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A contemporary advancement of intelligent machining and sustainability aspects in hard machining area: A Critical Review

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Abstract. The intelligent manufacturing devotes considerable effort to towards machining process. This phenomenon is engendered by the growing demand for advanced machining process for manufacturing of precise parts by adopting optimization techniques. This article illustrates the most significant developments in the sustainability aspects as well as optimization and modelling techniques adopted to solve the problems and complexity in hard machining process. Machining realisation necessitates recent and future breakthroughs in technological innovations for Industry 4.0. A significant amount of focus is also paid to the different sustainability aspects, modelling strategies and performance analysis during hard machining process. Many avenues for future study on the needs of intelligent manufacturing are discussed in this article. The future directions for intelligent machine systems and sustainability factors are also discussed for the green, sustainable, and high dimensional accuracy manufacturing in hard machining area.

Keyword: Hard machining; intelligent machining; sustainability; optimization; modelling

1. Introduction

In accordance with the Sustainable Development Goals of the United Nations, by 2030 the member nations need to have made significant attempts to update their businesses and get them additional sustainable using clean technology and environmentally responsive procedures. As one of the most widely used manufacturing processes for producing components across a range of industries, machining requires a paradigm shift in order to become more sustainable and effective [1].

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This shift requires input from all sector stakeholders, including those in industry and academia. Sustainable machining requires nontoxic oils and cryogenic coolants instead of synthetic oil-based emulsion Additionally, it is preferable to use cooling and lubrication techniques that, over time, use less energy overall (rather than just considering the cost of initial implementation) [2]. This comprises the power needed to create vast quantities of metalworking fluid, to cut the material, and to start the supply system, which includes pumps and air compressors. The future is sustainable machining, which entails modifying existing techniques or developing new ones that stress environmental friendliness. [3]. Higher cutting speeds meet demand without compromising product quality or process efficiency. The cutting tool tip must be active while machining on hard materials in order to maintain a balance between product quality, environmental safety, and process effectiveness, [4].

Currently, industries are facing tough competition and stringent environmental regulations while striving to achieve high production volumes, superior product quality, and sustainable manufacturing processes. Sustainable cutting fluids such disposable oils, synthesized esters, ionic fluids, cryogenic refrigerants, and nanofluids are employed in the industry to address these difficulties [5]. However, it is challenging to make manufacturing processes eco-friendly, cost-effective, and efficient while working with advanced materials and meeting tight deadlines. Consequently, this study focuses on the concept of sustainable machining, which considers factors such as material properties, machining operations, process parameters, and cooling environments to achieve ecological, economic, and sustainable manufacturing objectives [6]. Establishing sustainable machining practises has become crucial in several sectors in order to advance sustainable development goals including supporting excellent health, respectable employment, economic expansion, and renewable technology. There is a pressing need to develop a flexible decision-making method that can offer the best sustainable solutions for a variety of machining scenarios, even if numerous attempts have been made to increase sustainability during manufacturing operations and optimise cutting conditions [7]. The journey towards sustainable manufacturing processes commences with the selection of raw materials and continues through the various stages of manufacturing until the final product is completed, while maintaining the organization's integrity and performance objectives. Among the different manufacturing activities, machining is a significant one, which involves a wide range of operational variables that can be transformed to support sustainable development goals. These operational variables include, but are not limited to, the cooling and lubricating fluids used during machining, disposal of working fluids, conservation of energy, lifespan of tools, and recycling of metal chips [8] A manufacturing paradigm refers to a combination of strategies, principles, and techniques aimed at achieving specific goals. "Green manufacturing" is a term used to describe the new manufacturing paradigm that uses various eco-friendly techniques to improve efficiency. The development of manufacturing systems is influenced by internal and external factors. In response to the increasing global concern for environmental risks and the need for efficiency to remain competitive, manufacturing systems are transitioning to a new paradigm. Green manufacturing aims to reduce the environmental impact through sustainable product design and system operation [9]. The concern for sustainability evaluations is increasing in various industrial fields due to their substantial utilization of natural resources and consequential environmental effects. Machining, which is among the most energy-intensive activities in the manufacturing sector, plays a significant role in the sector's ecological impact, accounting for 40% and 25% of the world's energy and resources usage, respectively [10]. The concept of sustainable manufacturing is now widely recognized as a worldwide term that includes critical components in all fields, including machining procedures. The goal of environmentally friendly machining in sustainable manufacturing is to ensure that these technologies are not only reliable and eco-friendly but also cost-effective. There is a growing body of research on

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sustainable manufacturing engineering, driven by a growing interest in the long-term viability of manufacturing processes. Improving the quality and streamlining manufacturing operations have become urgent requirements for achieving sustainability [11-12].

In hard turning process difficult to cut heat treated material s are processed by single point cutting tool to achieve desired shape size. However, these materials have hardness level from 45 HRC to 72 HRC, make theses material very complex to cut. During hard machining high amount of heat generate at the cutting zone which leads the cutting tool wearing rapidly and simultaneously degrade the workpiece surface by changing the microstructure of the material [13,14]. During machining operators work under different speed, feed and depth of cut without any proper guideline resulted in severe tool wear such as abrasion, adhesion, chipping, edge fracture, BUE etc. So due to low tool life of cutting inserts production cost rises and due to severe wear product quality also decreases. To mitigating this problem operators are advised to follow the optimum combination of speed, feed and depth of cut. Now a days many researchers are applying different type of optimization technique to get the best possible combination of input parameters so that industries can achieve best product quality with lowering the production cost [15,16]. Prediction modelling are used to create a model to analyse the idea, process and to predict the solutions without performing unnecessary experiments [17,18]. In this literature study an in-depth analysis has conducted on the various optimization and modelling strategies now in use to alleviate manufacturing-related issues, with a focus on the challenging machining domain. Also, the study analyses in depth how different sustainability factors influence hard machining. The results from several studies on the state of the art in hard machining with regards to sustainability, optimization, and modelling techniques have been compiled, and a brief discussion has conducted on the topics that need further investigation Finally, based on the analysis of hard machining's optimization, modelling, and sustainability concerns, clear conclusions and potential future applications are drawn.

2. Influence of optimization techniques in hard machining

In recent years many researchers and industry specialists have paid attention towards into different single and multi-criteria optimization techniques to solve problems in hard machining sector. MCDM techniques as well as algorithm-based optimization techniques are able to find the optimum parameter solutions for the machinist to avoid undesirable accidents and moreover increase the product quality and reducing overall manufacturing cost. Recent progress in optimization techniques used in hard machining area are discussed below:

Qasim et al. [19] utilized statistical techniques to optimize machining parameters and minimize cutting forces and temperature during the machining of AISI 1045 steel. To assess the impact of rake angle, feed, speed and depth of cut, Taguchi S/N ratio-based optimization was employed, and ANOVA analysis was also introduced. They used finite element simulations and statistical calculations, and the outcomes indicated that feed and depth of cut were the most crucial aspects for achieving optimal cutting forces, while cutting speed and rake angle played a significant role in decreasing temperatures. The researchers also found that carbide cutting tools were a better choice than uncoated cemented carbide cutting tools. Mia et al. [20] conducted research on the impact of machining factors on MRR, tool wear and surface finish in hard turning with MQL environment, using a coated cemented carbide tool. Furthermore, Taguchi based design experiment was performed and S/N ratio-based optimization was used to analyze the data. The results showed that cutting speed had an impact on surface roughness, cutting depth had an impact on tool wear, and feed rate had an impact on material removal rate. Aouici et al. [21] used RSM model for optimize the data for better surface roughness and lower machining force in hard part turning of AISI H11 steel. For the hard turning procedure of AISI 4340 steel, Sahoo et al. [22] used response surface approach and grey-based Taguchi method for mathematical modelling and parametric optimization. The study tested the economic viability of a multilayer coated carbide implant. Cutting speed affected flank wear, whereas feed affected surface roughness. The ideal parametric combinations improved tool wear and surface finish and correlated fairly with experimental results. Alok et al. [23] tested a novel coating material, HSN2, with 12mm thickness on carbide inserts for cutting 55 HRC AISI 52100 steel. Regression models and statistical design of studies are used to determine how cutting factors affect machinability. Response surface approach and confirmation tests enhance cutting settings. The investigation found acceptable percentage of errors for surface roughness, machining force, and flank wear Das et al. [24] performed experimental and statistical investigation of machining parameters as flank wear, material removal rate, tool tip temperature, surface roughness parameters, chip shape, chip thickness, and dimensional deviations. Experimental design and statistical analysis using Taguchi's L27 orthogonal array. Mathematical models were created using regression analysis, and a neuro-genetic algorithm selected the best machining settings. Results showed optimal input variables and machining parameter settings. Kuntog˘lu et al. [25] modified input parameters in turning AISI 1050 steel using the Taguchi S/N ratio and evaluated tangential cutting force, tool wear, and acoustic emission (AE). Cutting velocity had the major impact on tool wear, followed by feed rate on tangential cutting force and AE. Tool flank wear was reduced by using a cutting velocity of 135 m/min, f2 = 0.214 mm/rev, and tool type P25. Optimum tangential cutting force and AE settings were also computed. Subbaiah et al. [26] employed desirability function to optimise process parameters in AISI 4340 steel hard turning operation utilising a wiper ceramic insert at distinct hardness values. To improve surface quality and reduce tool wear, input parameters were optimised. With a desirability value of 0.988, hardness of 45, cutting speed of 166.51 rpm, feed rate of 0.050 mm/rev, and depth of cut of 0.135mm, the ideal solution was found. Surface roughness and flank wear were minimised. Machining forces, surface integrity, chip study, tool wear, and chip reduction coefficient were examined by Bhandarkar et al. [27].

A hybrid Taguchi-Grey relational analysis was used to optimise feed, velocity, and tool type for decreased cutting force, surface finish, and chip reduction coefficient. The best parameters were feed rate = 0.18 mm/rev, cutting speed = 250 m/min, and tool type 1 (multilayer CVD TiCN and AL2O3 coated). Tool type and feed rate interacted. Predicted and experimental values were found to be close. The combined impact of process factors on performance traits during hard turning of AISI 52100 bearing steel using a CBN tool was examined by Bouacha et al. [28]. Using the response surface approach, ANOVA analysis is utilised to model process parameters and performance measures. Grey-Taguchi, composite desirability function, and genetic algorithm are used to enhance process parameters for performance. Yet, the GA optimization technique outperformed the others. The approaches given can be used to optimise and improve hard turning by upgrading machining technology and implementing cost-effective manufacturing procedures. Umamaheswarrao et al. [29] used a combination of grey theory and principal component analysis optimization method to determine the optimal parameters for surface roughness when performing hard turning on AISI 52100 steel conducted hard turning on AISI H13 steel, using various combinations of speed, feed, and depth of cut. A genetic algorithm was utilized to optimize two objectives, surface roughness and MRR. A validation test was then performed to confirm the predicted optimal result, with an error of 3.73% for surface finish and 4.54% for MRR. Umamaheswarrao et al. [31] optimised machining settings for PCBN-hard turned AISI 52100 steel. TOPSIS optimised the experimental data to provide best possible combination. The trials varied rake angle(negative), cutting velocity, cutting feed, nose radius, and cutting depth while monitoring workpiece surface temperature and roughness. After ANOVA analysis, the optimal turning parameters were 200 rpm speed, feed as 0.1 mm/rev), depth of cut as 0.7 mm, nose radius as 1.2 mm, and negative rake angle as 45°.

3. **Adopted Modelling techniques in hard machining**

Purpose of this review is to be analysed and identify the most recent and popular modelling techniques adopted in the area of hard machining. Intelligent machining adopted different modelling techniques in machining applications to analysed and identify the data and provide proper solution to avoid the complexity of data. According to the suitability with high accuracy percentage modelling techniques can be adopted to solve the problems and challenges in hard machining area. Some previous works on modelling techniques utilized in hard machining area are summarized below:

Aouici et al. [21] studied the effects of cutting velocity, depth of cut, feed rate, and component hardness on surface quality and cutting force components while hard part turning of difficult to cut AISI H11 steel using a CBN cutting tool. ANOVA and RSM were used to develop mathematical models that demonstrated that cutting depth and component hardness had a significant impact on cutting force components. Surface roughness was substantially influenced by feed rate and workpiece hardness. According to the comparison graphs Fig.1a and Fig.1b of Cutting force and surface roughness between predicted and actual values confirmed that quadratic regression based RSM modelling may be used for hard machining solutions. Umbrello et al. [32] used FEM modelling to predict residual stresses in hard turned AISI 52100 bearing steel components. White and dark layer formation affect machining-induced residual stresses. The study reveals that integrating microstructural changes from machining processes might improve residual stress state prediction. The estimated residual stress distribution following white layer removal helps choose process settings for a good surface integrity condition. Sharma et al. [33] examined the cutting force produced during hard turning AISI D3 steel in wet cutting conditions. Taguchi's L9 orthogonal array and ANOVA were used to analyse cutting speed, feed, and depth of cut. The fuzzy model predicted cutting force better than regression models. Feed and depth of cut significantly affected cutting force. The L9 orthogonal array was suitable for testing and fuzzy models with less than 11% root mean square error predicted cutting force.

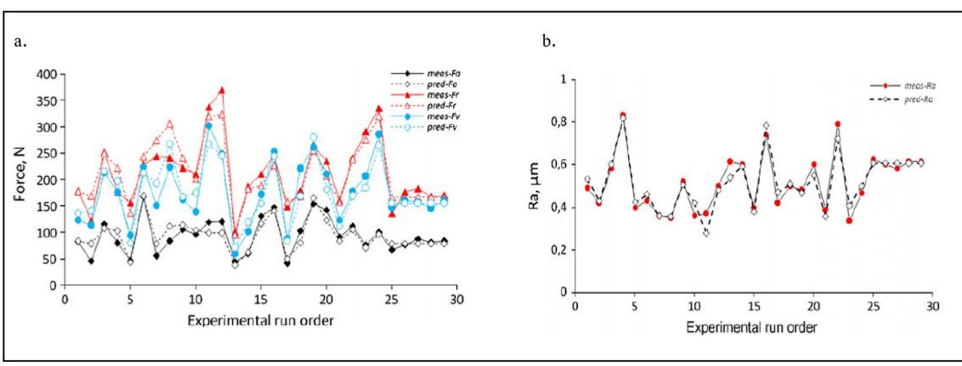

Fig.1. Comparison graphs between predicted and actual values of (a) cutting force (b) surface roughness.[21]

Kumar et al. [34] used computational and experimental approaches to evaluate uncoated and composite ceramic inserts in hard part turning procedure of AISI 52100 steel (62 HRC). AlTiN coating on uncoated Al_2O_3-TiCN inserts is deposited using a 3D finite element model. Cutting tool wear and turning trials were done. Coated ceramic inserts with AlTiN coating of 4 μm coating texture perform best in machining. The study shows that the suggested finite element model can predict machining forces, tool temperature, interface temperature, chip shape, and wear behaviour. Figure 3 shows that cutting force forecast values closely match experimental data. In order to construct a model employing first order and second order regression modelling approach, Sahoo et al. [35] utilized both coated and uncoated carbide inserts during hard part turning operations of AISI 4340 steel. This suggests a better model-to-data fit for the multilayer TiN-coated carbide insert compared to the 1st order model, it was observed. The ZrCN-coated carbide insert matches the 2nd order flank wear model better than the surface roughness model, according to an ANOVA study.

While hard turning AISI 52100 steel, Kumar et al. [36] looked into the impact of an AlCrN coating on the efficiency of the Al2O3/TiCN ceramic inserts. The experimental results were additionally supported by a 3D finite element model with a hybrid friction criterion, which revealed good agreement between anticipated and experimental results in terms of machining forces, tool temperature, chip morphology, and coefficient of friction. Coupled-Eulerian-Lagrangian technique was used by Tekkaya et al. [37] in Abaqus/Explicit software to forecast the microstructural behaviour during severe machining of AISI 4140 steel. It was shown that this Coupled-Eulerian-Lagrangian technique can properly anticipate the production of white layers and the integrity of surfaces with a maximum inaccuracy of 0.36 m. Agarwal et al. [38] utilised three different modelling strategies in hard turning operation of AISI 4340 steel and compare the outcome with experimental data. Random forest modelling fared better than other modelling techniques, such as multiple regression and quantile regression approach, during the hard turning operation for predicting surface roughness. Sivarajan et al. [39] employed fuzzy logic modelling technique to foresee the surface finish in hard part turning of EN31 steel. MATLAB R2020b software is used to develop the model. According to the model performance fuzzy logic can be adopted as a predictive model for hard machining solutions with an error of 3.74% which is within acceptable limit. Li et al [40] employed a new modelling technique named as dislocation density-based model through FEM analysis to predict the size in hard milling of AISI H13 steel. Regarding grain size, the projected grain size of around 330 nm corresponds well with the observed sub grains or dis-location cellular structure in the range of 200-400 nm. The qualitative variation of dislocation density has a similar tendency to that of simulated dislocation density. Kumar et al. [41] applied ANN and RSM based modelling model to hard turning of AISI D2 steel to predict the flank wear value. According to the experimental data ANN is more accurate than RSM in predicting flank wear value in hard machining. However, while determining the predictive result for surface roughness and cutting temperature RSM outperformed ANN based prediction model. Mia et al [42] analysed the effect of different modelling procedure in hard turning of AISI 1060 steel. Support vector analysis and RSM modelling technique are compare and it was compared that SVR is better in predicting the surface roughness and can be adopted for hard machining problems.

4. Sustainability aspects in hard machining

The global challenges of economy, society, environment, and technology require sustainable approaches in manufacturing industries. One area of focus is sustainable machining processes, which involves integrating environmental assessments into operational activities. The hard turning process has implemented various sustainable strategies from an environmental and economic perspective, such as reducing the use of lubricants to minimize pollution and gain economic benefits. Sustainable techniques are crucial in machining processes, and tool wear progression is an unavoidable aspect of precision cutting. The metal cutting sector significantly impacts the global economy. The sustainable platform for designing intelligent MQL system in scenario of industry 4.0. Bio-oil-based cutting fluids have replaced hazardous cutting fluids in machining applications owing to global environmental sustainability. Several researchers have investigated sustainability and utilised various methods to establish its requirements. Sustainable manufacturing necessitates resource- and energy-efficient machining. Energy consumption and economic productivity collide when high hardened materials are being machined for the automobile and aerospace sectors, which makes eco-efficiency challenging [43]. Sustainable machining may improve efficiency while protecting the environment. Reduce resource consumption by utilising analysis and optimization tools to identify the optimal cutting insert selection, cutting settings, cooling and lubrication conditions, and more. Cutting fluids based on petroleum are still utilised, but their environmental impact and high cost make them unsuitable for a green economy. As a result, metal cutting operations must employ long-lasting cutting fluids and appropriate settings [44-45]. The conservation of energy and natural resources is the key component of sustainability in manufacturing. Processes that are optimised to have the least possible negative environmental effects are becoming more and more crucial for modern manufacturing. By using less energy and more clean, renewable sources, it is possible to increase energy efficiency [46-47].

Life cycle analysis is presently the most essential type of sustainability analysis tool for calculating the cost of production, environmental impact, carbon emissions, water consumption, and energy consumption while machining hard materials[48].The cutting forces and product quality were also evaluated. The "triple bottom line" (TBL) theory broadens company performance measures to include societal, environmental, and economic factors. People, planet, and prosperity are the "three P's" of sustainability [49]. Environmental health and protection, economic growth and prosperity, and society welfare and health are all directly affected by sustainable machining. Sustainable machining minimises environmental impact, improves energy and resource efficiency, decreases waste, increases operational safety, and enhances human health [50,51]. Cutting inserts use machine, spindle, and process energy and pollute the environment [52].Various researchers have performed different experimental work on sustainability aspects and came with their own recommendations are follows:

Liu et al. [53] examined the influence of tool wear progression on energy consumption were evaluated at the machine, spindle, and process levels during dry milling of AISI H13. Cutting speed rose due to strain hardening, but material removal rate (MRR) decreased machine and spindle specific energy. When considering environmental effects, avoid neglecting tool wear. MRR's impacts on energy, emissions, and environmental impact were quantified using predictive models. Khan et al. [54] evaluated Xcel-modified tools for hardened D2 steel turning. For chamfer supply, A1 (1 mm) Xcel inserts outperformed A2 (2 mm) inserts. Tool wear was homogeneous with A1 inserts, but A2 inserts generated considerable chipping/fracture. The modified inserts outperformed previous studies in terms of material removal rates, tool life, and surface roughness, making them ideal for long-term one-step machining. A1 inserts are chosen over A2 inserts because to lower energy consumption, tool wear, and surface integrity. Kim et al. [55] explored the cryogenic cooling's economic and environmental effects on hard part turning machining. Cryogenic coolant liquid nitrogen was the cryogenic coolant used in this study. Compared to dry and wet environments, cryogenic aided ceramic cutting tool life increased 3–6 times. LCA (Life Cycle Analysis) has been conducted for the sustainability assessment of AISI 52100 steel in hard turning process. Based on tool-life statistics, economic implications were assessed. The cryogenic procedure increased the ceramic cutting tool's tool life, reducing machine operating time and power and carbon dioxide emissions than dry and wet cooling technology effectively is shown in comparison index Figure 2. It was concluded that with a reduction in the environmental effect, cryogenic cooling application may be appropriate for green industrial processes. Fernandes et al. [56] investigated the economic feasibility of turning AISI D6 tool steel with PCBN inserts using liquid nitrogen (LN2). The delivery mechanism and flow rate monitoring approach delivered LN2 to the cutting zone. High flow rates of LN2 increased cutting tool life in both dry and wet settings without raising production costs. Emulsion had no effect on tool life. As a result, LN2 may replace mineral-based emulsions indefinitely without incurring economic losses.

Abbas et al. [57] optimised machining parameters for long-term manufacturing. Surface quality, energy consumption, environmental impact, waste management, and safety were all investigated. The weighted sustainability index for nanofluid minimal quantity lubrication was 0.7. This approach is optimised for a cutting speed of 116 m/min, a depth of cut of 0.25 mm, and a feed rate of 0.06 mm/rev. The assessment model was validated by comparing predicted and optimal responses. Padhan et al. [58] used central composite design, response surface methodologies, and desirability function analysis to optimise AISI D3 die steel hard turning. Electricity usage is investigated for economic analysis, carbon footprint reduction, and Pugh matrix sustainability evaluation. Hard turning under optimal machining conditions reduced energy consumption by 52.15%, lowering machining costs and CO2 emissions while enabling industrial green manufacturing and clean production. Khan et al. [59] investigated the long-term performance of AISI-52100 external turning with emulsion cooling and Cryo-LN2 cooling. Cryo-LN2 outperformed emulsion cooling in aspects of surface finish, energy efficiency, cutting tool span, and cost of production. Cryo-LN2 spent 18% less energy and generated 70.9% lower-cost items under hard part cutting circumstances. When time was reduced, cryo-LN2 consumed 9-18% less energy. Cryo-LN2 can increase output while decreasing costs, but only under extreme cutting circumstances.

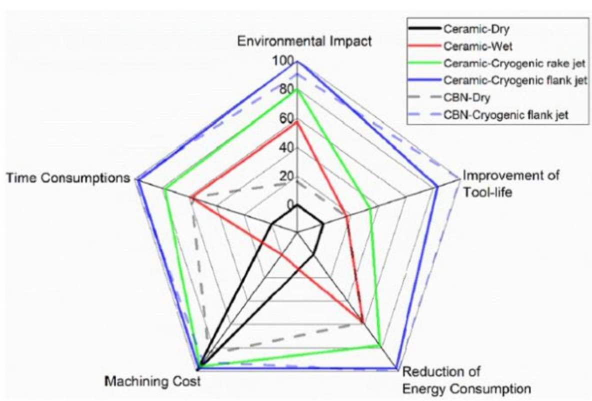

Fig. 2. Comparison index sustainability assessment in different cooling condition.[55]

Dash et al. [60] examined AISI D3 steel hard turning under nanofluid lubrication-cooling. The minimal quantity lubrication approach based on nanofluids enhanced machinability, decreased energy consumption and CO2 emissions, and assured eco-friendliness and techno-economic feasibility. Gürbüz et al. [61] checked the sustainability aspects of different cutting condition like wet, MQL and dry environment in hard machining operation. Due to its improved outcomes and positive effects on environmental pollutants and human health, MQL was preferred. As compared to wet and dry cutting, MQL cutting considerably reduced cutting tool wear, primary cutting force, and surface roughness. The Pugh matrix technique showed that MQL machining was more sustainable and cleaner than wet and dry machining, and feed rate was the major influencing character impacting force and surface finish of the hard component. Das et al. [62] examined the efficiency of AlTiSiN coating material applied to a carbide insert using the scalable pulsed power plasma technique for hard turning AISI D6 die steel. Gilbert's machining economic model was used to calculate the overall machining cost. The results show that the developed nanostructured AlTiSiN coating improved tool wear and surface quality, and that dry machining is technically and economically feasible, which improves sustainability.

5. Conclusions and future scope

The incorporation of sustainability practices is a beneficial technique to improve the quality of the surface of machined parts, dimensional accuracy, tool wear, and easy chip removal. Literature indicates for organizations and academia prefers to evaluate machining characteristics performed in a sustainable machining environment. In recent years, there has been a growth in the number published articles on sustainable machining. Conventional cutting fluid should be avoided by the industries due to their toxic effect on environment as well as on operator. Instead of that vegetable oil and nano additive substances dispersed in vegetable or nontoxic mineral oil used by MQL technique can be a better choice towards sustainable manufacturing. Cryogenic coolants such as LN2 and Cryogenic coolant with MQL technique can be an emerging technique for product process improving and enviro-friendly applications This research strengthens the existing knowledge base by providing insights into intelligent machining processes used in the machining sector. RSM and FEM based modelling are widely used to predict surface roughness, MRR, cutting force and tool wear in hard machining. Taguchi signal noise ratio-based optimization and grey relational analysis are popular among hard machining to get best possible combination for advanced manufacturing process. However, some studies illustrate genetic algorithm and decision tree type optimization techniques can be useful in hard machining for minimizing the production cost by lowering tool wear, power consumption and improve product cost by producing superior precise and finishing products. Popular algorithm-based optimization techniques such as PSO (particle swarm optimization), Jaya optimization technique and MCDM techniques like TOPSIS, WASPAS, COPRAS, DEAR method applications are rarely investigated, can be adopted in future applications of hard machining manufacturing process.

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