Nebot et al. (2024) noted.

When it comes to energy, more instantaneous power doesn't necessarily mean more total energy, as a deeper cut can be accomplished in fewer passes. It is indeed the largest depth of cut tested (0.100 mm) coupled with the lowest spindle speed (Tayisepe et al., 2024a) that will give optimum energy in honing. Hamdi et al. (2024) studied the effect of specific cutting energy in CNC turning of polypropylene along with feed and minimum-quantity-lubrication conditions. For wood planing, the dominant factor was the depth of cut for total cutting energy for saligna and pine, but not for teak (Tayisepe et al., 2023). Therefore depth of cut should be assessed by more than one energy indicator, and optimised with the other parameters, simultaneously, rather than alone.

4.5 Trade-offs between surface quality, energy and productivity (RQ4)

It's concluded from the reviewed studies that optimizing one parameter or one response in isolation will result in an undesirable result for another response. The war shows up in three different shapes and sizes. The war comes up in particular shapes and sizes. The first is that as feed and depth of cut increases, productivity increases and SEC decreases, but roughness and cutting load increases. Second, speed better reduces roughness but at the same time means more power and greater tool wear, as in the case of milling, where the optimal spindle speed for a specific range of roughness was at one end, and the optimal spindle speed for tool wear was at the other (Mapindu et al., 2026b). Third, in a single process, there is often an optimum for energy, power, and roughness, as demonstrated in honing, where the minimum energy, power and roughness optima are 125 rpm, 0.025 mm and 310 rpm respectively (Tayisepe et al., 2024a).

When the conflict is explicitly discussed in studies, significant achievements are reported. In addition to the reduction of energy due to surface quality and productivity, Khan et al. (2019) achieved a 20.7% reduction in energy, and Jia et al. (2022) achieved a 21.0% increase in processing efficiency, 15.3% reduction in energy and 5.5% reduction in roughness. Feng et al. (2022a) modelled energy, machining time and roughness together and found that they are competing objectives; Feng et al. (2022b) demonstrated that the combination of tool-path planning and parameter selection further reduces the hole machining time. However Kumar, Bilga and Singh (2017) warn that the compromise optimum will depend on the weighting of the responses, which must be based on the actual priorities of the manufacturer.

4.6 Optimisation techniques (RQ3)

A comparison of the major families of techniques is provided in Table 5. Most traditional statistical techniques (Taguchi, ANOVA, response surface methodology) have been used due to their experimental economy and transparency.

Pınarbaşı et al. (2020) employed Taguchi method for selecting optimal cutting conditions for roughness and cutting energy while in the milling, honing and wood studies authors group used Taguchi arrays with ANOVA (Tayisepi et al., 2023; Tayisepi et al., 2024a; Mapindu et al., 2026b). The major disadvantage they have is that the single-response S/N optimum could be out of the tested runs, and could even be conflicting between the responses, hence why GRA or TOPSIS is often appended (Kumar, Bilga and Singh, 2017; Mapindu et al., 2026b). Other research in recent years have used ANN and metaheuristic methods to deal with non-linear relationships and multiple goals, such as that of Çakıroğlu et al. (2022) who developed ANN models to surface quality, energy and time in CNC wood machining, with the energy consumption reduced by 12.33% and SEC by 20.01% with respect to the empirical values, compared to the values obtained with whale-optimisation-tuned back-propagation network combined with NSGA-II and entropy-weighted TOPSIS, developed by Xie, Mei and Zhang (2025) for CNC wood machining. Li et al. (2019) presented a complete energy-optimised approach for CNC milling, which integrates energy modelling with multi-objective search.

Table 5: Comparison of optimisation techniques used in the reviewed studies.

Technique	Strengths	Limitations	Examples
Taguchi OA, S/N, ANOVA	Few runs; robust to noise; ranks factors; easy to apply on the shop floor	Main effects only in saturated arrays; single response; optimum may be an untested extrapolation	Camposeco-Negrete (2013); Pınarbaşı et al. (2020); Tayisepi et al. (2023, 2024a)
GRA / TOPSIS	Converts multiple responses to one index; simple	Result sensitive to normalisation and weights	Yan and Li (2013); Kumar, Bilga and Singh (2017); Mapindu et al. (2026b)
Regression / RSM	Explicit models; captures curvature and interactions	More runs; limited extrapolation	Yan and Li (2013); Tayisepi et al. (2023)
ANN / machine learning	Captures strong non-linearity; can use process signals	Data-hungry; less interpretable; overfitting risk	Lin et al. (2020); Xie et al. (2021); Çakıroğlu et al. (2022)
Metaheuristics (NSGA-II, PSO, WOA)	Generates Pareto fronts; handles constraints	Needs a surrogate or analytical model; parameter tuning	Khan et al. (2019); Jia et al. (2022); Xie, Mei and Zhang (2025)
Physics-based force/power models	Physically meaningful constraints (power, force)	Calibration effort; machine-specific	Ma et al. (2017); Wu et al. (2021)

4.7 Findings across processes and materials (RQ5)

The overall trends of the parameters are similar for all the processes, but the magnitude and order vary significantly with the process and workpiece. Feed is the dominant factor in the case of metal turning and milling while depth of cut is the dominant factor in the case of the roughness in the process (Kant and Sangwan, 2014; Pınarbaşı et al., 2020). For honing, a process in which material removal is abrasive and small, spindle speed and tool-path geometry plays a more dominant role in roughness than the depth of cut does, which accounts for energy (Tayisepi et al., 2024a). For teak, saligna and pine, the most important factor and the best value of the parameters were different on the same planer (Tayisepi et al., 2023), and similar variability with respect to cutters was shown for fibreboard (Bal et al., 2022), and for walnut and ash (Çakıroğlu et al., 2022). Some materials like polymers introduce thermal sensitivity in the energy–quality relationship (Hamdi et al., 2024), while other materials like Inconel 718, SiC-reinforced aluminium composites and other superalloys include tool wear and cooling strategy as first-order variables (Bhushan, 2013; Khanna et al., 2020; Binali et al., 2022). The results address an explicit statement that was reported by various primary studies: that optimum parameters, and percentage contributions, cannot be moved between materials, tools or cooling conditions without re-validation (Mapindu et al., 2026b; Mapindu et al., 2026c).

5 DISCUSSION

5.1 Answering the research questions

RQ1 and RQ2. In turning and milling, the feed rate is the most significant factor affecting surface roughness, while cutting speed, within a limited range, will affect surface roughness by improving it; and depth of cut will have more influence on the power, force and MRR. The bottom line to remember for energy is that while increasing MRR typically increases power, it also decreases total energy and SEC, and that minimum-power settings are not necessarily minimum-energy

settings (Kara and Li, 2011; Li et al., 2017). RQ3. The use of Taguchi-ANOVA designs is still the most common, being subsequently expanded to GRA (compromise solutions) and ANN surrogates (Pareto optimisation) using NSGA-II or other methods. RQ4. The tradeoff is structural not incidental and explicit treatment in a multi-objective fashion resulted in energy savings of around 12-21% in the studies that quantified them (Khan et al., 2019; Jia et al., 2022; Xie, Mei and Zhang, 2025). RQ5. Direction of effects is generally consistent but there are variations in rank and magnitude depending on process and material. In Section 7, the query “RQ6” is discussed.

5.2 A conceptual framework for energy-aware parameter optimisation

Figure 2 is a conceptual framework that summarises the synthesis. The controllable inputs affect the CNC process and the energy state of the machine tool in three sets of responses: surface quality, energy and productivity/tool condition. These conflicting responses result in not one but a set of compromises, called a Pareto set, as a result of the optimisation process. An Industry 4.0 feedback loop optimises the optimum, as the tool ages and conditions vary, and five complementary families of methods are used for the optimisation layer.

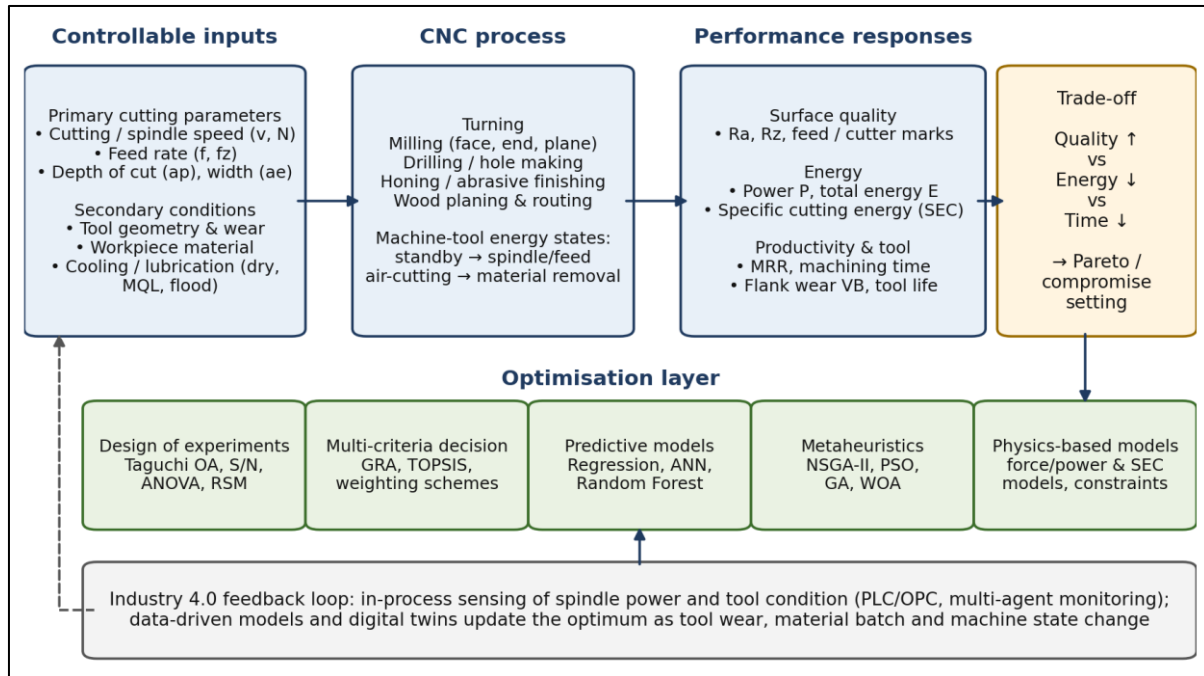


Figure 2: Conceptual framework for cutting-parameter optimisation for surface quality and energy efficiency (developed by the authors from the reviewed literature).

5.3 Implications for practice in resource-constrained manufacturing

The results have significant implications for manufacturers with poor and expensive electric power supply. If boiler reliability at the dominant thermal station is undermined and outages are common (Senda et al., 2026) and if decentralised renewable generation (e.g. roadside vertical-axis wind turbines) is at prototype level (Muyambo et al., 2025), then the machine tool is the most immediate demand side lever.

In this context, Taguchi-based optimisation is ideal, because it necessitates a relatively small number of runs, and requires modest instruments including a three-phase power meter, a portable roughness tester and toolmaker's microscope; the studies of honing, wood-planing and milling were carried out using the above instruments in Zimbabwean workshops and laboratories (Tayisepi et al., 2023; Tayisepi et al., 2024a; Mapindu et al., 2026b). But technique isn't the only factor in adoption. According to a survey of the manufacturing companies in Zimbabwe, the widespread presence of sensors, PLCs and computers is not well connected and the key challenges include the lack of an Industry 4.0 strategy and the high costs of the solutions (Muhla et al., 2025a).

These firms require more flexibility to compete with imports but NBTs and rapid-prototyping are scarce (Muhla et al., 2023). A multi-agent self-diagnostic system using OPC server and JADE agents and a PLC offers a practical solution: a spindle power and tool condition monitoring system based on sensors, PLC, and agents has been validated for real-time condition monitoring of induction furnace equipment in a Zimbabwean plant (Mashava et al., 2026) and this sensor-PLC-agent pattern can be reused to log spindle power and tool condition on CNC machines, providing the data for training ANN and Random Forest models (Senda et al., 2026).

Economical machining is also critical for product-development projects: the aluminium 6061-T6 frame of the dual-mode smart wheelchair makes the device accessible for Zimbabwean users while keeping costs down (Munotyaani et al., 2026), an application where energy and quality-aware parameter selection are most important. Last, but not least, the human factor cannot be overlooked. Cognitive overload and insufficient training and management support are reported as persistent issues in human factors research of manufacturing processes in Zimbabwean industries (Muhla et al., 2025b), while parameters are often determined in local plants via trial and error or a catalogue. Optimised settings should thus be fed in as simple validated parameter sets or decision support interfaces, centered on the operator. Learning factories offer a suitable setting for students and practitioners to try out such optimisation using real equipment and a mechanism for extending learning factories across Southern Africa has recently been suggested (Ndiyamba et al., 2026).

5.4 Research Gaps and Future Directions

The review identified the following gaps (RQ6):

1. **Inconsistent energy indicators.** Studies report power, total energy, current or SEC, often without standardised measurement boundaries, which prevents meta-analysis. Future work should report SEC together with machine-level total energy and state the system boundary explicitly (Li et al., 2017; Chen et al., 2021).
2. **Tool wear and embodied energy are under-represented.** Few studies include tool wear, tool life or the embodied energy of tools and cutting fluids alongside surface quality and machine energy, even though speed-driven wear can overturn a roughness-optimal setting (Chen et al., 2021; Mapindu et al., 2026b).
3. **Static rather than adaptive optimisation.** Most optima are determined offline for new tools. In-process adaptive optimisation that uses spindle-power and condition signals to update settings as the tool wears remains rare (Xie et al., 2021; Mashava et al., 2026).
4. **Interactions and extrapolation.** Saturated orthogonal arrays cannot estimate interactions, and predicted optima frequently lie outside the tested runs. Larger arrays (L18, L27), response surface designs and mandatory confirmation experiments are needed (Mapindu et al., 2026a; Mapindu et al., 2026b; Mapindu et al., 2026d).
5. **Limited industrial validation.** Much of the evidence comes from laboratory machines, single tool–material pairs and short tests. Validation on production machines and over realistic batch sizes is required.
6. **Integration with process planning.** Parameter selection is seldom optimised together with tool-path strategy, allowance distribution and scheduling, although integrated approaches show additional savings (Wu et al., 2021; Feng et al., 2022b).
7. **Evidence from developing economies.** Studies from sub-Saharan Africa are scarce, and the influence of unreliable supply, older machine tools and local materials (for example indigenous hardwoods) on optimal settings is largely unexplored (Tayisepe et al., 2023; Muhla et al., 2025a).
8. **Explainable and transferable models.** Machine-learning models achieve high accuracy but are rarely interpretable or transferable across machines; hybrid physics-informed and explainable models, embedded in digital twins, are a promising direction (Soori et al., 2024).

5.5 Limitations of the Review

The review only included English-language publications from three databases; other databases or articles in different languages may have included relevant studies. The synthesis is narrative due to the heterogeneity of processes, materials, energy indicators and experimental designs. Optimisation results for positive outcomes are likely to be published. Lastly, several studies included were written by members of the authors' research group, and these were also evaluated for inclusion and evaluated in the same way as all other studies.

6 CONCLUSIONS

This systematic review is the first to combine research on the optimisation of cutting parameters for surface quality and energy efficiency in CNC machining. Feed rate is the most important control of surface roughness, depth of cut is the main control of power and material removal and cutting speed can improve finish within some limits, while increasing power and tool wear. In general, minimum-power and minimum-energy are not the same, and energy should not be considered as power, but as specific energy or total energy. The quality–energy–productivity trade-off is structural and the desired result of optimisation will be a compromise or Pareto set, depending on the manufacturer's preferences. Methodologically, the field has evolved from single-response Taguchi–ANOVA studies to integrated methods using designed experiments, grey relational analysis or TOPSIS, machine-learning surrogates and Pareto-based metaheuristics, and this approach has reported a reduction in energy consumption of just 12–21% without reducing surface quality. Future research should focus on establishing a standard for energy reporting, incorporate tool wear and embodied energy, shift from offline to adaptive in-process optimisation, test the results on production machines and

finally gather data from manufacturing economies of limited resources where the value of low-cost, energy-conscious parameter optimisation may be most significant.

STATEMENTS ON COMPLIANCE WITH ETHICAL STANDARDS

Acknowledgments

We acknowledge the Department of Industrial and Manufacturing Engineering Department of the National university of Science and Technology.

Disclosure of conflict of interest

The authors declare no conflict of interest.

REFERENCES

- [1] Abellán-Nebot, J.V., Vila Pastor, C. and Siller, H.R. (2024) 'A review of the factors influencing surface roughness in machining and their impact on sustainability', *Sustainability*, 16(5), 1917. Available at: <https://doi.org/10.3390/su16051917>
- [2] Bal, B.C., Mengeloğlu, F., Akçakaya, E. and Gündeş, Z. (2022) 'Effects of cutter parameters on surface roughness of fibreboard and energy consumption of CNC machine', *Kastamonu Üniversitesi Orman Fakültesi Dergisi*, 22(3), pp. 264–272. Available at: <https://doi.org/10.17475/kastorman.1215347>
- [3] Bhushan, R.K. (2013) 'Optimization of cutting parameters for minimizing power consumption and maximizing tool life during machining of Al alloy SiC particle composites', *Journal of Cleaner Production*, 39, pp. 242–254. Available at: <https://doi.org/10.1016/j.jclepro.2012.08.008>
- [4] Binali, R., Patange, A.D., Kuntoğlu, M., Mikolajczyk, T. and Salur, E. (2022) 'Energy saving by parametric optimization and advanced lubri-cooling techniques in the machining of composites and superalloys: a systematic review', *Energies*, 15(21), 8313. Available at: <https://doi.org/10.3390/en15218313>
- [5] Cai, W., Liu, F., Zhou, X.N. and Xie, J. (2016) 'Fine energy consumption allowance of workpieces in the mechanical manufacturing industry', *Energy*, 114, pp. 623–633. Available at: <https://doi.org/10.1016/j.energy.2016.08.028>
- [6] Çakıroğlu, E.O., Demir, A., Aydın, İ. and Büyüksarı, Ü. (2022) 'Prediction of optimum CNC cutting conditions using artificial neural network models for the best wood surface quality, low energy consumption, and time savings', *BioResources*, 17(2), pp. 2501–2524. Available at: <https://doi.org/10.15376/biores.17.2.2501-2524>
- [7] Camposeco-Negrete, C. (2013) 'Optimization of cutting parameters for minimizing energy consumption in turning of AISI 6061 T6 using Taguchi methodology and ANOVA', *Journal of Cleaner Production*, 53, pp. 195–203. Available at: <https://doi.org/10.1016/j.jclepro.2013.03.049>
- [8] Chen, X., Li, C., Tang, Y., Li, L. and Li, H. (2021) 'Energy efficient cutting parameter optimization', *Frontiers of Mechanical Engineering*, 16(2), pp. 221–248. Available at: <https://doi.org/10.1007/s11465-020-0627-x>
- [9] Deng, J.L. (1989) 'Introduction to grey system theory', *The Journal of Grey System*, 1(1), pp. 1–24.
- [10] Erçetin, A., Aslantaş, K., Özgün, Ö., Perçin, M. and Chandrashekarappa, M.P.G. (2023) 'Optimization of machining parameters to minimize cutting forces and surface roughness in micro-milling of Mg13Sn alloy', *Micromachines*, 14(8), 1590. Available at: <https://doi.org/10.3390/mi14081590>
- [11] Feng, C., Guo, H., Zhang, J., Huang, Y. and Huang, S. (2022a) 'A systematic method of optimization of machining parameters considering energy consumption, machining time, and surface roughness with experimental analysis', *The International Journal of Advanced Manufacturing Technology*, 119, pp. 7383–7401. Available at: <https://doi.org/10.1007/s00170-022-08772-6>
- [12] Feng, C., Chen, X., Zhang, J., Huang, Y. and Qu, Z. (2022b) 'Minimizing the energy consumption of hole machining integrating the optimization of tool path and cutting parameters on CNC machines', *The International Journal of Advanced Manufacturing Technology*, 121. Available at: <https://doi.org/10.1007/s00170-022-09343-5>
- [13] Hamdi, A., Yapan, Y.F., Uysal, A. and Merghache, S.M. (2024) 'Investigation of MQL and CNC turning parameters on the machinability of unreinforced polypropylene: study of surface roughness, temperature, and specific cutting energy', *The International Journal of Advanced Manufacturing Technology*, 130, pp. 717–730. Available at: <https://doi.org/10.1007/s00170-023-12761-8>

- [14] Jansen, K.C., Mapindu, I., Muhla, T.M., Kanyemba, G. and Mashava, D. (2025) 'Optimization of edible oil quality through vacuum bleaching: an experimental design and analysis study', *Open Access Research Journal of Science and Technology*, 13(2), pp. 68–78. Available at: <https://doi.org/10.53022/oarjst.2025.13.2.0051>
- [15] Jia, S., Wang, S., Zhang, N., Cai, W., Liu, Y., Hao, J., Zhang, Z., Yang, Y. and Sui, Y. (2022) 'Multi-objective parameter optimization of CNC plane milling for sustainable manufacturing', *Environmental Science and Pollution Research*. Available at: <https://doi.org/10.1007/s11356-022-24908-3>
- [16] Kant, G. and Sangwan, K.S. (2014) 'Prediction and optimization of machining parameters for minimizing power consumption and surface roughness in machining', *Journal of Cleaner Production*, 83, pp. 151–164. Available at: <https://doi.org/10.1016/j.jclepro.2014.07.073>
- [17] Kara, S. and Li, W. (2011) 'Unit process energy consumption models for material removal processes', *CIRP Annals*, 60(1), pp. 37–40. Available at: <https://doi.org/10.1016/j.cirp.2011.03.018>
- [18] Khan, A.M., Jamil, M., Salonitis, K., Sarfraz, S., Zhao, W., He, N., Mia, M. and Zhao, G. (2019) 'Multi-objective optimization of energy consumption and surface quality in nanofluid SQCL assisted face milling', *Energies*, 12(4), 710. Available at: <https://doi.org/10.3390/en12040710>
- [19] Khanna, N., Agrawal, C., Dogra, M. and Pruncu, C.I. (2020) 'Evaluation of tool wear, energy consumption, and surface roughness during turning of Inconel 718 using sustainable machining technique', *Journal of Materials Research and Technology*, 9(3), pp. 5794–5804.
- [20] Kumar, R., Bilga, P.S. and Singh, S. (2017) 'Multi objective optimization using different methods of assigning weights to energy consumption responses, surface roughness and material removal rate during rough turning operation', *Journal of Cleaner Production*, 164, pp. 45–57. Available at: <https://doi.org/10.1016/j.jclepro.2017.06.077>
- [21] Li, C., Li, L., Tang, Y., Zhu, Y. and Li, L. (2019) 'A comprehensive approach to parameters optimization of energy-aware CNC milling', *Journal of Intelligent Manufacturing*, 30(1), pp. 123–138. Available at: <https://doi.org/10.1007/s10845-016-1233-y>
- [22] Li, L., Li, C., Tang, Y. and Yi, Q. (2017) 'Influence factors and operational strategies for energy efficiency improvement of CNC machining', *Journal of Cleaner Production*, 161, pp. 220–238. Available at: <https://doi.org/10.1016/j.jclepro.2017.05.084>
- [23] Lin, Y.-C., Wu, K.-D., Shih, W.-C., Hsu, P.-K. and Hung, J.-P. (2020) 'Prediction of surface roughness based on cutting parameters and machining vibration in end milling using regression method and artificial neural network', *Applied Sciences*, 10(11), 3941. Available at: <https://doi.org/10.3390/app10113941>
- [24] Ma, F., Zhang, H., Cao, H. and Hon, K.K.B. (2017) 'An energy consumption optimization strategy for CNC milling', *The International Journal of Advanced Manufacturing Technology*, 90, pp. 1715–1726. Available at: <https://doi.org/10.1007/s00170-016-9497-0>
- [25] Mapindu, I., Foya, A., Muhla, T.M., Chinguwo, K.N. and Kanyemba, G. (2026a) 'Minimizing defects in injection molding using the Taguchi method', *World Journal of Advanced Engineering Technology and Sciences*, 20(2), pp. 240–252. Available at: <https://doi.org/10.30574/wjaets.2026.20.2.0419>
- [26] Mapindu, I., Munhuwamambo, G., Mashava, D. and Ngwenya, L. (2026b) 'Optimization of cutting parameters in CNC milling using the Taguchi method', *Global Journal of Engineering and Technology Advances*, 28(2), pp. 149–162. Available at: <https://doi.org/10.30574/gjeta.2026.28.2.0223>
- [27] Mapindu, I., Muhla, T.M., Chinguwo, K.N. and Foya, A. (2026c) 'Process parameter optimization for 3D printing using the Taguchi method', *Open Access Research Journal of Science and Technology*, 18(1), pp. 34–45. Available at: <https://doi.org/10.53022/oarjst.2026.18.1.0082>
- [28] Mapindu, I., Mashava D., Shangwa, V., Chigavazira-Gwara, T.T., Munhuwamambo, G (2026d) 'Taguchi-based optimization of GMAW welding parameters for joint strength', *World Journal of Advanced Engineering Technology and Sciences*, 20(3), pp. 206–219. Available at: <https://doi.org/10.30574/wjaets.2026.20.3.0448>
- [29] Mashava, D., Muhla, T.M., Munhuwamambo, G., Mapindu, I., Chinguwo, K.N. and Wachenuka, T. (2026) 'A multi-agent system framework for real-time self-diagnostic condition monitoring of induction furnace equipment in developing industrial economies', *Open Access Research Journal of Science and Technology*, 17(2), pp. 28–43. Available at: <https://doi.org/10.53022/oarjst.2026.17.2.0071>
- [30] Moayyedean, M., Mohajer, A., Kazemian, M.G., Mamedov, A. and Derakhshandeh, J.F. (2020) 'Surface roughness analysis in milling machining using design of experiment', *SN Applied Sciences*, 2(10), 1698. Available at: <https://doi.org/10.1007/s42452-020-03485-5>

- [31] Moradnashad, M. and Unver, H.O. (2017) 'Energy efficiency of machining operations: a review', *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture*, 231(11), pp. 1871–1889. Available at: <https://doi.org/10.1177/0954405415619345>
- [32] Muhla, T., Mapindu, I., Munyau, M., Mashava, D., Mhlanga, S. and Goriwondo, W. (2023) 'Agility as a strategy in Zimbabwean manufacturing industries', *Zimbabwe Journal of Science & Technology*, 18, pp. 1–11. Available at: <https://www.ajol.info/index.php/zjst/article/view/271920>
- [33] Muhla, T.M., Mashava, D., Kanyemba, G., Mapindu, I. and Goriwondo, W.M. (2025a) 'An assessment of the implementation of Industry 4.0 in Zimbabwean manufacturing industries', *World Journal of Advanced Engineering Technology and Sciences*, 15(2), pp. 970–984. Available at: <https://doi.org/10.30574/wjaets.2025.15.2.0653>
- [34] Muhla, T., Kanyemba, G., Mapindu, I., Chinguwo, N., Mashava, D. and Goriwondo, W. (2025b) 'Enhancing safety in Zimbabwean manufacturing industry: the role of human factors engineering in reducing workplace accidents', *Open Access Research Journal of Science and Technology*, 13(2), pp. 19–30. Available at: <https://doi.org/10.53022/oarjst.2025.13.2.0037>
- [35] Munotyaaani, S., Bawono, N.M.H., Tayisepi, N., Mapindu, I., Anggoro, P.W., Bawono, B., Pamosoaji, A.K. and Adi, A.Y.N.M.P. (2026) 'Design and development of a dual-mode smart wheelchair prototype with obstacle detection for Zimbabwe', *Jurnal Rekayasa Mesin*, 21(1), pp. 51–66. Available at: <https://doi.org/10.32497/jrm.v21i1.6954>
- [36] Muyambo, R.D., Muhla, T., Kanyemba, G., Mashava, D., Munhuwamambo, G. and Mapindu, I. (2025) 'Design and development of a vertical axis wind turbine for slip stream energy harvesting', *Global Journal of Engineering and Technology Advances*, 23(3), pp. 10–20. Available at: <https://doi.org/10.30574/gjeta.2025.23.3.0166>
- [37] Ndiyamba, D., Murena, E., Kasukusa, S., Mafuratidze, F., Nenzhelele, T., Mpofu, K. and Mapindu, I. (2026) 'Learning factories as a catalyst for innovation in Southern African engineering education', in *CLF 2026 Book of Short Papers on Learning Factories: Proceedings of the 16th Conference on Learning Factories*, Bolzano, Italy, 5–7 May 2026. Bolzano: Free University of Bozen-Bolzano, pp. 93–99. Available at: <https://doi.org/10.5281/zenodo.20780648>
- [38] Page, M.J., McKenzie, J.E., Bossuyt, P.M., Boutron, I., Hoffmann, T.C., Mulrow, C.D. et al. (2021) 'The PRISMA 2020 statement: an updated guideline for reporting systematic reviews', *BMJ*, 372, n71. Available at: <https://doi.org/10.1136/bmj.n71>
- [39] Pınarbaşı, A., Külekçi, M.K., Boğa, C. and Eşme, U. (2020) 'Optimization of the effect of processing parameters on surface roughness and cutting energy in CNC milling of Al-7075 material', *Çukurova Üniversitesi Mühendislik-Mimarlık Fakültesi Dergisi*, 35(2), pp. 345–356. Available at: <https://doi.org/10.21605/cukurovaummfd.792420>
- [40] Ross, P.J. (1996) *Taguchi techniques for quality engineering*. 2nd edn. New York: McGraw-Hill.
- [41] Senda, S., Muhla, T.M., Mapindu, I., Ngwenya, L., Mushangure, R.O. and Mashava, D. (2026) 'Machine learning enabled preventive maintenance strategy for improving boiler reliability of a thermal power station', *Open Access Research Journal of Science and Technology*, 17(2), pp. 18–27. Available at: <https://doi.org/10.53022/oarjst.2026.17.2.0070>
- [42] Sihag, N. and Sangwan, K.S. (2020) 'A systematic literature review on machine tool energy consumption', *Journal of Cleaner Production*, 275, 123125. Available at: <https://doi.org/10.1016/j.jclepro.2020.123125>
- [43] Snyder, H. (2019) 'Literature review as a research methodology: an overview and guidelines', *Journal of Business Research*, 104, pp. 333–339. Available at: <https://doi.org/10.1016/j.jbusres.2019.07.039>
- [44] Soori, M., Karimi Ghaleh Jough, F., Dastres, R. and Arezoo, B. (2024) 'Sustainable CNC machining operations, a review', *Sustainable Operations and Computers*, 5, pp. 73–87. Available at: <https://doi.org/10.1016/j.susoc.2024.01.001>
- [45] Tandi, O., Mapindu, I., Muhla, T.M., Chinguwo, N.K. and Tayisepi, N. (2025) 'Design and analysis of a passive upper limb exoskeleton for augmented construction worker strength', *Open Access Research Journal of Science and Technology*, 13(2), pp. 79–88. Available at: <https://doi.org/10.53022/oarjst.2025.13.2.0050>
- [46] Tayisepi, N., Mugwagwa, L., Mnkandla, A.N., Mapindu, I. and Muhla, T.M. (2024a) 'Experimental investigation and simultaneous optimisation of honing parameters of dry cast iron cylinder relining sleeves of motor vehicle engine blocks for surface finish and energy use', *Computational Engineering and Physical Modeling*, 7(4), pp. 88–103. Available at: <https://doi.org/10.22115/cepm.2024.473138.1324>
- [47] Tayisepi, N., Mnkandla, A.N., Tigere, G., Gwatidzo, O., Mutenhabundo, W., Ndala, E. and Wagoneka, L.M. (2024b) 'Taguchi full factorial design of experiments optimisation of cutting parameters for energy efficiency and surface roughness during the dry turning of EN19 material', *World Journal of Engineering and Technology*, 12(2), pp. 438–454. Available at: <https://doi.org/10.4236/wjet.2024.122028>

- [48] Tayisepi, N., Svosve, R., Tigere, G., Mnkandla, A.N. and Mapindu, I. (2023) 'Comparative optimisation of the cutting parameters for surface quality and energy efficiency during the machining manufacturing of teak, saligna and pine wood materials', *Journal of Engineering Research and Reports*, 25(11), pp. 73–87. Available at: <https://doi.org/10.9734/JERR/2023/v25i1111023>
- [49] Wu, B., Zhang, Y., Liu, G. and Zhang, Y. (2021) 'Feedrate optimization method based on machining allowance optimization and constant power constraint', *The International Journal of Advanced Manufacturing Technology*, 115, pp. 3345–3360. Available at: <https://doi.org/10.1007/s00170-021-07381-z>
- [50] Xie, J., Zhao, P., Hu, P., Yin, Y., Zhou, H., Chen, J. and Yang, J. (2021) 'Multi-objective feed rate optimization of three-axis rough milling based on artificial neural network', *The International Journal of Advanced Manufacturing Technology*, 114, pp. 1323–1339. Available at: <https://doi.org/10.1007/s00170-021-06902-0>
- [51] Xie, N., Zhou, J. and Zheng, B. (2018) 'Selection of optimum turning parameters based on cooperative optimization of minimum energy consumption and high surface quality', *Procedia CIRP*, 72, pp. 1469–1474. Available at: <https://doi.org/10.1016/j.procir.2018.03.099>
- [52] Xie, Y., Mei, S. and Zhang, C. (2025) 'Optimisation decision of machining process parameters considering milling energy consumption and specific cutting energy', *Alexandria Engineering Journal*, 128, pp. 786–795.
- [53] Yan, J. and Li, L. (2013) 'Multi-objective optimization of milling parameters – the trade-offs between energy, production rate and cutting quality', *Journal of Cleaner Production*, 52, pp. 462–471. Available at: <https://doi.org/10.1016/j.jclepro.2013.02.030>
- [54] Zhao, G.Y., Liu, Z.Y., He, Y., Cao, H.J. and Guo, Y.B. (2017) 'Energy consumption in machining: classification, prediction, and reduction strategy', *Energy*, 133, pp. 142–157. Available at: <https://doi.org/10.1016/j.energy.2017.05.110>
- [55] Zhao, G., Guo, Y., Zhu, P. and Zhao, Y. (2018) 'Energy consumption characteristics and influence on surface quality in milling', *Procedia CIRP*, 71, pp. 111–115. Available at: <https://doi.org/10.1016/j.procir.2018.05.081>