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Machine learning and artificial intelligence in CNC machine tools, A review

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ABSTRACT

Artificial Intelligence (AI) and Machine learning (ML) represents an important evolution in computer science and data processing systems which can be used in order to enhance almost every technology-enabled service, products, and industrial applications. A subfield of artificial intelligence and computer science is named machine learning which focuses on using data and algorithms to simulate learning process of machines and enhance the accuracy of the systems. Machine learning systems can be applied to the cutting forces and cutting tool wear prediction in CNC machine tools in order to increase cutting tool life during machining operations. Optimized machining parameters of CNC machining operations can be obtained by using the advanced machine learning systems in order to increase efficiency during part manufacturing processes. Moreover, surface quality of machined components can be predicted and improved using advanced machine learning systems to improve the quality of machined parts. In order to analyze and minimize power usage during CNC machining operations, machine learning is applied to prediction techniques of energy consumption of CNC machine tools. In this paper, applications of machine learning and artificial intelligence systems in CNC machine tools is reviewed and future research works are also recommended to present an overview of current research on machine learning and artificial intelligence approaches in CNC machining processes. As a result, the research filed can be moved forward by reviewing and analysing recent achievements in published papers to offer innovative concepts and approaches in applications of artificial Intelligence and machine learning in CNC machine tools.

1. Introduction

CNC machining operation is one of the most important part-production methodologies, and it is often referred to as the engine of modern manufacturing processes. The automotive and medical sectors, aerospace, gas and oil, and warehousing services, are using the CNC machining operations to create parts in different applications [1]. CNC machining is generally used in manufacture of every machine, molded part, or finished product as one of the most important manufacturing processes. CNC machinery has paved the way in manufacturing and machining, allowing businesses to achieve their goals and targets in a variety of ways. However, because manufacturing methodologies is always evolving and new technologies are being introduced, it is critical to consider future of CNC machining operations [2, 3]. Machine learning (ML) is the study of computer algorithms that gives computers the capacity to automatically learn from data and prior experiences in order to find patterns and make predictions without human involvement. The ML and applications in different areas of study are considered to be a component of artificial intelligence [4–6].

Machine learning and artificial intelligence in particular raise plenty of concerns about the future of CNC machining operations and how these concepts will evolve future works of manufacturing companies [7]. The way a machine learns, adapts, and optimizes output can also be influenced by real-time data, analytics, and deep learning. Data sets are essential for operators to understand how a machine works and, eventually, how a whole floor of machines works together [8, 9]. Due to the development of affordable, reliable, and resilient sensors and acquisition and communication systems, novel implementations of machine learning approaches for tool condition monitoring can be presented [10]. Machine learning systems are capable of completely examine data and identify various types of areas which should be modified. Machine tools are increasingly being equipped with edge computing options to record internal drive signals at high frequency in order to supply the necessary vast quantity of data for the use of machine learning techniques in manufacturing [11]. Productivity and efficiency are two areas where

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artificial intelligence can modify CNC machine tools operations in order to enhance accuracy of CNC machining operations[12]. Machines can generate and analyze production data and provide real-time findings to human operators are effective devices for increasing productivity in part production processes. As a result, shop owners can quickly adjust the way a machine operates using the modified data generated by advanced machine learning algorithms in order to enhance productivity of part manufacturing [13]. Having more knowledge and making better decisions in process planning strategies means less downtime on the work floor during process of part production. Production and maintenance process of part manufacturing using CNC machine tools can be developed using the machine learning and the artificial intelligence in order to enhance efficiency in part manufacturing operations [14].

The CNC machining operations must be optimized in order to save money and time and increase overall profit per production period [15]. Artificial intelligence can forecast periods of servicing and equipment of CNC machine tools structures by linking to production data such as machine performance and tool life. Data from AI will also indicate how long a machine can operate before it requires maintenance. So, the predictive data of the AI implies fewer tool failures, longer tool life, reduced downtime, and machining time which can lead to money savings in part production [16, 17].

Applications of deep learning in CNC machining and monitoring systems is reviewed in order to develop the monitoring systems of machining operations using the deep learning and neural network systems [18]. In order to detect defects in manufacturing operations, applications of deep learning systems in part production is reviewed [19]. A review on machine and deep learning methods applied to industrial challenges is presented in order to develop the operation management during process of part production [20]. Applications of machine learning systems in sustainable manufacturing is reviewed to modify models of big data analysis in process planning of part production [21]. Deep learning for smart manufacturing is reviewed in order to improve performances of part production process [22]. A review in smart manufacturing systems using the machine learning is presented in order to present future directions in the process of part production [23].

Soori et al. [24–27] provided improvement of CNC machining in digital settings using virtual machining methods and processes. Soori et al. [28] provided a review of current developments in friction stir welding operations in order to examine and improve efficiency in the process of component manufacturing employing welding techniques. Soori and Asamel [29] investigated applications of simulated milling systems to reduce residual stress and deflection error throughout five-axis end milling of turbine blades. Soori and Asmael [30] created applications of virtual machining system in order to assess and reduce the cutting temperature during machining processes of components. Soori et al. [31] proposed an improved virtual machining method to improve surface properties throughout milling operations of turbine blades. To decrease displacement error during five-axis milling procedures of impeller blades, Soori and Asmael [32] invented virtual milling approaches. Soori and Arezoo [33] presented a review in residual stress to assess and decrease residual stress during machining processes. To minimize surface integrity and residual stress during grinding operations of Inconel 718, optimized machining parameters using the Taguchi optimization approach is presented by Soori and Arezoo [34]. To increase cutting tool life during machining operations, different methods of tool wear prediction is studied by Soori and Arezoo [35]. Computer aided process planning is reviewed by Soori and Asmael [36] in order to enhance productivity in process of part manufacturing. Soori and Asmael [37] provided a summary of existing developments from published articles in order to examine and improve the parameter optimization technique of machining processes. Dastres et al. [38] conducted research on RFID-based wireless manufacturing systems to increase energy efficiency, data quality and availability throughout the supply chain, and accuracy and reliability during the components manufacturing process.

Developments in web-based decision support systems is presented by Dastres and Soori [39] in order to build decision support systems for data warehouse operations. Dastres and Soori [40] presented a review of current research and uses of artificial neural networks in a variety of disciplines, including risk analysis systems, drone control, welding quality analysis, and computer quality analysis to develop the application of artificial neural networks in performance enhancement of engineering products. In order to decrease the effects of technology development to the natural disaster, Dastres and Soori [41] discussed the use of information and communication technology in environmental conservation. To enhance security in the networks and web of data, secure socket layer is presented by Dastres and Soori [42]. Advances in web-based decision support system is reviewed by Dastres and Soori [43] in order to develop the methodology of decision support systems by analyzing and suggesting the gaps between presented techniques. To enhance security measure in networks, a review in recent development of network threats is presented by Dastres and Soori [44]. Advanced image processing systems is reviewed by Dastres and Soori [45] to develop the capabilities of image processing systems in different applications.

Applications of machine learning and artificial intelligence systems in CNC machine tools are investigated in the research work by reviewing and analyzing recent achievements from published papers. The research works are organized into categories based on the applications of MA and AI in CNC machine tools, and future research work directions in the field are also recommended. As a result, new ideas are presented by studying and analyzing recent achievements from published papers in order to enhance productivity and added value in component manufacturing processes employing CNC machining operations.

2. Methodology of review in data extraction

Different applications of ML and AI in CNC machining operations regarding to the effects of the algorithms to output of CNC machining operations is reviewed in the study. Reducing machine downtime, optimization of CNC machine tools, cutting tool wear prediction, cutting force model, CNC machine tool maintenance, monitoring of machining operations, surface quality prediction and energy prediction systems are considered in order to review the applications of ML and AI in CNC machining operations. The challenges as well as advantages of methods in terms of productivity enhancement of CNC machining operations using ML and AI are reviewed in order to present the gap between the published research works. Finally, future directions of research work are suggested in order to develop the applications of ML and AI in productivity enhancement of CNC machining operations.

3. Reducing machine tool downtime

Equipment failures are a constant occurrence in shipping and industrial sectors. Unanticipated equipment failures or vehicle breakdowns can have detrimental effects on production schedules, transportation planning, and capacity management throughout the production process [46, 47]. Recent improvements and trends in predictive maintenance using the data-driven approaches is presented in order to improve safety, reliability and enabling predictive maintenance decision-making in different industrial applications [48]. Workflow of predictive maintenance is shown in the Fig. 1 [48].

Bad maintenance, machine tool part failure, numerous shift changes, and other factors can cause downtime in machining processes. The machining downtime should be minimized in order to increase efficiency in part production processes [49]. Standard components on CNC drills, lathes, and mills can be monitored by the sensors, in order to predict failure and life cycles of machine tool parts. The life time of cutting tool is an important factor of advanced machining operations due to the tool wear in order to decrease downtime in process of part production [50]. Sensor-assisted planned downtime allows for precisely the proper amount of maintenance and increases the working life of CNC machine

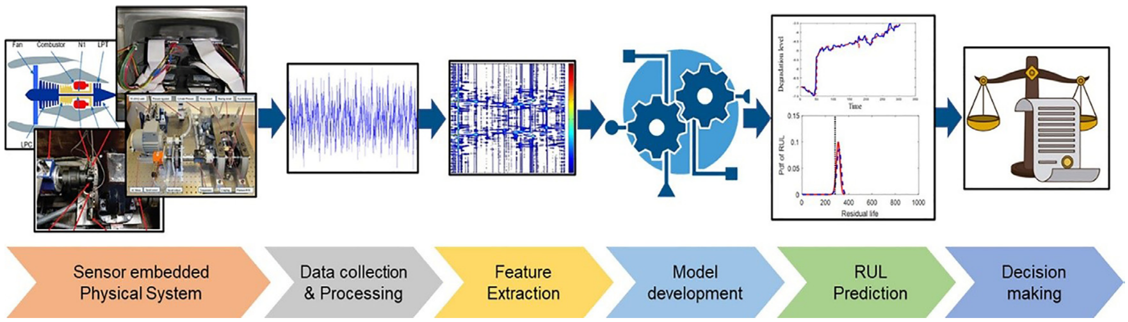

Fig. 1. Workflow of predictive maintenance [48].

tool components [51]. Machine learning and artificial intelligence (AI) can interpret the data and assist manufacturers in determining the optimal time to schedule downtime. Hundreds of different manufacturing businesses and thousands of various equipment provide streaming data of raw materials to the company [52]. When a machine tool is not working due to some reasons, maintenance of machine tool can be implemented. As a consequence, efficient maintenance period regarding the reduction of machine downtime can be obtained using the applications of ML and AI in CNC machining operations in order to save money, time, and resources during the manufacturing process using CNC machine tools.

4. Optimization of CNC machine tools

Optimization of machining operations are recently considered as a crucial aspect of machine learning in different research works. Optimization approaches using machine learning are more studied when the amount of data grows exponentially and model complexity rises [53]. Incremental optimization is at the heart of future manufacturing, from the supply chain to the completed items. The optimization of CNC machine tool operations is crucial for saving money and eventually increasing overall profit per production run, resulting in increased productivity and fewer defects in the components produced [54]. To generate an optimal motion-cueing algorithm, motion system kinematics is used in order to improve simulator performance in restricting actuator extensions during coupled movements [55]. In order to enhance the accuracy and efficiency of component manufacturing utilizing CNC machining operations, optimization processes for machine tool performance and CNC machining parameters are required [56]. Using online data from the production process, artificial intelligence and machine learning can make optimization more automated. As a result, the accuracy of machined component and productivity of part manufacturing can be increased using the optimized machining parameters [57].

To optimize machining conditions and performance, a generalized technique for multi-response machining process optimization employing machine learning and genetic algorithms is developed [58]. The application of Multi-Objective evolutionary algorithm during CNC machining operations in order to improve the convergence speed and performance of part production is shown in the Fig. 2 [58].

Machine learning is utilized to improve parallel metaheuristics on the shop floor CNC machining operations in order to increase efficiency during part production processes [59]. Aapplication of machine learning in optimization process of CNC machine tools is studied to increase component production stability and decrease the risk of unexpected failure [60]. Response surface approach and machine learning technology are used in order to optimize cutting settings when turning Ti-6Al-4 V [61]. To optimize machining variables in end milling operations, the machine learning methodology as the Nelder–Mead simplex method is developed [62]. As a consequence, optimized machining parameters regarding the flexible conditions and parameters of workpiece and machining parameters can be obtained using the applications of ML and AI in CNC machining operations to enhance productivity in process of part production.

5. Cutting tool wear prediction

Machine learning-based technologies is considered an advanced option of tool wear prediction due to its capability to cope with complicated processes. Due to the non-linear character of tool wear, ANNs are the most preferred machine learning approach for evaluating wear [63]. To foresee and avoid bad situations for cutting tools and machinery, modern sensors and computational intelligence are used in order to perform tool condition monitoring and machine tool diagnostics [64]. The need for building self-sustaining and intelligent autonomous machining systems prompted the development of cutting tool health monitoring. In recent years, the requirement for tool condition monitoring or Tool health monitoring has grown in order to enhance lifetime of cutting tools during machining operations [65]. The strategies for tool condition monitoring are often divided into two categories: 'Offline/Direct methods' and 'Online/Indirect methods.' Direct approaches are most suited for examining and analyzing complicated failures (hard faults) which are typically unexpected, making them inappropriate for machine learning [66, 67]. An adaptive neuro-fuzzy inference system can also be used in an online tool system of wear prediction in turning process in order to provide advanced tool wear monitoring systems [68]. The procedures of the online tool wear monitoring system in turning operations is presented in Fig. 3 [68].

Deep learning-based tool wear monitoring approach for complicated component milling is implemented to accurately estimate the tool wear during milling operations [69]. The procedure of the developed methodology in the tool wear prediction is shown in the Fig. 4 [69].

In the face milling process, a deep neural network as advanced machine learning system is used to automatically detect tool wear during chip formation process [70]. Drill wear tolerance analysis and optimization is implemented utilizing an adaptive neuro fuzzy –genetic algorithm approach for long-term usage of cutting tool to maximize cutting tool life during drilling operations [71]. Advanced neural network systems is developed in order to accurately predict the cutting tool wear regarding the specific cutting energy during CNC machining operations [72]. To monitor cutting tool wear in machining operations, simple machine learning combined with data-driven approaches is developed [73]. Machine learning-based in-situ batch detection of materials during metal cutting operations is developed to increase the product quality and decrease manufacturing costs [74]. Tool wear estimation utilizing cloud-based parallel machine learning is developed in order to increase cutting tool life during machining operations [75].

A comparative study on machine learning algorithms for smart factories is implemented in order to predict the tool wear during machining operations using random forests [76]. To assess tool wear conditions during milling operations under a variety of cutting circumstances with

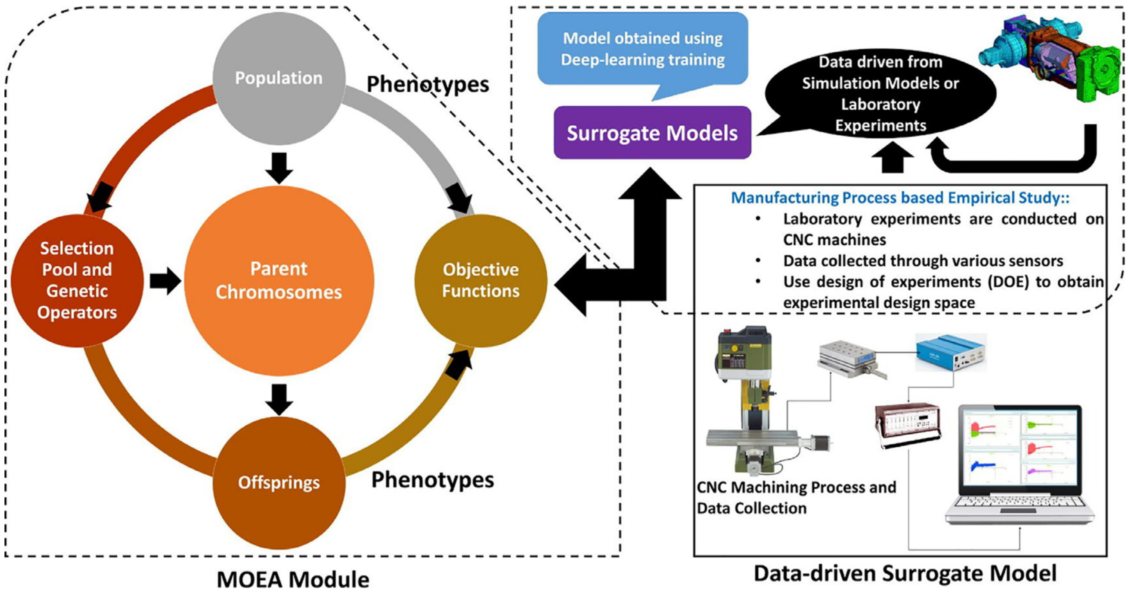

Fig. 2. Data-Driven Multi-Objective evolutionary algorithm Framework in CNC machining optimization [58].

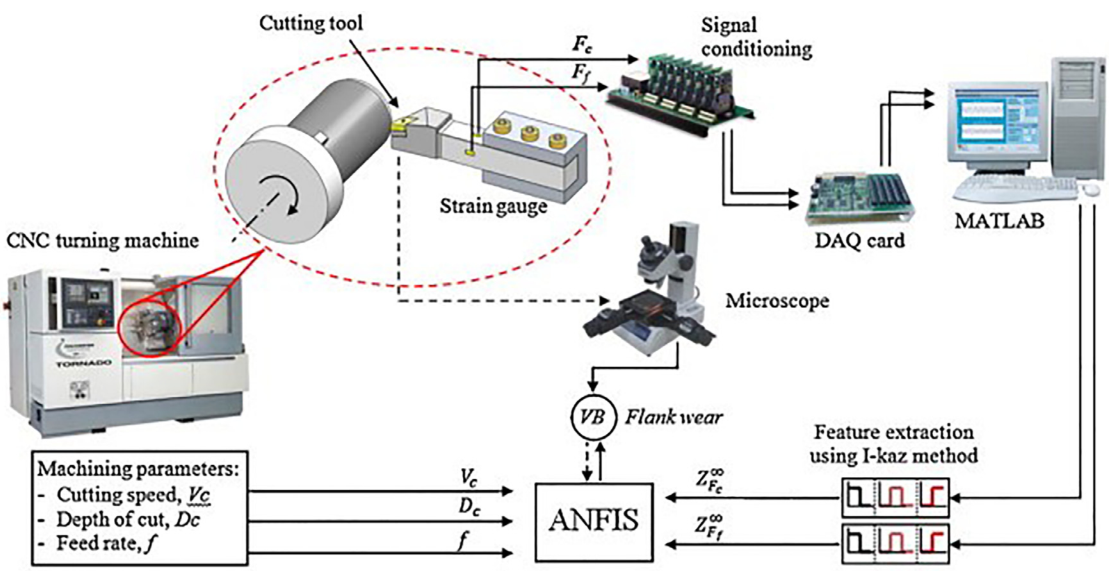

Fig. 3. The procedures of the online tool wear monitoring system in turning operations [68].

a high rate of response, sound waves signals utilizing advanced machine learning algorithms are used [77]. On a vertical machining center, a machine learning technique based on the vibration-based multiple network is developed in order to predict cutting tool insert during machining operations [78]. To predict tool wear progression in the repeated milling process, calibration-based tool condition monitoring is developed [79]. Tool wear estimation is presented using acoustic emission signals using a novel machine learning-based methodology in order to accurately predict the condition of cutting tool wear during milling operations [80]. Machine learning for automated flatness deviation estimation while taking the wear of the face mill teeth into account is developed to increase accuracy of machine-learning models in tool wear prediction systems [81]. Artificial neural networks as machine learning system is developed in order to evaluate tool wear on a modified CNC milling machine [82]. Therefore, cutting tool life during chip formation process of different materials of workpiece and machining parameters can be analyzed and enhanced using the applications of ML and AI in prediction process of tool wear in CNC machining operations.

6. Cutting force model

Cutting force is the most important factor in influencing the milling operation's productivity and quality which can be accurately predicted by using the ML systems [83]. A hybrid force analysis approach in milling operations has been developed using a machine learning-based simultaneous cutting force model [84]. Modeling framework for hybrid cutting force model is shown in the Fig. 5 [84].

A variety of machine learning algorithms, including support vector regression, k-nearest neighbor, polynomial regression, and random forest, are utilized in order to accurately estimate cutting forces in milling operations. [85]. In high-speed turning operations, machine learning cutting force, surface roughness, and tool life is presented in order to provide prediction models of cutting forces [86]. A hybrid technique that uses machine learning using the conventional linear regression method to estimate cutting forces while considering the tool wear conditions is investigated and developed to accurately predict the cutting forces along machining paths [87]. Wavelet packet transform analysis

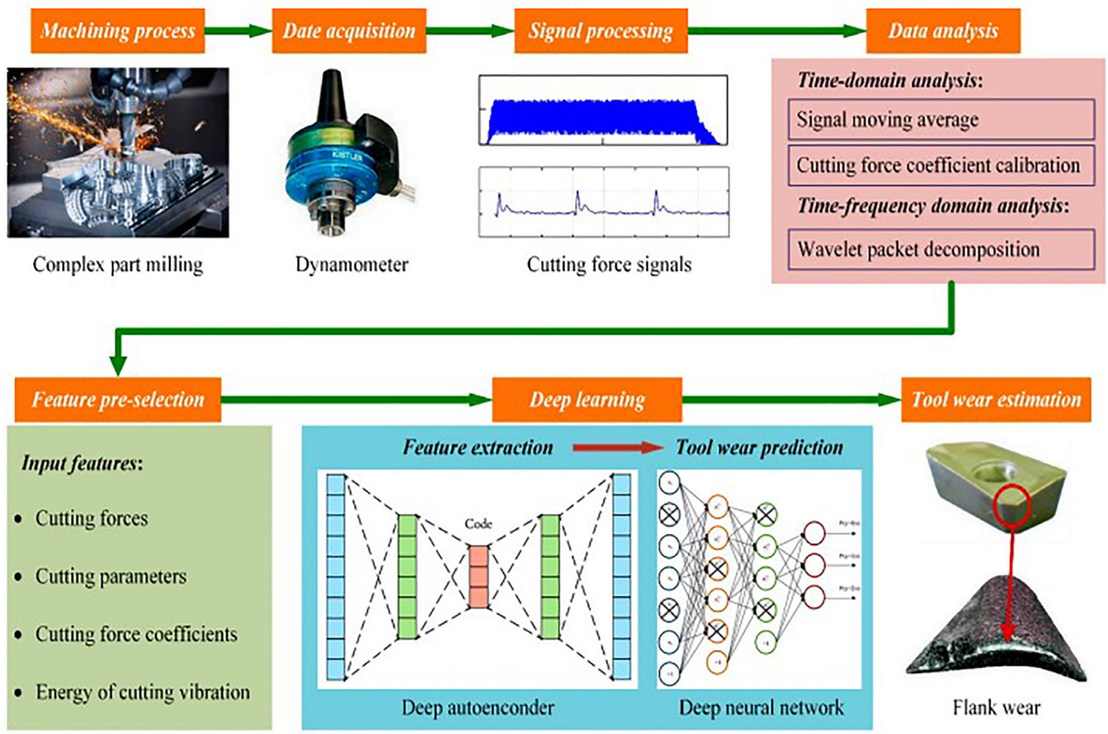

Fig. 4. Deep learning-based tool wear monitoring approach for complicated component milling [69].

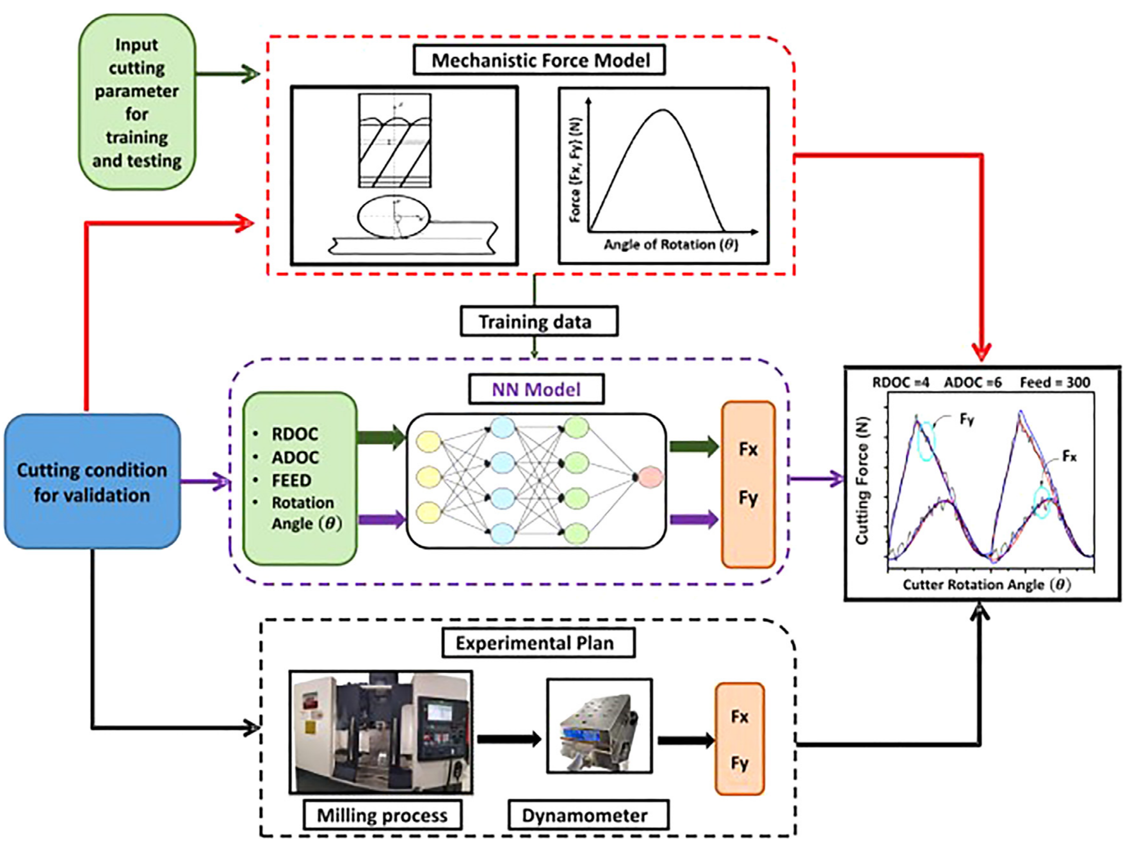

Fig. 5. Modeling framework for hybrid cutting force model [84].

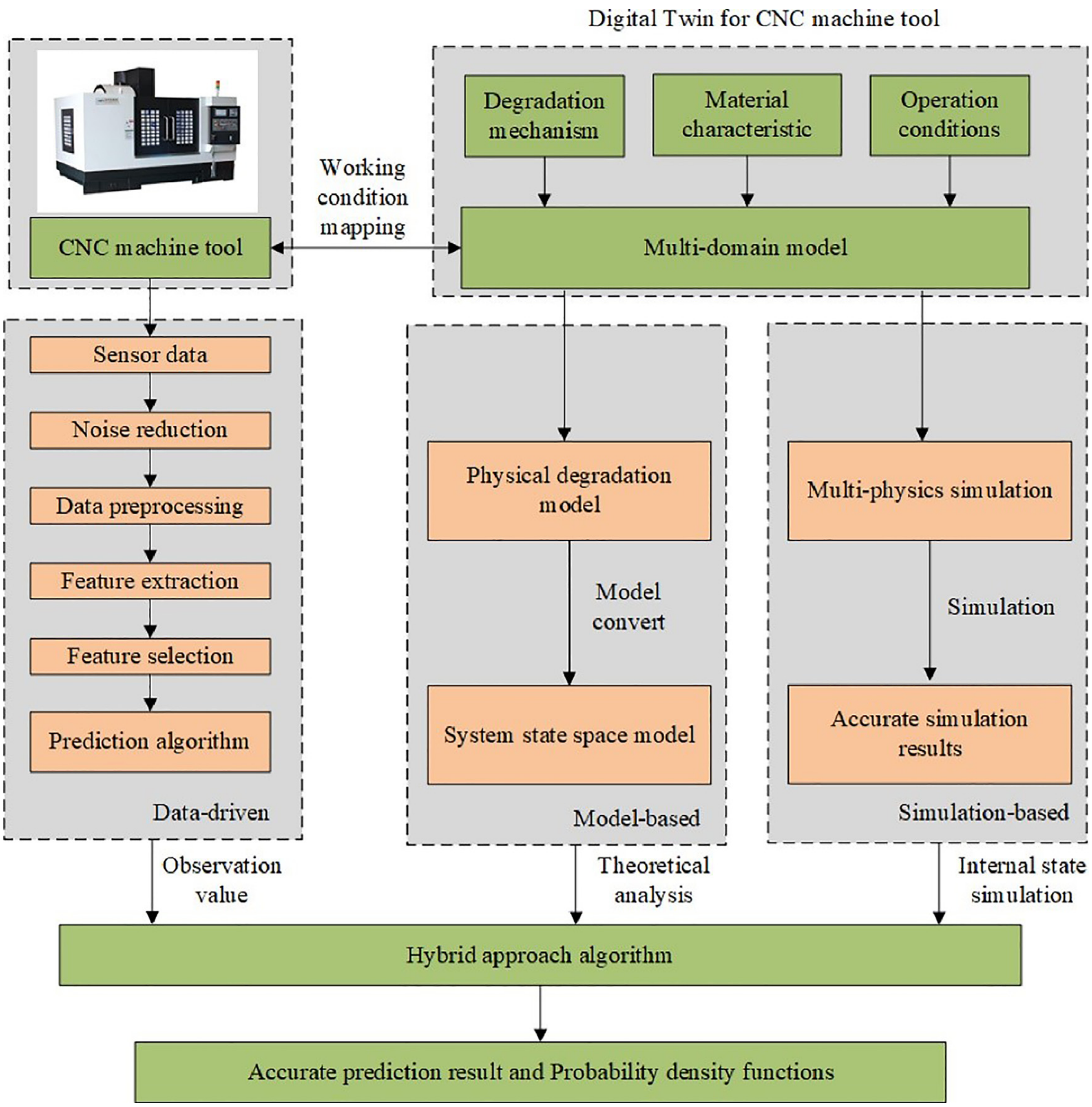

Fig. 6. Developed method of maintenance approach for CNC machine [98].

of cutting force data for surface texture assessment in CNC turning operations is developed to remove noise and chatter during chip formation processes [88]. An offline cutting parameters prediction model related to image representation of cutter workpiece contact geometry is developed using a neuro-physical learning approach in order to increase prediction accuracy in varied cutting situations [89]. To improve the accuracy of cutting force modeling systems, a machine learning-calibrated smart tool holder for measuring cutting force in precise turning operations of S15C low carbon steel has been created [90]. Using real-time cutting force measurements and a CNN approach as machine learning system, online tool wear categorization during dry machining operations is developed [91]. Artificial Neural with signal spectrum image analysis using the cutting force prediction systems is developed to determine the cutting tool's amount of damage during machining operations [92]. Thus, accuracy as well as flexibility of cutting force models during different conditions of CNC machining operations are developed using the applications of ML and AI in cutting force perdition methodologies.

7. CNC machine tool maintenance

The CNC machine tool maintenance process always needs time and money. Accurate prediction of calibration, component modifications, and service of CNC machine tools is one of the most difficult aspects and challenges of running a CNC machine tool [93]. Machine learning and artificial intelligence are closely tied to machine tool maintenance, advancing prediction and preventative approaches aimed at lowering downtime and improving productivity [94]. Machine learning can accurately predict when machine tools need to be serviced and present the optimal time to repair the machine tools in order to minimize the time and cost of CNC Machine tool maintenance [95]. Predictive machine tool maintenance procedures may be done accurately when a machine is driven by machine time and condition data and operators get real-time streams of data feedback. Automatic warnings can be applied when a machine tool needs to be maintained, a part replaced, or a function corrected before it breaks down, in order to provide stable workflow in machine tool and smoothly keep production process running in process of part production using CNC machine tools [96]. So, cause-and-effect links can be created using the connections of artificial intelligence and CNC machine tools. As a consequence, more information and better decision-making for CNC machine tool production processes can be generated, in order to increase added values in process of CNC machine tool component manufacturing [97]. A hybrid predictive maintenance approach for CNC machine tool driven by digital twin is presented in or-

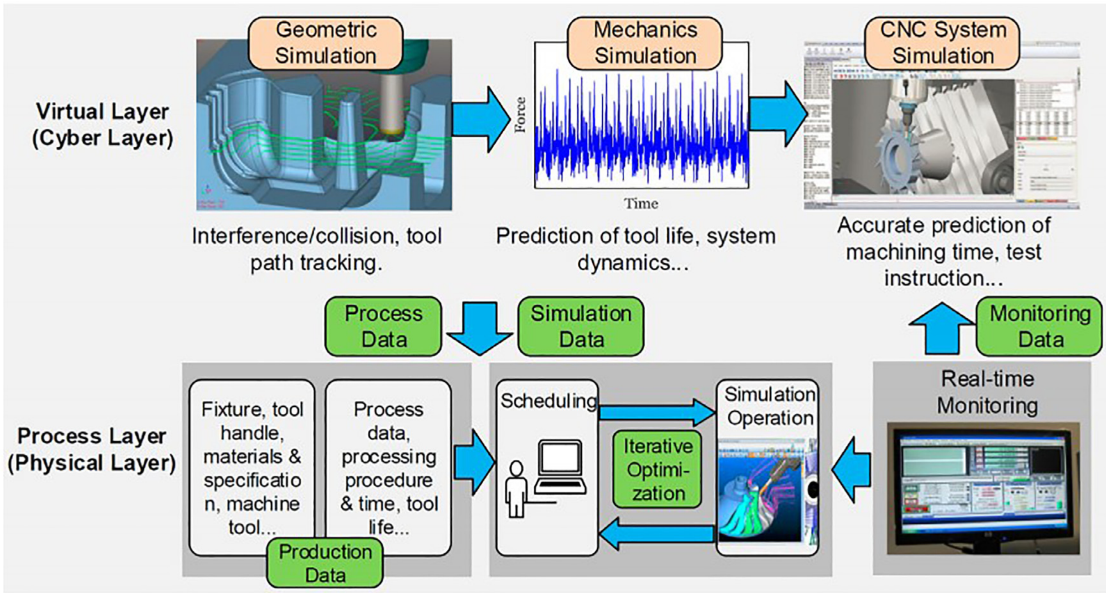

Fig. 7. A combination of physical and virtual modeling of the milling process in the smart CNC machine monitoring system [103].

der to provide accurate prediction methodologies during process of part production using CNC machine tools [98]. Developed method of maintenance approach for CNC machine tool is shown in the Fig. 6 [98].

Advanced machine learning systems is developed to evaluate the maintenance operations including tool wear monitoring in the CNC machine tools [95]. To monitor data in assessing CNC machine tool and cutting process conditions, advanced machine learning system is developed [99]. A tool health monitoring system is created using machine learning techniques in end milling process in order to increase cutting too life and enhance efficiency of part production [100]. Thus, advanced procedures of CNC machine tool maintenance can be obtained as a result of applying the ML and AI to the working time of CNC machine tools during process of part production.

8. Monitoring of machining operations

The application of machine learning in health monitoring of CNC machine tools is recently developed in an era of artificial intelligence systems in order to enhance efficiency in part production using machining operations [101]. Condition monitoring systems is an essential step in maintenance of CNC machine tools in order to keep the CNC machining operations safe and reliable [102]. A cyber-physical manufacturing and engineering structure is presented in order to provide a smart monitoring system for CNC cutting tools [103]. A combination of physical and virtual modeling of the milling process in the smart CNC machine monitoring system is generated which is shown in the Fig. 7 [103].

To monitor and obtain the performances of CNC machine tools during part production processes, advanced decision making application is presented [93]. By using advanced machine learning system, performance monitoring and the impact of process parameters such as cutter speed, feed rate and depth of cut on outputs in turn-milling operations are studied [104]. Six rotating sensors on joints of three legs are used to solve forward kinematics in the Stewart structure in order to increase accuracy during the movement of Stewart structure [105]. Monitoring of CNC machining operations using adaptive neuro-fuzzy integration of multi-sensor signals is implemented in order to prevent and detect the cutting tool errors during machining operations [106]. To enhance accuracy of CNC machining operations, method of machining processes monitoring using virtual reality and a digitized twin systems is developed [107].

Planning and optimization of machining parameters is developed using the online monitoring systems the for AISI P20 removal rate while milling operations to minimize total manufacturing time and boost material removal rate during machining operations [108]. To boost productivity during machining operations of tough to cut materials, machine learning approaches such as decision trees, artificial neural networks, and support vector machines are examined for chatter predictions in titanium alloy (Ti-6Al-4 V) high-speed milling [109]. In-process tool wear prediction system based on machine learning techniques and force analysis regarding the speed of spindle and feed rate machining parameters is developed to obtain the flank wear during machining operations [110]. Response surface technique incorporating desirability function and genetic algorithm approach is developed in order to obtain the CNC machining parameter optimization [111]. To enhance the capabilities and accuracy of machine tool monitoring systems, applications of artificial neural network is presented [112]. As a result, the process of obtaining and analyzing the data through monitoring of machining operations are developed by using the ML and AI in the advanced monitoring and decision making in computer aided process planning systems.

9. Surface quality prediction

Surface roughness is a critical metric for assessing the quality of produced products. Advanced machining procedures aim to produce parts with high geometrical accuracy and enhanced surface finishes while lowering the cost of final products. As a result, certain traditional machining techniques are unable to meet the industrial requirements, necessitating the use of a post-machining surface finishing process to obtain a high-quality surface finish [113]. One of the most important grading standards for product quality is surface roughness. Surface roughness of machined parts can be minimized in order to enhance working life of produced parts [114]. To predict and analyze surface finish of machined components, Neural Networks by using the advanced AI systems is used [115]. Applications of machine learning algorithms in prediction of surface roughness characteristics are developed in order to accurately anticipate surface quality of machined components utilizing turning operations [116]. Linear regression, random forest and decision tree as advanced machine learning systems is applied in order to predict the surface quality of machined parts [117]. Machining accuracy and surface quality for CNC machine tools is predicted using data driven approach in order to accurately predict surface roughness in

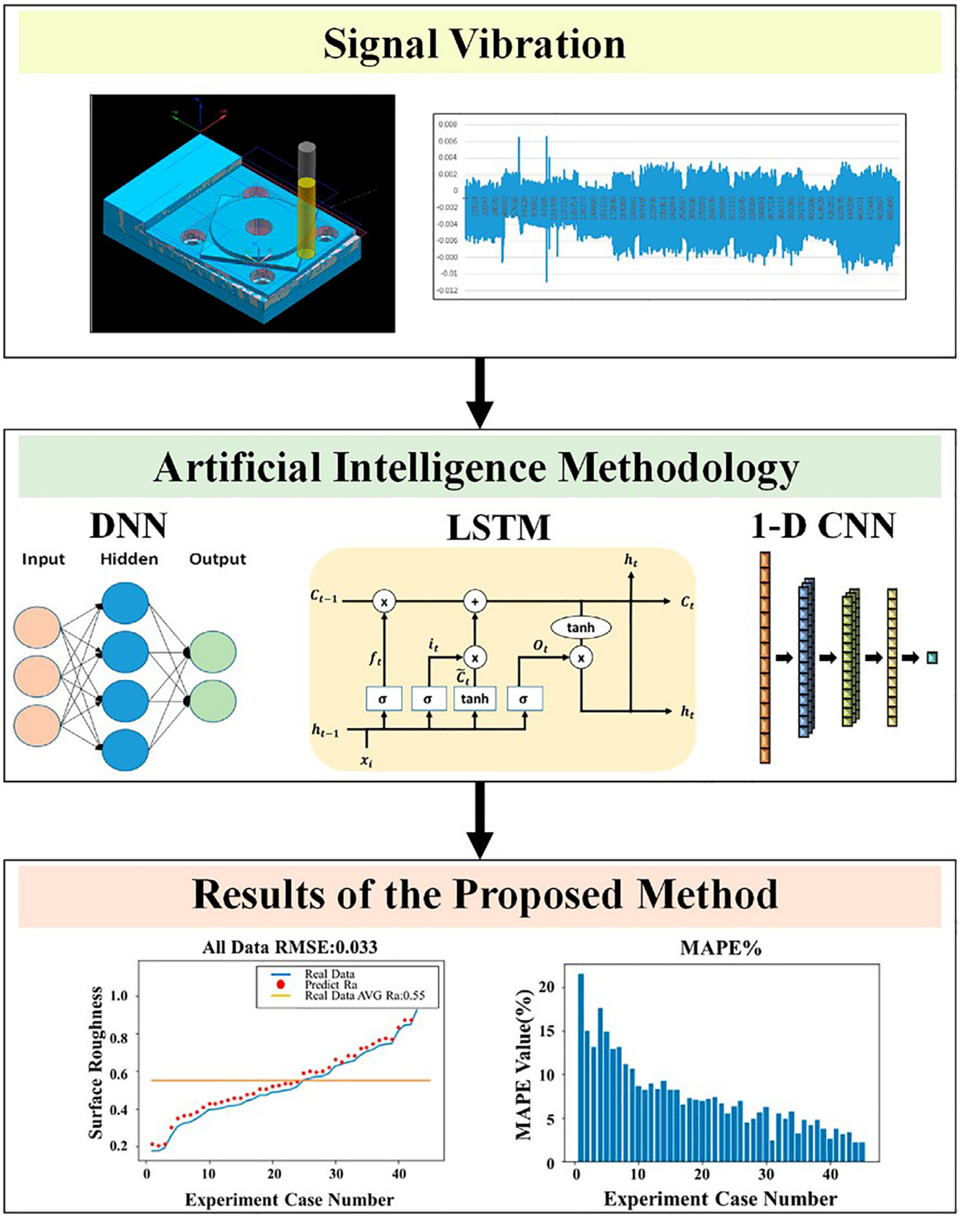

Fig. 8. Application of AL in surface roughness prediction of machined parts [119].

machining operations [118]. To predict surface roughness in machining operations, application of deep learning neural network using vibration signal analysis is studied [119]. The developed methodology of study in application of AL in surface roughness prediction of machined parts is shown in Fig. 8 [119].

To increase accuracy and reliability in terms of surface quality enhancement of machined components, autonomous surface roughness prediction based on wear of face mill teeth is developed [120]. Neural network analysis as multi-layer perceptron model and a radial basis function model is developed to predict the and surface roughness in aluminum alloy machining operations [121]. Machine learning was used to analyze cutting forces in the helical ball end milling process in order to provide advanced methodology in cutting forces calculation [122]. Surface roughness measuring systems on-machine and in-process for precise production is developed in order to increase surface quality of machined components [123]. Advanced surface metrology system in a manufacturing line is illustrated in the Fig. 9 [123].

Machine learning algorithms based on a sensory milling machine tool for real-time monitoring and evaluation of surface roughness have been developed to enhance surface quality of machined components [124]. Multimodal data-driven hybrid machine learning is developed in order to provide condition prediction of cutting tool using advanced machine learning system, [125]. Deep learning-based tool wear detection system is developed utilizing multi-scale feature fusion and a channel attention mechanism in order to enhance cutting tool life [126]. To provide advanced method of surface roughness prediction in machined parts, a nested-ANN model using the impacts of cutting forces and tool oscillations is developed [127]. As a result, surface quality of machined parts can be enhanced using the applications of ML and AI in surface prediction of machined components using CNC machine tools in order to enhance productivity of CNC matching operations.

10. Energy prediction systems

Due importance of decreasing energy waste during industrial production, building energy perdition and management systems are considered in different research works [128, 129]. Machine learning techniques are recently used in prediction models of energy consumption during ma-

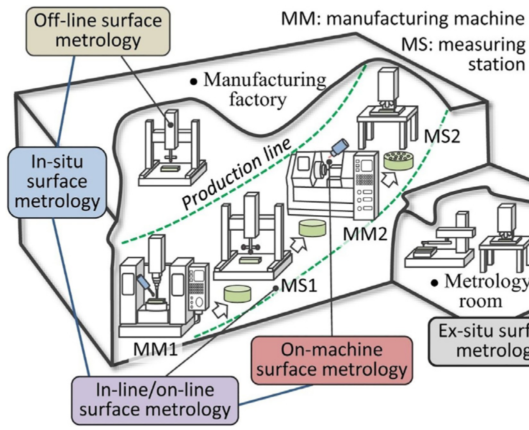

Fig. 9. Advanced surface metrology system in a manufacturing line [123].

chining operations. The accuracy, durability, and precision of traditional time series forecasting methods, as well as their generalization capacity, are greatly improved by using the ML models in terms of efficiency enhancement of energy consumption of CNC machine tools [130]. An approach of deep learning embedded semi-sup learning method is proposed in order to provide an advanced energy consumption modeling [131]. Applications of AI and machine learning-based strategies in energy management systems is presented in order to increase the accuracy of energy consumption prediction [132]. Accurate and quick forecast of CNC machining energy usage is an efficient way to implement lean management of CNC machine tool energy consumption and achieve the manufacturing industry's long-term sustainability [133]. To increase energy prediction performance during machining processes, a deep learning-based energy prediction method are developed [134]. Fig. 10 shows the overall framework of the deep learning-based energy prediction approach [134].

Hybrid methodology combining machine learning and process mechanics is developed in order to estimate specific cutting power during CNC machining operations [135]. Data-driven simulation methodology as an advanced machine learning systems is developed to predict the energy consumption in five-axis process planning operations [136]. To predict energy usage of machine tool spindle during machining operations, advanced fault diagnosis methods, random forest and time series forecasting are developed [137]. An integrated method of process planning and cutting parameter optimization using the machine learning systems is developed in order to minimize power consumption during CNC machining operations [138]. A multi-objective optimization of CNC turning process variables incorporating transient-steady state energy consumption is developed in order to achieve high quality and power saving machining of computer numerical control (CNC) lathes [139]. Thus, more added values can be achieved by applying the ML and AI in prediction systems of energy consumption during chip formation process in terms of productivity enhancement of part production using CNC machining operations.

11. Conclusion

Machine learning and artificial intelligence are applied to various industrial applications in order to improve performances of industrial process. To increase accuracy as well as efficiency during CNC machining operations, different applications of the machine learning and artificial intelligence systems are studied in different research works. Reducing machine downtime, optimization of CNC machine tools, cutting tool wear prediction, cutting force model, CNC machine tool maintenance, monitoring of machining operations, surface quality prediction and energy prediction systems are some examples of machine leniting applications in the development of CNC machining operations. ML techniques are recently applied to energy consumption prediction models in order to decrease the energy consumption during CNC machining operations. Accuracy and radiality of energy consumption models are significantly enhanced using the ML methodologies in comparison to the tradition's methods of energy usage predictions during CNC machining operations.

The applications of machine learning and artificial intelligence systems in CNC machine tools are examined in this study by analyzing recent achievements from published papers. The main aim of this study is to provide an overview of current studies on machine learning and artificial intelligence techniques in CNC machining operations in order to provide a useful study for the researchers in the interesting field. Network of sensors and cloud data sources can connect CNC machines

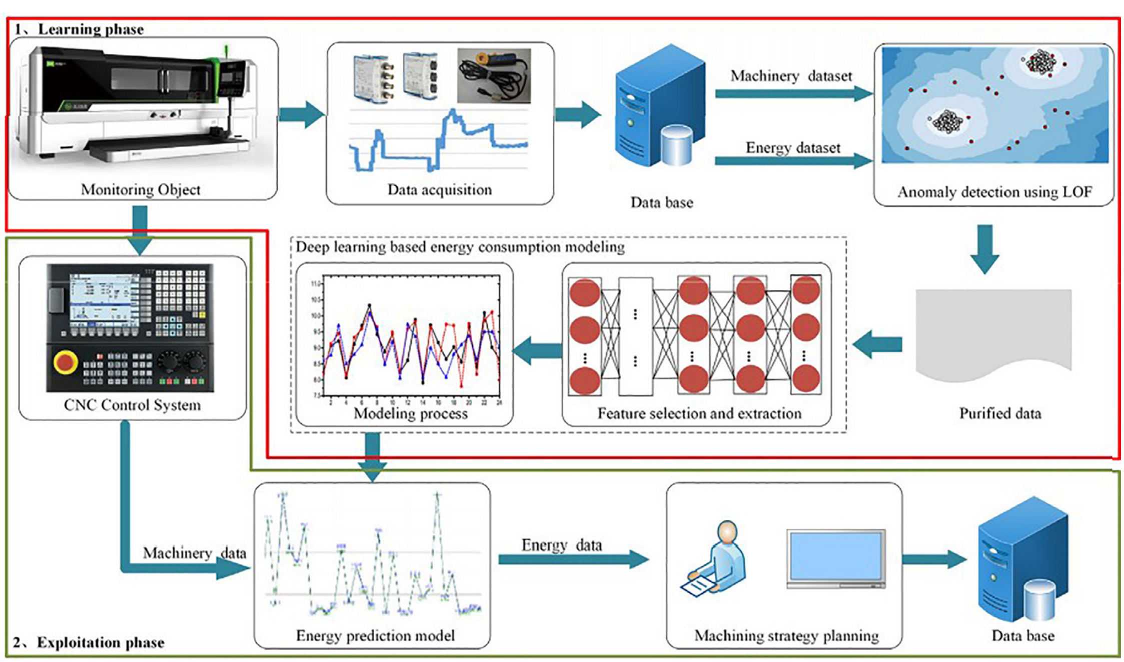

Fig. 10. The general framework of the energy prediction method based on deep learning [134].

together can be employed to provide smart CNC machine tools. The machining industry's efficiency can be increased as it transitions to smart machining techniques, allowing it to achieve self-optimization and adaption to uncontrolled circumstances. However, developing the applications of advanced machine learning systems in CNC machining operations as the combination of physical, computers, and networking process created challenges and difficulties regarding the safety and security of the web of data. In order to provide secure and advanced connections between the different CNC machine tool, the security of networks should be enhanced.

12. Future research directions

Advanced data collection, data mining approaches, data fusion neural networks, virtualization, and smart decision-making methodologies in computer-aided process planning can be employed to increase improve accuracy and performance in the part production process using machine learning systems. The virtual machining systems can be developed by using machine learning applications in CNC machining operations to increase the power of simulation and analysis of CNC machine tools in virtual environments. Cutting tool paths modification, cutting tool selection and error compensation methodologies during CNC machining operations can be modified by using the applications of machine learning systems. The designing process of work-holding fixtures can be developed by using the machine learning system in order to provide accurate fixtures during CNC machining operations. Deep machine learning networks can be applied to CNC machine tools in order to increase the effectiveness of machine learning applications in efficiency enhancement of part production. Spatial iterative learning control method can be applied to the cutting tool paths during machining to enhance accuracy of machined parts by error compensation methodologies.

In order to modify the Collison detection systems during CNC machining operations, Optimized cutting tool paths can be obtained using the applications of ML and AI. Also, to provide advanced operation training systems for CNC machining operators, applications of ML and AI can be implemented. ML and AI can be applied to the industrial robots in order to make robots smarter and more collaborative. Also, decision making can be applied to the robots using the ML and AI in order to enhance performance in flexible conditions of working. Moreover, automation during the process of part production can be developed as a consequence of applying the ML and AI to big data analysis of production process in terms of productivity enhancement of part manufacturing. Online integration and description of machining resources capabilities can be implemented using the applications of ML in cloud manufacturing systems. Advanced Cyber manufacturing systems using CNC machining operations can be presented using the applications of ML in virtual manufacturing. Intelligent machine tool can be presented using the applications of AI in CNC machining operations in order to present the autonomous optimization and decision-making, and autonomous control and execution during machining operations.

Applications of the internet of things in developing smart CNC machine tools can be studied in order to increase the monitoring capabilities of machining process. Sustainable smart manufacturing in industry 4.0 can be developed by using the applications of advanced machine learning systems in CNC machining operations. Smart machining systems can be developed by using advanced machine learning and artificial intelligence systems in order to provides smart manufacturing processes for industry 4.0. The ML and AI can enhance accuracy in process of part production using CNC machine tools in order to decrease waste materials and cost per unit for the manufacturers in terms of advanced lean production systems. Advanced computer-aided process planning can be presented using the applications of ML and AI in CNC machine tools in order to enhance the efficiency of process planning in the flexible conditions and parameters of part productions using CNC machine tools. The integration of the fuzzy technique in applications of ML during CNC machining operations can be studied in order to enhance efficiency of part manufacturing using the optimized procedures of machining operations. These are suggestions for future research works in the research of machine learning and artificial intelligence in CNC machine tools. As a result, performance and reliability of part manufacture can be improved by using advanced ML and AI systems in order to enhance productivity of part manufacturing using CNC machining operations.

Declaration of Competing Interest

It is confirmed that there is no conflict of interest regarding the submitted manuscript number SMSE-D-22-00026, Machine Learning and Artificial Intelligence in CNC Machine Tools, A Review to the Sustainable Manufacturing and Service Economics.

Data Availability

No data was used for the research described in the article.

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