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Review

Posture Optimization Techniques for Enhanced Robotic Machining Performance: A Review

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Abstract: With the advancement of technology and the digitalization of manufacturing processes, optimized production of large-scale structural components faces increasing challenges due to mass product customization, workspace constraints, and the high cost of equipment such as CNC machines. Arm-based robotic manufacturing systems, as a substitutive or complementary alternative with strong potential, have gained significant attention as a means to address current challenges in machining. This work presents a state-of-the-art review of existing techniques and methods for optimizing robotic machining performance, with a particular focus on research advances in posture optimization of articulated robots. These advances are enabling the use of serial robotic arms in material removal operations as a technically and economically viable alternative to conventional machine tools. The document is structured as a comprehensive knowledge recap and systematic analysis of the technical barriers and limitations that affect dimensional quality in robotic machining—primarily due to the limited mechanical stiffness inherent in robotic arms when performing cutting tasks. It compiles and classifies a range of robot posture optimization tools. A SWOT matrix is used to identify the key technical factors that influence the suitability of optimization methods in different industrial contexts. Unlike previous reviews that address posture or dynamics in isolation, this work (i) consolidates posture optimization methods into a practical three-pillar framework (optimize–sense–compensate), (ii) maps methods to a decision-oriented SWOT for industrial selection, and (iii) extends the analysis to collaborative machining, including posture–safety trade-offs under collaborative machining standards.

Keywords: machining; posture optimization; robotic arm; SWOT

1. Introduction

The manufacturing industry has a long history of growth and has consistently been the economic foundation that supports wealth creation for society. The process removes material from the workpiece using a rotating cutter that follows a programmed toolpath, and machining is a key manufacturing process. Common machining operations such as milling, deburring, and drilling are widely used to produce parts for industries like metalworking, energy, aerospace, and automotive. These processes are known for their high efficiency, accuracy, and ability to create complex shapes. While CNC machines have long dominated machining tasks, growing demands for flexibility and efficiency have opened the door to alternative solutions, such as robotic arms. Robotic arms stand out for their flexibility and favourable workspace-to-floor-space ratio, and their relatively low acquisition and operating costs. These features make robotic arms an attractive option for machining applications involving large-scale components with complex geometries and limited access for machining head [1,2].

As a result, the use of robotic arms in real factory environments has steadily increased, particularly in flexible and customized production. Companies aim to boost productivity, quality, and safety. But when robots are used for very precise work, there are still technical and cost problems. Compared to conventional CNC machines, robots are more flexible and can save labour, but they are less rigid, less accurate, and more expensive to set up. The main benefits and drawbacks of robotic machining compared to CNC systems can be summarized in Table 1.

Table 1. Robots vs. CNC: Key Benefits and Risks.

Benefit	Drawback
Continuous operation (24/7 production)	High upfront cost for setup and integration
Flexible for different part geometries	Lower mechanical stiffness than CNC machines
Safer for workers in hazardous tasks	Lower accuracy, challenging for tight tolerances
Quick switching between tasks	Complex programming and skills needed
Large working area possible	Susceptible to vibrations and tool chatter
Real-time data tracking and control	Higher maintenance, possible unexpected downtime
Easy installation with modular design	Faster tool wear due to multiple orientations

These benefits and risks become especially clear when robots are used as milling tools in machining applications. Arm robots with milling tools are useful when there is a high variety of parts, small batch sizes, or a need for flexibility, since they can be easily reprogrammed for used in different tasks. Although they are less rigid than conventional CNC machines, improvements in sensors, control, and algorithms allow them to reach acceptable accuracy for light machining or softer materials. They are not ideal for very tight tolerances or heavy material removal, but they work well for roughing, minor finishing, or flexible operations. To ensure quality, vibration control, proper tooling, and frequent calibration are required. In short, their success depends on carefully balancing benefits and risks according to production needs and part requirements. A comparison between robot arms and CNC machines highlights their respective strengths and limitations is shown in Table 2.

Table 2. Comparative Technical Analysis of Robotic Arms and CNC Systems.

Aspect	Robot Arm	CNC Machine
Workspace	Large, flexible, multiple positions	Fixed, limited to enclosed area
Part Topology	Complex shapes, multi-angle access	Prismatic shapes, single orientation
Materials	Metals, plastics, composites (less rigid)	Wide range (hard metals)
Loading/Unloading	Full automated (grippers, conveyors)	Usually manual, semi-automated
Operator Training	Higher, focus on programming and setup	Lower, familiar setup and basic use
Adaptability	High, reprogrammable for many tasks	Limited, new part requires setup
Precision	±0.05–0.2 mm, not for highest tolerances	±0.01–0.02 mm, precise machining
Maintenance	5–12% of purchase price	8–15% of purchase price

Cost remains a decisive factor when selecting between robotic arms and CNC machining centers. A meaningful comparison must consider not only the initial investment but also ongoing aspects such as maintenance, flexibility, precision, and productivity. For industrial robots, market prices vary greatly depending on payload capacity, reach, and precision. An entry-level new robot can cost around USD 25,000, while mid-range models designed for light machining tasks range from USD 50,000 to 100,000, as reported in recent market analyses [3]. For more demanding applications, requiring higher payloads, longer reach, or compensation systems, costs can exceed USD 100,000–150,000 when sensors, advanced algorithms, and specific tooling are included [4].

In contrast, CNC machining centres show a broader range of initial investment. Low- to mid-range 3-axis vertical models typically cost between USD 30,000 and 70,000, while 5-axis machines with larger travel, higher rigidity, and advanced features often exceed USD 100,000–200,000, or more, depending on the manufacturer and auxiliary systems such as cooling, chip removal, and control software [4,5]. When comparing equivalent setups, a robotic arm equipped for basic milling in low-volume, high-flexibility environments may cost USD 50,000–90,000, while a 3-axis CNC machine falls within USD 80,000–150,000. In more demanding scenarios, a robot with advanced sensors and compensation reaches USD 120,000–200,000, whereas a 5-axis CNC with similar performance usually costs USD 150,000–300,000 The decision between both technologies must balance cost with technical performance. Robots stand out for their flexibility and ease of reprogramming, while CNC machines provide greater rigidity and accuracy for tight tolerances. The optimal choice depends on investment capacity, production volume, precision requirements, and the level of adaptability sought in the manufacturing plant. Unlike prior reviews that address posture or dynamics separately, this work integrates both viewpoints and delivers three specific contributions: (i) a practical three-pillar framework (optimize–sense–compensate) to structure posture optimization in robotic machining; (ii) a decision-oriented SWOT that maps methods to industrial selection criteria; and (iii) an extension to collaborative machining that makes explicit the posture–safety trade-offs under ISO 10218:2025 (The abbreviations and their definitions are listed in Table 3).

These practical considerations in industry are mirrored by academic research, which increasingly recognizes the potential of serial robots in machining and the development of advanced manufacturing systems. Reflecting the growing interest in this line of research, the number of scientific contributions focused on robotic machining operations has increased significantly over time. This trend is evident in the results of searches conducted in high-prestige databases such as Web of Science and Scopus. The steady rise in publications over the past 10 years, based on Scopus data, is shown in Figure 1.

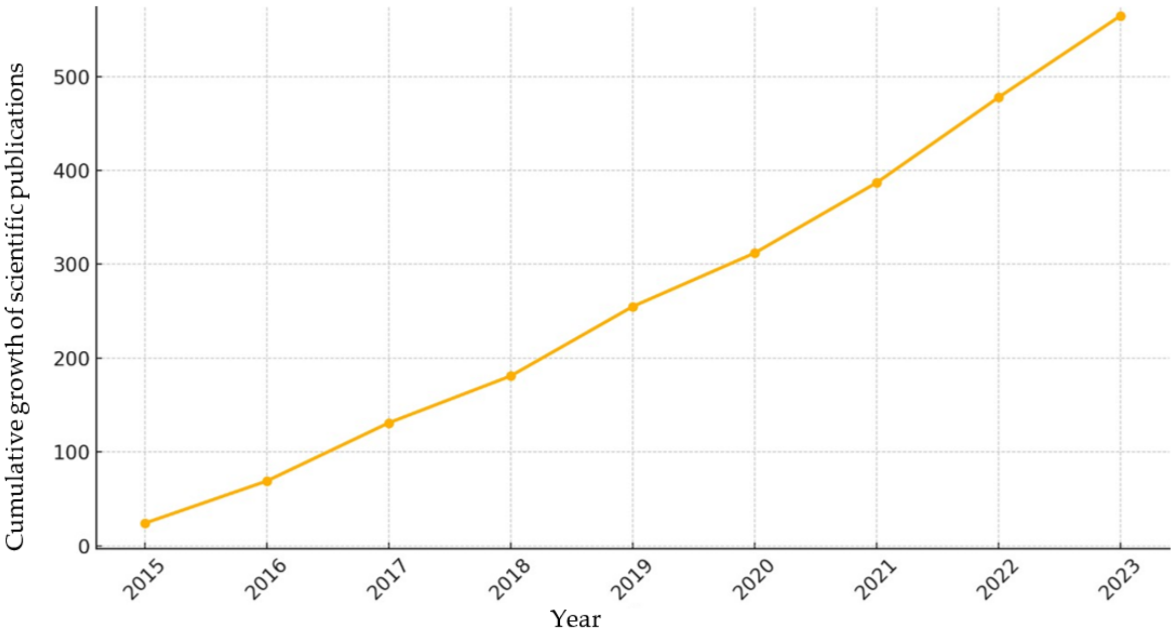

Figure 1. Time-based cumulative trend of scientific contributions on robotic machining (Scopus).

The inherently low stiffness of robotic arms is the most critical technical limitation identified in the scientific literature. It continues to pose significant challenges that impact machining quality, particularly in terms of dimensional accuracy, geometric precision, and surface finish. The main errors observed in robotic machining can be classified into three major categories [6]:

- Inaccuracies in absolute positioning: Deviation errors between the robot's theoretical positions and the actual position of the cutting edge of the machining tool.
- Fluctuating deformations of the robot under alternating forces from the machining process: Deviation errors in the actual cutting path resulting from the interaction between the machining forces and the mechanical behaviour of the robotic arm.
- Vibrations due to coupled frequency modes or regenerative chatter: Tool deviation errors caused by the combined effect of cutting conditions and the vibration modes of the robotic arm.

The growing use of industrial robots in machining operations has driven the development of multiple strategies to improve their accuracy, stability, and performance. Considering the limitations and barriers associated with these systems—mainly due to their low structural stiffness, limited operational stability margin under dynamic fluctuations, and vibrations caused by the excitation forces generated by the machining process itself—the scientific literature identifies several key areas for improvement.

One such area includes state-of-the-art advancements in robot posture optimization, aimed at minimizing dimensional deviation errors and surface quality issues. In this study, posture denotes the robot's joint-space configuration (arrangement of joints and links) together with the end-effector orientation relative to the workpiece and robot base; it is distinct from the TCP position (Cartesian coordinates), tool-frame rotation (orientation) and the Cartesian pose (both position and orientation). Based on recent literature [7,8], these advancements can be classified according to their intended purpose, which facilitates their analysis and comparison:

- Posture optimization methods: These contribute to the proper selection of the manipulator and optimal use of the robot's structural capacity.
- Acquisition of information about the machining process state: Aimed at understanding the robot's dynamic response in order to select the most favourable cutting conditions.
- Compensation of force-induced deformations: Involves solutions focused on compensating for errors either in real time (online) or offline.

As an example of posture optimization considering stiffness and error compensation, a notable contribution is the integrated model that combines cutting-plane stiffness and posture accuracy, optimized using the Grey Wolf Optimizer (GWO) algorithm [9]. Methods have also been proposed to enhance toolpaths by optimizing posture and spindle speed, leading to a significant reduction in vibrations, such as the work by Hou et al. [10]. Xin et al. demonstrated that posture-dependent stiffness directly influences stability and gives rise to Stability Boundary Improvement Domains (SBID), which are useful for robot trajectory planning [11].

Regarding recent scientific advances in process monitoring, a growing trend focuses on developing advanced methods for cutting force detection and prediction, such as the PSO-LSTM models introduced by Wu et al. for real-time process monitoring [12]. To detect and suppress chatter, researchers have employed approaches based on wavelet transforms and entropy features, such as the method proposed by Yang et al. [13], as well as active actuators featured by Guo et al. to enhance dynamic stiffness [14]. Deformation compensation, significant contributions include approaches based on nonlinear stiffness models and adjusted trajectory planning, enabling offline and in some cases online compensation, as suggested by Klimchik et al. [15]. The development of specialized actuators and controllers, such as those by Sahu et al., equipped with innovative technical capabilities for vibration suppression and adaptive trajectory control, is driving a growing trend toward online compensation solutions [16].

Table 3. List of Abbreviations.

Abbreviation	Meaning
AE	Acoustic Emission
AI	Artificial Intelligence
CNC	Computer Numerical Control
CAM	Computer Aided Manufacturing
DOF	Degree of Freedom
D-H	Denavit-Hartenberg
DL	Deep Learning
FEA	Finite Element Analysis
FRFs	Frequency Response Functions
GA-BPNN	Genetic Algorithm—Backpropagation Neural Network
GWO	Grey Wolf Optimizer
ISO	International Organization for Standardization
LSTM	Long Short-Term Memory
ML	Machine Learning
MLP	Multi-Layer Perceptron
MRR	Material Removal Rates
MSA	Matrix Structure Analysis
MSTMM	Modified Stiffness Transmission Matrix Method
MTGP	Multi-task Gaussian Process
PFISE	Periodic Force-Induced Surface Errors
PSO	Particle Swarm Optimization
RCSA	Rigidity-Conditioned Stability Analysis
SBID	Stability Boundary Improvement Domain
SeDANN	Self-enhanced Dual Attention Neural Network
SFE	Surface Form Errors
SLD	Stability Lobe Diagram
SLE	Surface Location Error
SQP	Sequential Quadratic Programming
SWOT	Strengths, Weaknesses, Opportunities, Threats
TCP	Tool Centre Point
VJM	Virtual Joint Modelling

Dimensional deviation errors caused by the low stiffness, or posture-dependent compliance of the robot, can be significantly reduced by optimizing the robot's joint configuration. The literature reports various solution approaches, ranging from stiffness modelling and identification to more recent advances involving global stiffness indices. The proposed tools have demonstrated reductions of 30% to 40% in TCP (Tool Centre Point) deflection and machining errors when the trajectory is replanned using the optimal posture [17,18]. The main reasons why robot posture optimization methods are considered the first-choice solution for reducing deviation errors in robotic machining are:

1. Ease of implementation and workshop-level adjustment. Posture Optimization Methods (POMs) can be integrated into the same CAM software already used by operators, and can recalculate joint angles within seconds. Schneider et al. [19] demonstrated the automatic generation of optimal postures directly from the toolpath program; Souflas et al. [20] validated, using a digital twin, that the technician can regenerate the path with a single dry run; and Liao et al. [21] achieved a final accuracy of 172 µm by adjusting the posture in situ.
2. Clearly favourable cost-to-benefit ratio. Compared to investing in a large-scale CNC machine tool, an industrial robot typically costs only 30–60% of the initial investment, and posture optimization often requires no additional hardware [22]. Ji and Wang [23] emphasize that even when accounting for structural enhancements, the investment remains an order of magnitude cheaper than purchasing a dedicated machine tool. Since POMs can deliver up to 40% improvement in dimensional accuracy, the overall economic return is highly favourable.
3. Complementarity with process sensing and dimensional error compensation. By first minimizing static deformation, the error bandwidth that sensing systems or active compensation algorithms need to correct is greatly reduced. Klimchik et al. [15] showed that compensation algorithms converge faster and require smaller actuator displacements when the trajectory is already posture-optimized. Several reviews recommend this sequential approach: optimize posture, sense, and compensate [24].

Therefore, posture optimization in robotic machining is considered the first logical intervention, and the proper selection of the optimization method is key to achieving significant improvement at marginal cost. It can be applied and adjusted directly on the shop floor, and it lays the foundation for the integration of process sensing and force-induced deformation compensation techniques, if needed.

2. Materials and Methods

This work analyses the existing scientific literature on advances in the field of robotic machining operations to address two research questions: (1) What are the significant historical events and the current state of research? (2) What new developments are emerging in research on posture optimization methods and techniques for robotic machining of large-scale components?

Previous studies by Faisal et al. [25] and Sheikhnejad & Yigitcanlar [26] support the suitability of using scientometric techniques, as these can visualize qualitative data and generate knowledge maps showing the connections among diverse progress in the domain. Scientometric analysis is widely accepted and allows a deep understanding of research trends, collaborative networks, and high-impact topics. For this reason, a search was conducted in a prestigious scientific and technical literature database on robotic machining. The queries and results were obtained from bibliographic repositories using the following keywords: serial-robot-based manufacturing, robotic machining, steel, aluminium, titanium, composite materials, posture optimization methods, deviation errors, and surface quality.

In parallel with industrial drivers, academic output on robotic machining has grown steadily, as illustrated in Figure 2. The Scopus repository by Elsevier was selected for the bibliographic search. According to its most recent datasheet (February 2025), Scopus contains over 100 million records, 31.2 thousand active serial titles (including 29.3 thousand peer-reviewed journals), and nearly 400 thousand books. This extensive coverage positions it as one of the most comprehensive and high-quality sources of scientific literature, offering powerful search and analysis tools that assist with the complex tasks of literature retrieval and review.

Given the scientific purpose of this work—to review the state of the art in the field of serial robotic machining applied to material removal processes for the construction of large-scale structural components—the research objectives focused on identifying scientific and technical innovations as well as literature trends in robotic machining.

The final search query used for this task employed the following TITLE-ABS-KEY sequence: "posture optimization" AND ("robotic machining" OR "manufacturing") AND "machining with a robotic arm". The literature search was conducted in February 2025, covering publications from March 2005 to February 2025. As a result, a total of 4532 publications were selected from the Scopus repository, including conference papers, journal articles, review papers, book chapters, and other scholar literature.

Publications lacking relevant information—such as those unrelated to the research topic or authored anonymously—were excluded. The full records of the resulting publications were exported, including citations and bibliographic data, abstracts, keywords, funding information, and other metadata.

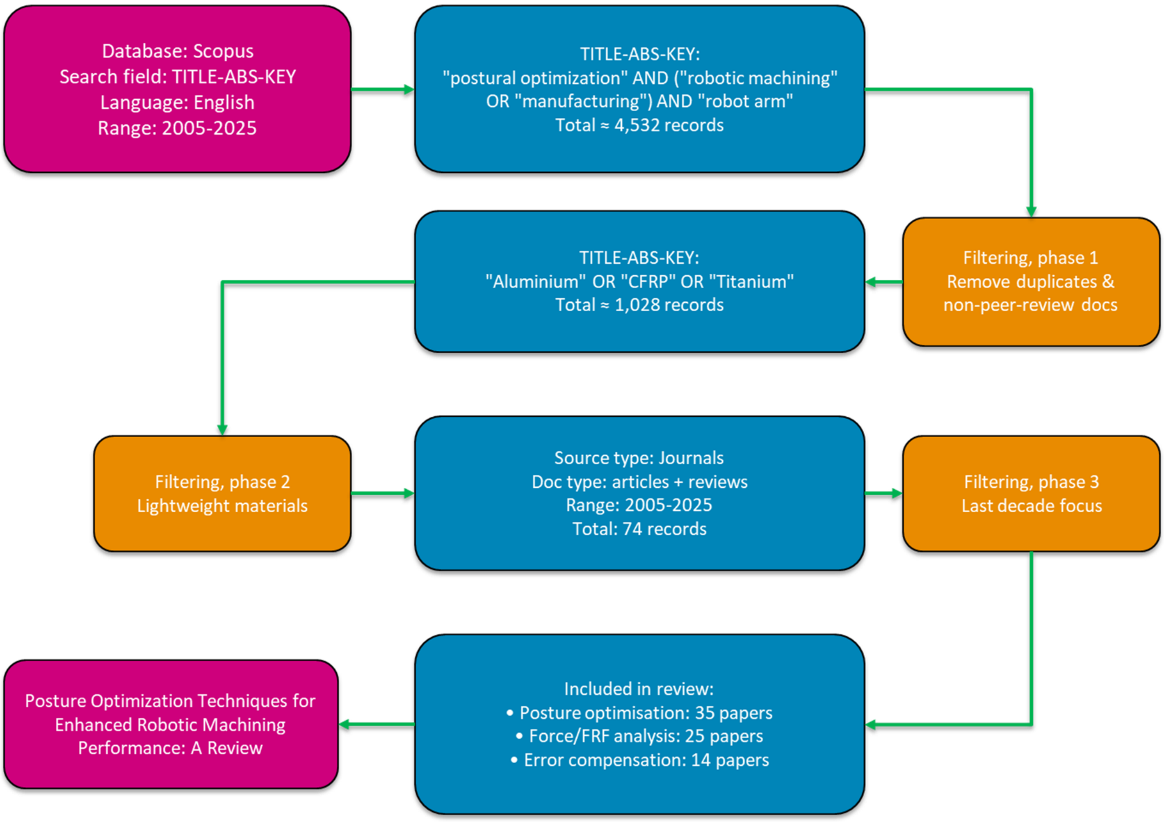

Figure 2. Representative Flowchart of the Systematic Literature Review.

3. Results

Posture optimization in milling robots has emerged as an effective solution to address structural stiffness issues. Although strategies such as the adoption of hybrid serial-parallel architectures [1,27] or the use of alternative materials in robotic arms and joints have demonstrated improvements in the system's overall stiffness [28], they also introduce significant complexity in design, manufacturing, and control, which limits their practical implementation in industrial settings, as noted by Guo et al. [14] and Ji & Wang, [23]. An alternative with lower structural impact involves introducing redundant degrees of freedom [29,30], such as tool axis rotation in five-degree-of-freedom systems, as proposed by Chen et al. [31].

Current research is primarily focused on six key areas of improvement: stiffness modelling, experimental stiffness identification, selection of posture optimization indices, cutting force direction control, and trajectory-based posture optimization.

3.1. Static Stiffness Modelling of the Robot

Structural stiffness determines a system's ability to resist elastic deformation under external forces. Although the forces involved in milling are dynamic and variable, static modelling has proven to be an acceptable approximation when operating far from the robot's natural frequencies, as noted by Cordes et al. [32]. Moreover, factors such as backlash [33], friction [34], and variable damping [35] complicate the development of accurate dynamic models. In this context, Virtual Joint Modelling (VJM) offers a balance between accuracy and simplicity. This method treats joints as torsional springs and links as rigid bodies, and has evolved from models with 6 up to 36 stiffness parameters [36,37].

On the other hand, Finite Element Analysis (FEA) provides the most detailed modelling approach by discretizing the robot into a mesh, where accuracy depends on boundary conditions, material properties, and mesh quality [38]. However, its results are valid only for specific postures, which requires frequent recalibrations [15,39].

Matrix Structural Analysis (MSA) models links as flexible beams and is more suitable for parallel robots and applications where the structural frame is rigid. Although its accuracy is lower in systems with flexible joints, it has been experimentally validated on Stewart-type platforms [40,41].

Therefore, as shown in the Table 4, Static stiffness modelling provides an essential foundation for predicting deformation and optimizing machining accuracy. While VJM offers simplicity and adaptability, FEA ensures high accuracy at the cost of computational intensity. MSA remains valuable for rigid and parallel mechanisms. The reviewed studies collectively highlight the trend toward integrated stiffness optimization in motion planning and toolpath generation.

Table 4. Static Stiffness Modelling of Industrial Robots.

Author	Main Purpose	Method or Model	Key Findings
Chen et al. [31], 2021	To improve pose planning for increased stiffness during milling	Finite Element Analysis (FEA) for posture-based stiffness evaluation	Demonstrated pose optimization improves machining accuracy
Cordes et al. [32], 2019	To enhance stability in robotic milling through redundancy optimization	Experimental and simulation-based stability analysis considering kinematic redundancy	Demonstrated that redundancy control improves milling stability by avoiding critical postures
Liu et al. [34], 2023	To optimize robot redundancy for smoother milling motions	Global optimization algorithm applied to 6R robot	Optimization reduces vibration and improves tool-path smoothness
Lehmann et al. [35], 2013	To model joint stiffness and identify parameters accurately	Experimental identification using the clamping method	Provided quantitative joint stiffness parameters
Klimchik, et al. [36], 2018	To develop stiffness models using Matrix Structural Analysis (MSA)	Analytical formulation of MSA for robot manipulators	Validated on Stewart-type platforms; effective for parallel mechanisms
Klimchik et al. [37], 2017	To assess robot performance in machining	Virtual Joint Modelling (VJM) with multiple stiffness parameters	Found trade-offs between model complexity and computational efficiency
Li et al. [39], 2023	To optimize tool posture considering joint loads and stiffness	Combined static and FEA-based posture optimization	Improved surface quality and reduced tool deflection
Khan et al. [40], 2020	To develop real-time optimization for robot motion control	DPSO algorithm applied to inverse kinematics	Improved accuracy and computational efficiency
Liao et al. [41], 2020	To generate optimized toolpaths considering stiffness distribution	Region-based optimization algorithm integrating stiffness modelling	Improved machining accuracy and reduced deflection errors

3.2. Static Stiffness Identification of the Robot

Since manufacturers typically do not provide stiffness parameters for robots, these must be identified experimentally [42]. Among the most commonly used methods are the immobilization of individual joints under load and the selection of postures with high inverse condition numbers to maximize stiffness sensitivity in joint space [9,11]. Zhang et al. proposed combining dexterity indices with conditioning metrics to define optimal measurement configurations [43], while Chen et al. developed joint transmission models based on both local and global parameters [19]. Traditionally, a constant stiffness coefficient has been assigned to each joint; however, in practice, this value varies nonlinearly with the joint angle [44]. Emerging methods such as variable stiffness modelling in spatial meshes [45] and the use of Reconfigurable Rotary Stiffness-Enhanced Actuators (RRSEAns) have been proposed to better capture these dynamics [46], though they are not yet widely adopted due to their complexity.

As shown in the Table 5, accurate identification and modelling of static stiffness is essential for posture optimization in robotic milling processes. While VJM provides a good balance between accuracy and complexity, FEA and MSA models offer value in specific scenarios. The future integration of variable-stiffness models holds promise for improved adaptability, though current strategies still favor the assumption of constant stiffness due to its practical effectiveness.

Table 5. Static Stiffness Identification of Industrial Robots.

Author	Main Purpose	Method or Model	Key Findings
Song et al. [9], 2024	To improve accuracy in robotic side milling through posture optimization	Kinematic modelling and stiffness sensitivity analysis using inverse condition numbers	Identified optimal postures with higher stiffness and accuracy; confirmed effectiveness for accuracy compensation in milling
Xin et al. [11], 2022	To analyze how robot structural modes affect regenerative chatter during milling	Experimental modal and stability domain analysis	Found that stiffness distribution strongly influences chatter suppression and stability limits
Nigus [42], 2014	To estimate stiffness parameters for a parallel kinematic machine	Semi-analytical formulation combining analytical and numerical modelling	Achieved accurate stiffness estimation without full FEA; confirmed the need for experimental identification since manufacturers rarely provide stiffness data
Zhang et al. [43], 2024	To develop a calibration method accounting for pose uncertainty and stiffness errors	Integration of dexterity indices with conditioning metrics for optimal measurement configurations	Improved accuracy and repeatability in stiffness-based pose compensation
Abrajan & Kelly [44], 2018	To examine nonlinear stiffness variation with joint angle	Dynamic modelling and experimental validation of joint compliance	Demonstrated that stiffness varies nonlinearly with joint angle, challenging constant-stiffness assumptions
Qian et al. [45], 2022	To design actuators with adjustable stiffness characteristics	Development and control of a Reconfigurable Rotary Series Elastic Actuator (RRSEA) with nonlinear stiffness	Enabled real-time stiffness adaptation to load and posture; highlighted potential for adaptive robotic systems
Guo et al. [46], 2015	To optimize robot posture for stiffness enhancement during machining	Static stiffness modelling combined with multi-objective optimization	Achieved higher machining precision and stiffness-oriented control efficiency

3.3. Selection of Indices and Posture

Posture optimization in robotic milling critically depends on the selection of indices that accurately represent the system's stiffness, stability, and dynamic capabilities. One of the most widely adopted approaches involves the use of stiffness ellipsoids at the tool–workpiece contact point. These ellipsoids enable the visualization and quantification of directional stiffness, helping to guide the selection of postures that offer optimal rigidity [46,47]. The strategy typically involves maximizing the ellipsoid radii in the cutting direction, thereby reducing elastic deformation induced by the tool.

Another common technique is the analysis of the Frequency Response Function (FRF), which evaluates the system's dynamic behaviour across different postures and identifies the configurations offering greater stability against chatter. This analysis has been applied to accurately predict stability regions in the frequency vs. depth-of-cut domain [48].

Additionally, composite indices have been developed that integrate kinematic, dynamic, and stiffness-related aspects into a unified optimization model. For example, recent studies have combined criteria such as trajectory smoothness, milling width, and proximity to singularities to generate optimal postures using sequential quadratic programming algorithms [49].

Bio-inspired optimization algorithms, such as the Grey Wolf Optimizer (GWO), have also been implemented to identify postures that simultaneously maximize stiffness in the cutting plane and positional accuracy of the system [19,50]. The choice of performance index is critical, as it determines the trade-offs accepted between stiffness, stability, accuracy, and kinematic feasibility [51,52].

Finally, statistical prediction methods, such as multi-output Gaussian Process Regression, have been explored to estimate the dynamic behaviour of untested postures. This enables generalization of identification results and supports real-time optimization in production environments [53].

In summary, as shown in the Table 6, posture optimization in robotic milling is evolving from simple geometric approaches toward multi-domain strategies that integrate dynamics, stiffness, and vibratory behaviour. The combination of mechanical indices with advanced optimization techniques enables the selection of postures that enhance process stability, surface quality, and machining precision.

Table 6. Posture Optimization in Robotic Milling.

Author	Main Purpose	Method or Model	Key Findings
Chen et al. [19], 2021	To optimize posture considering spindle weight and cutting force effects	Comprehensive deformation index and sequential quadratic programming	Achieved posture configurations minimizing deformation while maintaining kinematic feasibility
Guo et al. [46], 2015	To optimize robot posture considering stiffness in robotic machining	Static stiffness-based optimization using stiffness ellipsoids	Maximizing stiffness ellipsoid in the cutting direction reduces elastic deformation and improves machining accuracy
Kito et al. [47], 2021	To refine workspace and posture selection using ellipsoid metrics	Minimum volume enclosing ellipsoid method in task space	Enabled quantitative representation of directional stiffness and safe workspace evaluation
Deng et al. [48], 2023	To predict dynamic behaviour and chatter stability across different robot postures	Frequency Response Function (FRF) analysis considering pose and feedrate	Accurately predicted stability regions in the frequency–depth-of-cut domain; improved chatter suppression
Liu et al. [49], 2022	To estimate deflection in industrial robots with flexible joints	Composite modelling integrating kinematic, stiffness, and dynamic parameters	Developed deflection estimation approach enabling multi-objective optimization of posture
Mirjalili et al. [50], 2014	To develop a metaheuristic optimization algorithm inspired by social hierarchy	Grey Wolf Optimizer (GWO) applied to multi-objective posture problems	Enhanced convergence speed and precision in stiffness and accuracy optimization
Lei et al. [51], 2023	To predict posture-dependent tool tip dynamics	Multi-task Gaussian Process Regression (GPR) model	Enabled real-time prediction of stiffness and vibration characteristics across postures
Zhang et al. [52], 2019	To define and optimize a comprehensive stiffness performance index for robotic milling	Analytical modelling combined with performance index optimization	Proposed a global stiffness performance index for posture evaluation and control
Tian et al. [53], 2017	To optimize layout and operational posture in robotic grinding systems	Statistical modelling and stiffness-based optimization using Gaussian Process Regression	Demonstrated effective prediction of untested postures and improved surface quality

3.4. Cutting Force Direction and Its Relationship with Performance

The direction of the cutting force during robotic milling has a direct impact on system performance, as it interacts with the robot's directional stiffness. Since industrial robots exhibit anisotropic stiffness, forces applied in certain directions result in greater deformations than in others, affecting both surface quality and the dynamic stability of the process [30,54].

Recent studies have shown that, for specific robot postures, maximum stiffness does not always align with the primary cutting direction, which can trigger conditions prone to chatter or geometric inaccuracies. To address this issue, models have been proposed that integrate the cutting force direction with the orientation of the stiffness ellipsoid in Cartesian space. By aligning the main cutting direction with the axis of maximum stiffness, structural deformation is minimized and milling performance is enhanced [13,55].

Additionally, certain low-frequency vibration modes, induced by the robot's structural configuration, may coincide with the tool's excitation frequencies in specific postures. In such cases, the cutting direction can either suppress or amplify these modes, affecting the critical depth of cut and, consequently, machining efficiency [11,56]. Active approaches have also been proposed, such as using contact actuators that apply counteracting forces opposite to the cutting force to neutralize unwanted deformations and suppress vibrations. These systems effectively modify the interaction between the cutting force and the robot's directional stiffness, improving dynamic behaviour without requiring posture reconfiguration [57,58].

In summary, as shown in the Table 7, the relationship between cutting force direction and the directional stiffness of the robotic system is a critical factor in posture optimization. Orienting the cutting process along structurally favourable directions enhances stability, accuracy, and milling efficiency, while active solutions can complement this strategy when reorientation is not feasible.

Table 7. Cutting Force Direction and Its Relationship with Robotic Milling Performance.

Author	Main Purpose	Method or Model	Key Findings
Xin et al. [11], 2022	To study influence of structural modes on chatter and stability boundaries	Experimental modal analysis and frequency domain stability evaluation	Revealed that certain postures amplify vibration modes when cutting direction aligns with low-stiffness axes
Yang et al. [13], 2023	To detect early chatter under varying postures and cutting parameters	Dynamic signal analysis and posture-dependent chatter prediction	Found that misalignment between cutting direction and maximum stiffness axis increases chatter risk
Ye et al. [54], 2021	To optimize workpiece placement to minimize contour errors due to posture-dependent stiffness	Task-dependent placement optimization using stiffness mapping and error modelling	Demonstrated that aligning the task with the robot's stiffest direction reduces contour errors and improves dimensional accuracy
Qu et al. [55], 2023	To optimize feed direction and posture for free-form surface milling	Profile-error-oriented optimization integrating stiffness ellipsoid orientation	Achieved minimal profile error by aligning feed direction with maximum stiffness axis
Lin et al. [56], 2022	To minimize contour errors via end-effector pose optimization	Contour-error-based optimization of tool orientation and cutting direction	Showed that posture reorientation mitigates vibration amplification and improves machining precision
Peng et al. [57], 2020	To improve toolpath smoothness and reduce deformation through active compensation	Path optimization using smoothness-oriented control with counteracting actuators	Active counterforce application reduces deformation and improves dynamic stability without posture changes
Chen & Ding [58], 2023	To enhance posture optimization using sequential quadratic programming under varying cutting loads	Sequential quadratic programming with integrated stiffness–force interaction modelling	Validated that active optimization of cutting direction improves stability and surface quality

3.5. Posture and Trajectory Optimization

The joint optimization of the robot's posture and the toolpath is one of the most effective strategies to improve robotic milling performance. This approach not only avoids low-stiffness configurations but also reduces vibration, enhances machining quality, and increases process efficiency [59]. Unlike traditional methods that optimize only the geometric trajectory, modern approaches incorporate mechanical parameters, such as directional stiffness and dynamic stability, into the planning process [57]. For instance, a model has been proposed that simultaneously optimizes posture by considering both trajectory smoothness and milling width, using sequential quadratic programming. This approach has been shown to improve surface finish and reduce total machining time [39].

Another relevant strategy is the prediction of the Frequency Response Function (FRF) across multi-posture trajectories. This method allows forecasting the system's stability along the entire toolpath, enabling the avoidance of chatter-prone regions and the automatic selection of cutting parameters and optimal posture for each segment [60,61]. Recent studies have also explored the joint optimization of posture and spindle speed. Coordinated adjustment of both parameters has led to significant reductions in peak acceleration and vibration amplitude, improving surface quality even along complex trajectories [62].

Furthermore, the use of AI-based prediction models has enabled the estimation of the system's dynamic performance at unmeasured points. For example, Gaussian Process Regression (GPR) has proven effective in predicting the robot's stiffness and modal behaviour along the toolpath, facilitating intelligent real-time planning [51,63].

In summary, as shown in the Table 8, the simultaneous optimization of posture and trajectory transforms robotic milling into an adaptive and intelligent process, capable of anticipating dynamic issues and automatically adjusting operational parameters. This strategy represents a key step toward the robust automation of complex manufacturing processes using industrial robots.

Table 8. Posture and Trajectory Optimization in Robotic Milling.

Author	Main Purpose	Method or Model	Key Findings
Li et al. [39], 2023	To optimize tool posture considering joint load and stiffness in surface milling	Sequential quadratic programming combining trajectory smoothness and milling width	Significantly improved surface finish and reduced total machining time
Lei et al. [51], 2023	To predict posture-dependent tool tip dynamics	Multi-task Gaussian Process Regression for dynamic prediction	Enabled real-time estimation of dynamic response across trajectories; supported intelligent planning
Liao et al. [59], 2024	To achieve constant load and stiffness-matched toolpath planning in surface milling	Integrated toolpath and posture optimization using stiffness matching and load balancing	Improved machining stability and uniform surface quality by maintaining constant load and stiffness along trajectory
Chen et al. [60], 2024	To generate optimized toolpaths for robotic flank milling based on stiffness and smoothness	Stiffness and smoothness optimization model integrated with posture planning	Increased stability and tool life through stiffness-oriented trajectory generation
Sousa et al. [61], 2020	To analyze cutting forces and their impact on process planning	Review and modelling of cutting-force estimation techniques	Highlighted the importance of incorporating cutting-force prediction in trajectory optimization
Cao et al. [62], 2017	To coordinate posture and spindle speed for improved milling performance	Integrated optimization of spindle dynamics and robot posture	Reduced peak acceleration and vibration amplitude; improved surface quality along complex paths
Majumder et al. [63], 2019	To review advances in multifunctional sensing and AI-based monitoring	Survey of multi-sensor systems and AI integration	Provided foundations for real-time adaptive optimization using sensor data and machine learning

3.6. Advanced Optimization Methods

Advanced optimization methods in robotic milling are designed to address complex problems involving multiple interrelated variables such as posture, stiffness, dynamic stability, precision, and surface quality. As requirements for accuracy and efficiency increase, classical solutions based on kinematic analysis or empirical testing become insufficient. As a result, there is growing adoption of global optimization algorithms, artificial intelligence (AI) techniques, and predictive models.

One of the most prominent approaches involves the use of evolutionary algorithms, such as the Grey Wolf Optimizer (GWO) and Particle Swarm Optimization (PSO), to identify optimal postures that simultaneously maximize stiffness and accuracy. These bio-inspired algorithms have demonstrated strong capability in navigating non-convex search spaces, where deterministic methods often fail. For example, robot positional errors have been reduced to below 0.05° after applying dual compensation based on GWO-optimized postures [40,41].

In dynamic prediction, techniques such as Multitask Gaussian Process Regression (MTGP) have been used to estimate Frequency Response Functions (FRFs) at unmeasured postures. This significantly reduces the number of tests needed to plan an optimal toolpath while maintaining the accuracy of the dynamic model [51].

Moreover, active compensation methods have been developed using actuators or adaptive vibration filters. For instance, inertial active damping systems can dynamically modify the robot's stiffness in real time, enhancing stability under aggressive cutting conditions or high-speed operations [64]. Strategies have also been explored that combine predictive modelling with the simultaneous optimization of multiple variables, such as posture, spindle speed, and feed direction. These strategies are implemented through hybrid algorithms, including objective function regression combined with heuristic search techniques [10,16].

Taken together, as shown in the Table 9, these advanced optimization methods mark the transition of robotic milling toward a process intelligence paradigm—systems that not only execute programmed tasks, but also adapt their dynamic parameters in real time to maximize performance under changing conditions. This approach represents a fundamental step toward robotic autonomy in demanding industrial environments.

Table 9. Advanced Optimization Methods in Robotic Milling.

Author	Main Purpose	Method or Model	Key Findings
Hou et al. [10], 2025	To jointly optimize robot posture and spindle speed for enhanced performance	Hybrid global optimization integrating heuristic search and objective function regression	Improved machining stability and reduced vibration amplitude through coordinated parameter optimization
Sahu et al. [16], 2024	To enhance robotic milling performance through active damping	Development of active damping control targeting low-frequency modes	Significantly reduced vibration levels and improved surface quality in flexible configurations
Khan et al. [40], 2020	To improve real-time inverse kinematics and posture optimization	Dual Particle Swarm Optimization (DPSO) algorithm applied to 6-DOF robotic systems	Achieved high accuracy and convergence efficiency; positional errors reduced below 0.05° after dual compensation
Liao et al. [41], 2020	To generate optimized toolpaths considering stiffness for freeform surface milling	Region-based toolpath optimization with stiffness integration	Improved machining precision and toolpath adaptability using stiffness-aware optimization
Lei et al. [51], 2023	To predict dynamic behaviour of robotic systems at unmeasured postures	Multitask Gaussian Process Regression (MTGP) for FRF prediction	Enabled accurate dynamic estimation with fewer experimental tests; facilitated intelligent planning
Ozsoy et al. [64], 2022	To evaluate feasibility of robotically assisted active vibration control in milling	Implementation of inertial active damping and adaptive vibration filtering	Demonstrated real-time modification of structural stiffness and improved dynamic stability under high-speed operations

4. Discussion

First, we note that this work has contributed to expanding the candidate's comprehensive understanding of the general issues affecting dimensional quality in robotic machining, particularly those arising from the limited mechanical stiffness properties of articulated robotic arms used for high material removal rate milling tasks. As a result of the conducted literature review, it is clear that current research spans multiple areas, including stiffness modelling, posture optimization, deformation compensation, and vibration suppression. A thorough analysis of this body of knowledge has led to the identification of four key research areas, which serve as guidance for selecting an appropriate optimization strategy:

1. Static stiffness modelling and identification: This is fundamental for posture optimization and involves approaches such as the Virtual Joint Modelling (VJM), Finite Element Analysis (FEA), and Matrix Structural Analysis (MSA) [30,38]. The exploration of variable stiffness modelling is highlighted as a promising direction to enhance system adaptability [39].
2. Posture optimization and selection of representative indices: This area focuses on correlating the robot's stiffness with its operational posture, considering cutting forces and other process parameters. The goal is to develop methodologies that improve flexibility and efficiency in robotic machining [49,54].
3. Acquisition of dynamic process information: Characterizing and analysing milling conditions is essential for vibration control and precision improvement. Methods such as Rigidity-Conditioned Stability Analysis (RCSA) and the Modified Stiffness Transmission Matrix Method (MSTMM) are assessed for their effectiveness under dynamic conditions [55–57,60,63].
4. Hybridization of the above techniques: This refers to the integrated application of the previously mentioned models and techniques, adapted to the specific requirements of the machining process and the mechanical characteristics of serial robots [7,10].

The growing integration of industrial robots in subtractive manufacturing operations requires not only maximizing the robot arm's capability relative to the technical demands of the process, or selecting the most suitable machining conditions based on the characteristics of the manufacturing system, but also carefully choosing the most appropriate optimization strategies according to the production context.

Based on a graphical and structural comparison of six advanced optimization methods, it becomes evident that no single universal solution exists for all machining processes. Instead, the choice should be primarily guided by the nature of process, application environment, and operational constraints. The SWOT matrix synthesising these findings, shown in Table 10, illustrates the current approaches.

Table 10. SWOT—Optimization Methods in Robotic Machining.

Strengths	Weaknesses
✓ High potential to improve dimensional accuracy, surface quality, and process stability. ✓ Enables adaptation to variable machining conditions. ✓ Reduces trial-and-error in process planning. ✓ Facilitates integration with AI and predictive models.	✓ High computational cost in real-time applications. ✓ Complexity in modelling robot dynamics and stiffness. ✓ Requires expert knowledge for tuning and implementation. ✓ Limited standardization across platforms and robot brands.
Opportunities	**Threats**
✓ Integration with Industry 4.0, digital twins, and smart manufacturing environments. ✓ Development of hybrid algorithms (AI + physics-based models). ✓ Increased demand for flexible automation in aerospace, energy, and large-component sectors. ✓ Growth of open-source tools and collaborative robotics platforms.	✓ Resistance to adoption due to conservative industrial practices. ✓ Risk of overfitting in data-driven models without sufficient experimental validation. ✓ Hardware limitations in low-end industrial robots (e.g., limited sensors or DOFs). ✓ Uncertainties in machining of novel or heterogeneous materials.

The SWOT matrix highlights that a well-chosen robot posture optimization technique stands out as a core strength of the robotic machining process. By minimizing elastic deformations and posture-induced errors, it ensures high dimensional accuracy. This presents a tangible opportunity to deploy production cells centred around serial robots—an approach whose technical maturity has already been validated in industry.

However, this advantage is balanced by the weakness of its technical complexity in implementation, and it faces the critical threat of high development and integration costs. These costs will only be manageable if the optimization strategy is planned from the system design phase, ensuring that integration challenges are addressed proactively rather than reactively.

The most prominent trend in conventional milling processes—typical in the automotive industry or general metal manufacturing—highlights the effectiveness of posture optimization considering stiffness and error compensation, as shown in Figure 3. This approach combines technological maturity with proven results in improving stability and surface quality. Although its technical implementation can be demanding, particularly in terms of modelling and sensing, its cost-effectiveness is evident in highly repetitive production environments, where the initial investment is justified [9,15].

On the other hand, weld seam overstock removal, common in petrochemical or energy sectors, presents a highly demanding scenario, where cutting forces are elevated and unstable vibrations severely compromise structural integrity and efficiency. In such cases, methods like chatter suppression using transforms and active actuators emerge as particularly effective solutions. Their ability to adapt dynamic stiffness in real time represents a significant advancement. Despite their cost and complexity, they enable operation under aggressive conditions without compromising quality.

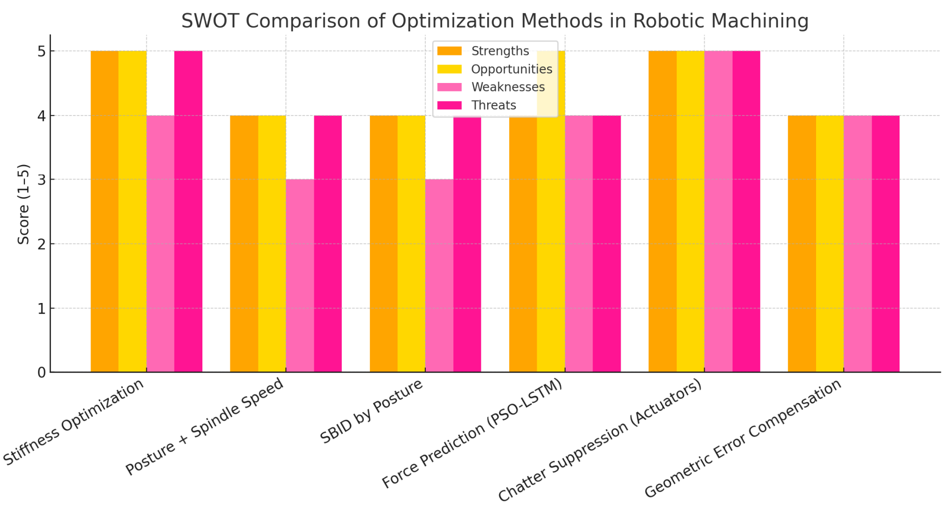

Figure 3. Representative Flowchart of the Systematic Literature.

In high-precision applications such as metal–CFRP drilling, PSO-LSTM models can anticipate cutting-force dynamics and proactively tune parameters, which is valuable in non-recoverable processes. Their main limitations are data dependence, computational cost, hyperparameter sensitivity, and vulnerability to noise/overfitting. In contrast, GWO is data-agnostic and effective in non-convex search, but may exhibit poor local refinement and become trapped in local optima, limiting consistent discovery of global solutions. In practice, hybrid pipelines—using GWO to explore promising regions and PSO-LSTM to refine real-time force prediction—mitigate individual weaknesses and align with the threats and opportunities identified in the SWOT.

This reflection reinforces the idea that the selection of optimization techniques must go beyond their technological sophistication, prioritizing their suitability for real process conditions and their integration potential. The key lies in balancing the added value in quality and productivity with implementation feasibility and return on investment, depending on the sector, material, and specific operation.

Future Research and Interests

Since Colgate et al. defined the collaborative robot in 1996 and Universal Robots released the UR5 in 2008, collaborative robotics has matured into a viable alternative for machining tasks that once required complete cell isolation [65]. Collaborative robots are typically lighter and less rigid than conventional industrial arms, which exacerbates posture-dependent compliance and dimensional errors. Consequently, posture optimization is not merely beneficial but essential in cobots machining, as it directly mitigates the increased compliance associated with lightweight designs. The logical next step would be to transfer this know-how to the collaborative domain, where human-robot proximity demands the preservation of dimensional quality without compromising safety or the flexibility that cobots offer. It must be emphasized that collaborative robots are usually lighter and less rigid than industrial arms, which makes them even more prone to stiffness-related errors.

As illustrated in Figure 4, the expected research trends in collaborative robotic machining focus on synchronising posture optimisation with safety standards, improving dynamic modelling, integrating trajectory and spindle planning, employing digital twins for real-time validation, and advancing multimodal AI interfaces for seamless human–robot cooperation. For this reason, posture optimization in cobots is not only relevant but essential, as it directly mitigates the increased compliance issues associated with their lightweight design, and the key priority research lines identified were:

1. Synchronizing posture optimization with collaborative safety standards. The 2025 update of ISO 10218 consolidates and strengthens requirements previously outlined in ISO/TS 15066. Meeting these force and energy limits while pursuing maximum stiffness will require algorithms that re-optimize posture in real time: every time the operator enters the cell, the cobot must switch from an "optimal machining posture" to a "safe posture" without degrading precision beyond acceptable thresholds.
2. Enhancing dynamic modelling specific to cobots. Compared to traditional robot-CNC cells, collaborative machining imposes even stricter stiffness limits. Here, multimodal prediction using PSO-LSTM is particularly relevant, as neural networks can anticipate force peaks before contact sensors trigger, enabling early compensation or feed rate reduction. Additionally, studies incorporating redundant axes (e.g., seventh linear axes, mobile platforms) show that the workspace can be expanded without compromising dimensional quality if posture is re-optimized based on stiffness utilization and adaptive filtering [66–68]. This knowledge is transferable to mobile cobots now emerging in aerostructure repair or modular construction.
3. Integrating posture-trajectory-spindle planning in industrial cobots. Recent methods that jointly optimize posture and spindle speed to minimize vibration and chatter [69,70], as well as potential field-based models that adjust both robot configuration and workpiece position [65,71], naturally fit into collaborative cells. These approaches reduce noise and cycle time—critical factors for human coexistence—and could limit reprogramming to selecting a new optimization parameter set instead of rewriting toolpaths.
4. Digital twins and low-cost sensors to lower the adoption barrier. One of the main threats identified in the SWOT matrix (Table 4) is the cost of integration. Recent literature shows that a "light digital twin," fed by in-process measurements, can keep VJM or FRF models up to date at a fraction of the cost of full strain gauge setups [72,73]. This approach closes the loop between cutting force direction optimization strategies and ISO 10218 safety requirements, offering a virtual layer where safe and efficient postures can be validated before execution.
5. Multimodal AI and adaptive interfaces for smooth cooperation. Breaking the traditional "human leader–robot follower" hierarchy requires voice, gesture, and vision interfaces to feed the optimization loop. The operator could state the goal (e.g., "re-machine this edge") and the system would adjust posture in seconds to maximize stiffness and minimize risk. Optimized MLPs (GA-BPNN, SeDANN) already exceed 90% accuracy in

vibration mode classification [74,75]; the next step is fusing this predictive capability with dynamic models to transparently reconfigure the cell.

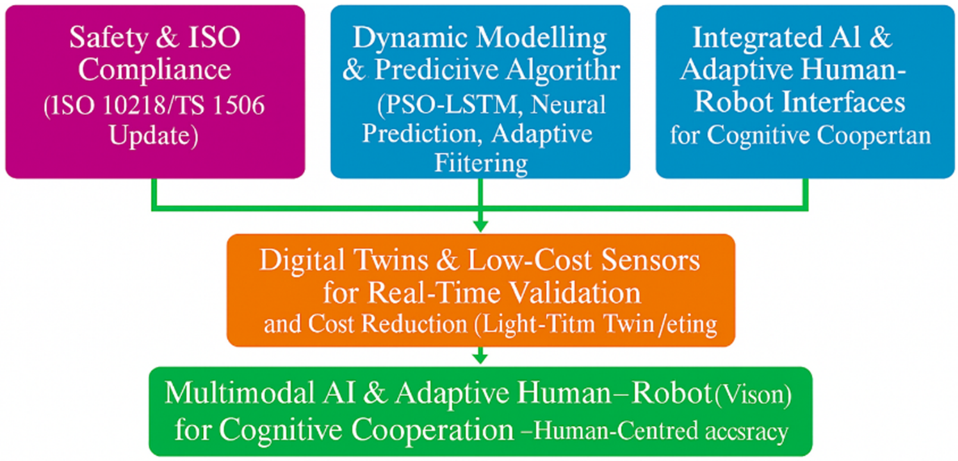

Figure 4. Future Trends in Robotic Posture Optimisation for Collaborative Machining.

5. Conclusions

The review of more than 4532 publications from 2005 to 2025 confirms that robot posture optimization is the most effective and cost-efficient intervention to mitigate the inherent low stiffness of serial manipulators during milling, drilling, and deburring of large parts. Experiments evidence shows typical reductions of 40% in tool centre point deflection and form errors when the toolpath is replanned using the optimal posture calculated via advanced global search techniques and updated stiffness models.

The state of the art converges on four technological pillars: accurate modelling and identification of static and dynamic stiffness, development of indices combining directional stiffness and vibrational stability, simultaneous planning of posture-trajectory-spindle speed, and the use of artificial intelligence algorithms to predict and compensate dynamic phenomena in real time. The maturity of evolutionary methods (PSO, GWO), statistical models based on Gaussian processes, and lightweight digital twin architectures demonstrates that posture optimization can now be integrated into standard CAM environments without requiring additional hardware and is compatible with continuous production cycles.

The SWOT matrix built for six representative techniques underscores that posture optimization considering stiffness and posture-induced errors is currently the option with the best balance between precision gain and technological risk—especially in aerospace and automotive sectors, where there is a track record of industrial deployment. Joint posture and spindle speed optimization appears as the second most robust alternative, adding systematic improvement in surface quality at a manageable integration cost. In contrast, methods such as predictive force detection and active chatter suppression offer clear opportunities for high-demand processes but require significant investment in sensors, actuators, and technical training.

Extending these methods to collaborative robotics opens a high-impact scenario: human-robot proximity imposes strict safety constraints per ISO 10218:2025, but it also adds flexibility and ease of reconfiguration. Real-time posture re-optimization, powered by digital twins and multimodal neural networks, enables micrometer-level tolerances to be maintained without exceeding the force and energy thresholds defined for safe interaction. Early trials with mobile cobots and seventh-axis platforms show that it is possible to expand the workspace, reduce cycle times, and preserve dimensional quality if the optimal posture is recalculated each time the workpiece setup or human presence changes.

Beyond synthesizing the state of the art, this review contributes a unified three-pillar framework (optimize–sense–compensate) and a decision-oriented SWOT that together act as a practical roadmap for industrial method selection. By explicitly extending posture optimization to collaborative machining and articulating posture–safety trade-offs, the work provides actionable guidance for deploying robot-based cells under ISO 10218:2025.

The research agenda must still overcome three decisive challenges: (1) establishing public, validated databases of stiffness parameters for a wide range of commercial robots; (2) developing posture re-optimization algorithms capable of complying with collaborative safety constraints while operating within industrial cycle times; and (3) rigorously evaluating the total cost of ownership of these solutions compared to large-format CNC machine tools. Closing these gaps would position posture optimization as the cornerstone enabling collaborative robotics to enhance precision outcomes without sacrificing the flexibility or cost-efficiency demanded by advanced manufacturing.

Author Contributions

I.I. and N.S.: conceptualization, methodology, software; I.I., J.-L.L. and N.S.: data curation, writing—original draft preparation; J.-L.L., C.A. and N.S.: visualization, investigation; I.I. and C.A.: supervision; N.S. and C.A.: software, validation; I.I. and J.-L.L.: writing—reviewing and editing. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest

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Use of AI and AI-Assisted Technologies

No AI tools were utilized for this paper.

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