Institute for Machine Tools and Industrial Management (iwb)
TUM School of Engineering and Design
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Methodical Approach for Analyzing Process Parameters and Optimizing Boundary Conditions in Multi-Axis Robot Programs

Methodischer Ansatz zur Analyse von Prozessparametern und Optimierung von Randbedingungen in Multi-Achs-Roboterprogrammen

Scientific work for obtaining the academic degree

Master of Science (M.Sc.)

at the TUM School of Engineering and Design of the Technical University of Munich

Supervised by Prof. Dr.-Ing. Michael Zäh
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Scope of Work

Title of the Master's Thesis:
Methodical Approach for Analyzing Process Parameters and Optimizing Boundary Conditions in Multi-Axis Robot Programs

Titel der Master's Thesis:
Methodischer Ansatz zur Analyse von Prozessparametern und Optimierung von Randbedingungen in Multi-Achs-Roboterprogrammen

Author:	Jan Nalivaika	**Supervisor:**	Ludwig Siebert
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Motivation:
Computer-aided manufacturing (CAM) is used to automatically generate tool paths for computer numerically controlled machines. The CAM software considers the models of the raw and finished parts, the constraints of the machine, the tools, and the manufacturing technology. Together with user-configurable parameters, tool paths for 3-axis, 5-axis, or robot-based machine tools are generated. The growing demand for flexibility in machine tools, such as the use of multiple manufacturing technologies in one machine or automated loading and unloading, has led to many machine tools being equipped with additional mechanical axes. Examples include robots mounted on linear axes and rotary-tilt tables. The tool paths created in CAM programs are usually defined by five degrees of freedom. The first three are the translational axes X, Y, and Z. The tilting and inclining of the tool are defined by the A- and B-axes. Occasionally, an additional rotation of the tool (C-axis) around the Z-axis (e.g., for dragging a swivel knife) is defined. Machines with more degrees of freedom than those limited by the toolpath often need user-defined constraints. These constraints are necessary to fully specify the movements of the machine axes. An example is the alignment of a part using the rotary-tilt table so that the Z-axis of the tool always points in the direction of gravity. This is helpful in processes like fused deposition modeling (FDM) and wire arc additive manufacturing (WAAM). It is common practice to set the user-defined constraints based on experience. The definition of these constraints does not affect the relative tool path generated by the CAM software. A preliminary literature review indicates that the configuration of

these degrees of freedom has an impact on the energy demand and stability of the process. As such, a methodical approach to optimize these constraints in terms of efficiency, speed, and energy demand of the machine is required. Currently, no literature provides a comprehensive analysis or methodology regarding this global optimization problem.

Objective:
This work aims to attain a methodical approach that analyzes a set of constraints and evaluates the influence of those constraints on a set of defined process variables. It will focus on a 6-axis robot with a rotary-tilt table, whereby the results should also be transferable to other machines. Furthermore, the experiments and validations will be limited to the manufacturing processes of WAAM and milling. First, the influence of the constraints on relevant process variables (energy demand, joint turnover, speed and acceleration peaks, and total joint movements) in a manufacturing process such as WAAM will be assessed. Subsequently, a process evaluation will be elaborated in the CAM software, by means of which the process quality can be determined. Depending on the respective process variables, approximation or machine learning methods will be investigated for the process evaluation. The process quality as a one-dimensional variable will be determined by weighting the process variables. Subsequently, a method for the optimization of the constraints will be elaborated. This task corresponds to an optimization problem in which the process quality will be maximized by selecting suitable constraints.

Procedure and working method:

The following work packages are conducted within this thesis:

- Literature research
- Familiarization with WAAM, milling machines, and CAM software
- Selection of suitable process parameters
- Elaboration of the proposed method in a suitable programming language
- Verification and validation of the elaborated method
- Documentation of the work

Agreement:

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Garching, 29.03.2024 ???

Prof. Dr.-Ing. Michael F. Zäh	B.Sc. Jan Nalivaika

Abstract

Place your abstract here.

Zusammenfassung

Hier könnte Ihre Kurzzusammenfassung stehen.

Contents

List of Abbreviations

AI	Artificial Intelligence
AM	Additive maufacturing
CAD	Computer-aided design
CAE	Computer-aided engineering
CAM	Computer-aided manufacturing
CMT	Cold Metal Transfer
CNC	Computer numerical control
DED	Directed energy deposition
DoF	Degree of freedom
ERP	Enterprise resource planning
FDM	Fused deposition modeling
GMAW	Gas metal arc welding
PSO	Particle swarm optimization
SLA	Stereolithography
SLM	Selective laser melting
TCP	Tool center point
TWA	Twist decomposition approach
WAAM	Wire arc additive manufacturing

Chapter 1

Introduction

1.1 Motivation

In the age of "Industrie 4.0", advanced technologies like digital twins, have greatly transformed industrial manufacturing (SINGH, FUENMAYOR, et al. 2021). A considerable amount of data can be gathered from various processes, like milling or 3D printing. By analyzing this data, it is possible to find new and optimized methods for improving efficiency as well as streamline and enhancing the manufacturing process (GHOBAKHLOO 2020). By doing so, a significant amount of resources, like time and money, can be saved while at the same time increasing the quality of the produced product (BIBBY and DEHE 2018; SIMONIS et al. 2016). Computer-aided manufacturing (CAM) has been introduced as a crucial tool to improve productivity and accuracy in creating customized products (FELDHAUSEN et al. 2022). CAM systems automate and optimize tasks such as machining, welding, and assembly (LALIT NARAYAN et al. 2013). One of the key strengths of CAM lies in its precision and consistency, ensuring that intricate components are produced with minimal error. Furthermore, CAM systems contribute to increased efficiency by minimizing material waste and reducing production time (DUBOVSKA et al. 2014). These capabilities play a significant role in achieving a carbon-neutral production process (SAXENA et al. 2020). One of the most important areas of CAM is the calculation of the tool path for computer numerical control (CNC) machines as well as the movement and behavior of multi-axis industrial robots (PAN et al. 2012).

Manufacturing machines are the backbone of modern industrial processes (BI and WANG 2020). These machines encompass a wide range of equipment, from CNC machining centers to 3D printers and automated assembly lines. Their primary ability lies in precision and efficiency. CNC machines, for instance, can repeatedly produce intricate parts with high accuracy (μm-scale), reducing human error and ensuring consistency (JIA et al. 2018; LIBERMAN and GORBUNOVA 2021).

Industrial robots are a dominant part in the area of manufacturing as they can perform multi-axis movements. These capabilities are especially helpful to fulfill the customers wishes for individualized products (SHERWANI et al. 2020). They are cheaper to acquire and more flexible compared to CNC milling machines, but have their own set of disadvantages like for example lower stiffness (Iglesias et al. 2015; Liberman and Gorbunova 2021). One of the most important advantages of industrial robots is their wide adaptability. They allow for quick reconfiguration to produce different components or products, promoting flexibility in manufacturing (Billard and Kragic 2019). Further, advancements in robotics and Artificial Intelligence (AI) have broadened their capabilities, enabling tasks that were once deemed too complex or hazardous for humans (Goel and Gupta 2020). For achieving better efficiency and continuous sustainability in the current fast-changing environment requires a thorough analysis of the interdependent relationships between the manufactured part, process parameters, and boundary conditions that govern multi-axis robot programs (Gadaleta et al. 2019; Pan et al. 2012). As the companies that work with industrial robots can place a strong emphasis on energy reduction, cycle-time minimization, or precision, optimizing these process parameters, by defining optimal boundary conditions, is essential. CAM enables the simulation of the planned process, thus adapting any boundary conditions in advance, to fit the selected goals (Kyratsis et al. 2020; Maiti 2017; Pan et al. 2012; Uhlmann et al. 2016). This thesis is focused on a methodical approach for analyzing process parameters and optimizing boundary conditions in multi-axis robot programs.

1.2 Problem Formulation

Manufacturing systems that incorporate redundant degrees of freedom (DoFs) offer significant advantages in terms of flexibility and adaptability (Anjum et al. 2022). One example of a system with redundancy is a 6-DoF industrial robot with a rotary tilt table, which brings the system to eight DoFs. However, these systems also present various conflict points that need to be carefully managed to ensure optimal performance (Boscariol et al. 2020).

One of the critical challenges in manufacturing systems with redundant DoFs is singularity avoidance (Kiréanski and Petrovié 1993; Wang et al. 2022). Singularities, which are critical points in the motion of a robot manipulator, arise when the system loses its ability to maintain full control or achieves limited mobility as a consequence of specific joint configurations (Malyshev et al. 2022). These configurations result in the loss of a DoF or make the system highly sensitive to small changes, leading to unstable or even unpredictable and dangerous behavior (Milenkovic 2021; Zhao et al. 2021). Limiting the possible positions by adding artificial constraints can help to avoid this problem (Faria et al. 2018).

Another significant aspect of manufacturing systems with redundant DoFs is joint acceleration and jerk, which is the rate of change of acceleration. The robot must allocate accelerations effectively among its joints to achieve smooth and coordinated motion. Failure to do so can result in jerky or erratic movements, which not only compromise precision but also impact the efficiency of the manufacturing process (Duong 2021). Rapid changes in acceleration and jerk can cause mechanical stress, decrease system lifespan, and compromise precision. Additionally, the joints can be limited in their ability to keep up with the required speed due to limitations in power (R.V. DUBEY et al. 1988). Therefore, advanced control algorithms and motion planning techniques are necessary to optimize joint motion and minimize conflicts in joint acceleration and jerk (DUONG 2021; VALENTE et al. 2017).

Extension control is another critical aspect that needs to be addressed in systems with redundant DoFs. Redundant DoFs can provide additional extension capabilities to industrial robots, allowing them to reach difficult-to-access areas (DUONG 2021). However, managing and controlling the extension can be challenging, particularly when precise positioning or maintaining stiffness is required (LIN et al. 2022). The robot must accurately determine the appropriate position for each joint to avoid unnecessary over-extension and collisions with the surrounding environment. The robot pose, which is the combination of position and orientation in three-dimensional space, also has a significant effect on robot stiffness (XIONG et al. 2019). An increased number of joints can introduce more play and reduce overall system stiffness. This can affect precision, accuracy and stability. Robot pose and its DoFs must be carefully considered to ensure the desired level of system rigidity (SHI et al. 2021; WANG et al. 2022).

Precision is a crucial element in manufacturing systems, and closely tied to its stiffness. The robot needs to have precise control over the movement of each joint to achieve the desired accuracy of positioning in the manufacturing process. However, achieving and maintaining high accuracy and repeatability can be difficult due to the increased complexity and sensitivity to various factors (DUONG 2021). Frequent changes in direction in the joints are another factor that affects precision. Due to the serial kinematics of industrial robots, the present play in the motor joints can add up the inaccuracies and impede the manufacturing process (CHEN-GANG et al. 2014; HUYNH et al. 2020). Thus, mechanical stresses, decreased precision, and increased energy consumption can all result from abrupt and frequent direction changes (GASPARETTO and ZANOTTO 2010). Furthermore, effectively coordinating the movement of multiple joints to execute rapid direction changes can prove to be a computationally intensive task (VANDE WEGHE et al. 2007). Poor robot configurations can result in prolonged and unnecessary movement times, ultimately hampering the overall productivity of the manufacturing process (REITER et al. 2016). Minimizing production time is crucial for improving efficiency and throughput. Optimal path planning, motion optimization, and parallel processing techniques can be employed to reduce non-value adding movements while leveraging redundant DoFs effectively, for significant process improvement (BOSCARIOL et al. 2020).

Energy use is also a significant concern in manufacturing systems employing redundant DoFs (DOAN et al. 2016). The presence of additional joints and their non-optimal usage can require more power to operate, potentially leading to increased energy consumption. As energy efficiency becomes a priority in modern manufacturing, efficient mitigation strategies are necessary (BOSCARIOL et al. 2020; BOSCARIOL and RICHIEDEI 2019).

While redundant DoFs may introduce potential conflicts and require special attention, they can also significantly enhance performance in manufacturing systems (AYTEN et al. 2016). The added DoFs increase flexibility and adaptability, enabling the robot to carry out complex tasks more efficiently. Redundancy enables multiple approaches to achieve a desired end-effector position or orientation. By effectively utilizing the surplus of DoFs, manufacturing systems can enhance their performance, increase efficiency, and exhibit greater flexibility in handling diverse tasks (BOSCARIOL et al. 2020).

Currently, there is no integrated system that can evaluate a computed tool path based on the configuration of the manufacturing machine as well as the chosen process parameter, such as combined direction changes or stiffness. Additionally, there is no option to provide an optimal or near-optimal solution for defining the necessary constraints for a specific goal like for example, minimizing energy usage while at the same time reducing joint accelerations.

1.3 Objective

The definition of the constraints for the redundant DoFs, as mentioned in Chapter 1.2, does not affect the relative tool path generated by the CAM software. As such, a methodical approach to optimize these constraints without altering the toolpath in terms of efficiency, speed, energy demand of the machine and further process parameters is required. Currently, no literature provides a comprehensive analysis or methodology regarding this global optimization problem. This work aims to attain a methodical approach that analyzes a set of constraints and evaluates the influence of those constraints on a set of defined process variables. This work is focused on a 6-axis industrial robot with a rotary-tilt table, whereby the results should also be transferable to other machines. Furthermore, the validations is limited to the manufacturing processes of wire arc additive manufacturing (WAAM) and milling.

First, the influence of the constraints on relevant process variables (energy demand, joint turnover, speed and acceleration peaks, total joint movements) in a manufacturing process such as WAAM is assessed. Subsequently, a process evaluation is elaborated, by means of which the process quality can be determined. Depending on the respective process variables, approximation methods or machine learning methods are investigated for the process evaluation. The process quality as a one-dimensional variable is determined by weighting the process variables. Subsequently, a method for the optimization of the constraints is elaborated. This task corresponds to an optimization problem in which the process quality is maximized by selecting suitable constraints.

Chapter 2

State of Science and Technology

The following chapter gives an overview of manufacturing technologies, CAM, and algorithms for optimization problems. Special attention is given to the comparison of optimization problems in manufacturing with redundant DoFs.

2.1 Manufacturing Technologies

Manufacturing technologies encompass a wide range of processes that are used to transform raw materials into finished products. Two major categories within this field are subtractive and additive manufacturing (AM) (IQBAL et al. 2020). Subtractive manufacturing involves removing material from a workpiece to shape it into the desired form (WATSON and TAMINGER 2015). On the other hand, AM, also known as 3D printing, typically involves building up layers of material to create an object. This process offers greater design flexibility and the ability to create complex geometries (DILBEROGLU et al. 2017).
Both subtractive and additive manufacturing play crucial roles in various industries, revolutionizing production methods and offering new possibilities for customization and innovation (BANDYOPADHYAY 2020; VAN LE et al. 2017).

2.1.1 Subtractive Manufacturing

Subtractive manufacturing, also referred to as subtractive fabrication or machining, is a precise and efficient method utilized in contemporary manufacturing processes (WANG et al. 2023). This approach entails the removal of material from a workpiece, resulting in the formation of a desired shape or product (CALLEJA et al. 2018). In contrast to AM techniques, subtractive manufacturing always relies on material that is removed (ABDULHAMEED et al. 2019).

Subtractive manufacturing involves various techniques such as milling, turning, drilling, and grinding that are mostly performed by using CNC machines (KUMAR et al. 2020). Such machines are programmed to precisely control the cutting tool movement to clear material from the workpiece based on a predetermined design (AMANULLAH et al. 2017).

The versatility and precision of subtractive manufacturing are two of its significant advantages. A CNC machine can process a diverse array of materials, such as metals, plastics, and composites, with high levels of precision and surface quality, allowing for the creation of intricate and complex components (TOMAZ et al. 2021; YANG et al. 2019). As a result, it finds applications in industries where precision and quality are critical, such as aerospace, automotive, and medical.

The process of subtractive manufacturing starts with the drafting of the intended component using CAD software. Subsequently, CAM software is used to generate instructions that are used to guide the CNC machine (see Chapter 2.2 for more details). The machining process begins with the machine operator setting up and securing the workpiece in the machine and starting the execution of the generated instructions (NEE 2015). The cutting tools then perform various operations, such as drilling holes, creating pockets or slots, and shaping the external contours of the part, by following the predetermined movements. In a typical 3-axis machine, the DoFs are along the X, Y, and Z axes. In a 5-axis machine, two additional DoFs in form of rotations are present. Additionally, recent research is trying to extend the machines possibilities by adding advanced abilities like constantly monitoring and adjusting the cutting parameters on the fly to ensure the most efficient cutting speed, feed rate, and tool engagement while minimizing errors (TIEN et al. 2021).

Subtractive manufacturing provides numerous advantages over alternative manufacturing techniques. This method allows for the creation of intricate and highly customizable components with tight tolerances and complex geometries (JAYAWARDANE et al. 2023). In addition, it results in exceptional surface finish, dimensional accuracy, and consistency, guaranteeing uniform quality across production runs. Moreover, it is cost-effective for small to medium production volumes as it does not necessitate the use of costly molds or part-specific tooling, which makes it a great option to produce a multitude of parts (GU and KOREN 2018).

One of the disadvantages of the process is the possibly long cycle time. Particularly for intricate and large-volume designs with a high material-removal-ratio, the process can result in significant material waste as well as long machining time (FALUDI et al. 2015). Furthermore, it may not be appropriate for high hardness or brittle materials, which can lead to excessive tool wear or breakage (HESSER and MARKERT 2019).

Another common issue in CNC machining is tool vibration. Tool vibration, also called chatter, refers to the unwanted oscillation or movement of the cutting tool during the machining operation (YUE et al. 2019). This phenomenon can have detrimental effects on the quality of the finished part and can lead to various problems, such as poor surface finish, reduced dimensional accuracy, increased tool wear, and even tool breakage (ASLAN and ALTINTAS 2018). Several factors contribute to tool vibration in CNC machining. One of the primary factors are the cutting parameters, which include the cutting speed, feed rate, and depth of cut. When these parameters are not optimized, excessive cutting forces can be generated, causing the tool to vibrate. It is crucial to find the right balance between economical material removal rates and minimizing tool vibration to ensure optimal efficiency (GIORGIO BORT et al. 2016). The tool holder and spindle also influence tool vibration. A rigid tool holder and spindle are necessary to minimize vibrations while at the same time maintain accuracy during machining (WAN et al. 2019). Any play or misalignment in these components can contribute to tool vibration. Thus, it is paramount to ensure stiffness for high-precision operations. Chapter 2.1.3 and Chapter 2.4.3 gives a more in-depth look regarding the stiffens in machining operations executed with industrial robots.

In summary, subtractive manufacturing offers a wide range of applications but should be carefully considered for each situation. CNC technology, in combination with subtractive manufacturing, has become indispensable across a variety of industries. Nonetheless, it is crucial to evaluate its restrictions and suitability for specific design needs and material characteristics.

Figure 2.1 shows the basic design of a CNC machine. In this configuration, the workpiece is placed on the worktable and secured using a vice to hold it in place. The worktable has the ability to move in two directions, namely the X and Y directions. This movement allows for precise positioning and maneuvering of the workpiece. On the other hand, the spindle, which is the rotating component responsible for cutting or shaping the workpiece, moves along the Z direction. This vertical movement of the spindle enables it to perform various machining operations at different depths. Additionally, the machine interface serves as the control panel for the CNC machine. It provides the user with options to select and load the desired CNC program.

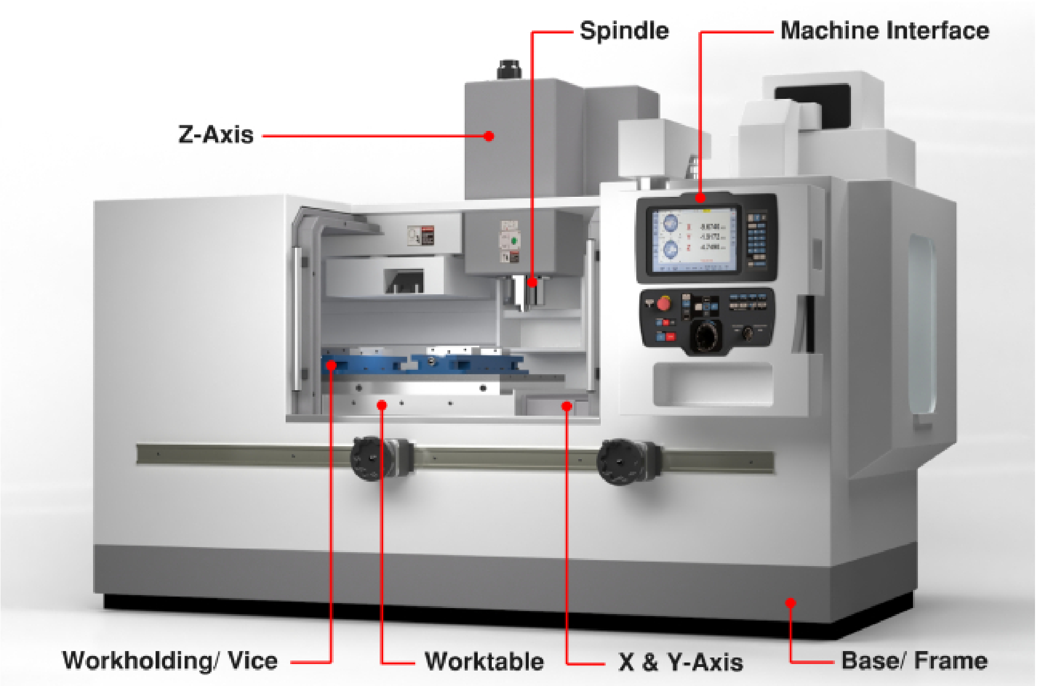

Figure 2.1: 3-Axis CNC Machine (*CNC Masters* 2022)

Figure 2.2 shows the schematic model of a 5-axis CNC machine. In this particular design, the spindle, which is responsible for cutting the workpiece, has the ability to move along three axes, namely the X, Y, and Z axes. This movement allows for precise control over the position and depth of the tool in relation to the workpiece.

In addition to the spindle movement, the machine features a rotary-tilt table that can adjust two additional axes, namely the A and C axes. These axes provide rotational and tilting capabilities to the worktable, allowing for more intricate movements and increased flexibility in part design. By adjusting the A and C axes, the workpiece can be positioned and oriented in different angles, enabling the CNC machine to access and machine complex geometries that would otherwise be difficult or impossible to achieve with fewer axes. The inclusion of these two additional DoFs in the 5-axis CNC machine significantly expands the range of operations that can be performed. This increased flexibility and versatility make the 5-axis CNC machine a valuable tool in industries that require high precision and intricate part production.

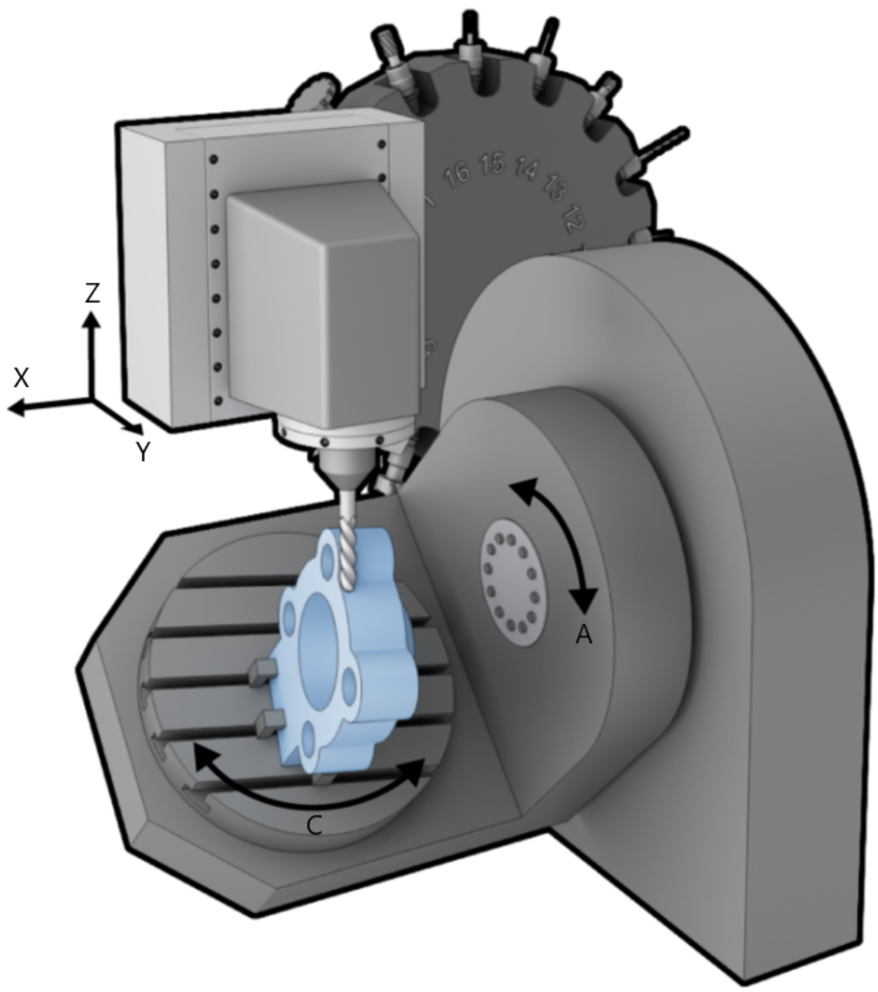

Figure 2.2: 5-Axis CNC Machine (*Manufacturing Guide* 2023)

2.1.2 Additive Manufacturing

AM consists of the conversion of digital designs into physical objects by building them layer by layer. This layering approach offers the possibility for creating complex geometries that would be extremely challenging or even impossible to produce using traditional manufacturing methods (Prakash et al. 2018). This advantage allows to fabricate intricate structures with internal cavities or undercuts, thus opening up new possibilities in engineering and design (Abdulhameed et al. 2019).

Various AM technologies utilize different methods to build the layers. Fused deposition modeling (FDM), for example, involves extruding molten thermoplastic filament through a heated nozzle, which solidifies as it cools, creating the desired shape (Wickramasinghe et al. 2020). Stereolithography (SLA) employs a liquid photopolymer resin that is solidified by a UV laser, while selective laser melting (SLM) uses a high-power laser to selectively fuse powdered materials, such as plastics or metals (Meier et al. 2017; Wang et al. 2016).

The compatibility of AM with a wide range of different materials is another significant advantage (Bose et al. 2018). It enables the production of components with diverse properties, including strength, flexibility, conductivity, and heat resistance. AM can accommodate various plastics, such as ABS, PLA, and nylon, as well as metals like titanium, aluminum, and stainless steel. Additionally, ceramics and even biomaterials, like hydrogels or living cells, can be used in AM processes. New materials specifically tailored for AM are continuously developed, expanding the possibilities for unique applications (Attaran 2017).

The design freedom offered by AM is a significant selection criterion when choosing a manufacturing method. Traditional methods often have design constraints due to limitations in tooling and manufacturing processes. With AM, designers have greater flexibility to create complex and organic shapes, lightweight structures, and intricate internal features. This freedom leads to optimized performance and improved functionality (Plocher and Panesar 2019).

However, AM also poses scientific challenges. Post-processing requirements, such as smoothing, polishing, or heat treatment, may be necessary to achieve the desired surface finish or material properties (Jandyal et al. 2022). Additionally, certain applications may have limited material options, particularly in terms of high-temperature or high-strength applications. Production speed can also be a constraint for large or complex parts, as AM processes can be time-consuming compared to traditional manufacturing methods (Dilberoglu et al. 2017).

As AM technologies continue to advance, they have the potential to transform supply chains. The concept of distributed manufacturing, where products are produced closer to the point of use, becomes feasible with AM (Jandyal et al. 2022). This reduces transportation costs, lowers carbon emissions, and enables on-demand manufacturing, leading to shorter lead times and increased sustainability (Haleem and Javaid 2019).

Wire Arc Additive Manufacturing

WAAM is a specific type of additive manufacturing process which is part of directed energy deposition (DED) processes (Svetlizky et al. 2021). According to the DIN EN ISO 52900 standard, DED involves using focused thermal energy to melt material during the application process to build up the individual layers (*DIN ISO 52900* 2022).

The operating principle of WAAM involves the generation of an arc through electrical discharge between an electrode and the workpiece. This arc transfers energy to the workpiece, causing melting in the fusion zone (Ou et al. 2018). Additionally, if a welding filler material in the form of a wire is introduced into the arc, it also melts and can be used to deposit additional material onto a metallic substrate (Cunningham et al. 2018). To ensure a continuous weld seam, a wire feed system must be employed (Ding et al. 2015). By placing multiple weld seams over each other, the workpiece is formed layer by layer.

The industrial manufacturing of components using WAAM involves a kinematic system that allows automated movement of the welding torch. This can be achieved using industrial robots or gantry systems (Schmitz et al. 2021). Alternatively, a spatially fixed welding torch, combined with robotic kinematics or rotary-tilt table, can be used to move the substrate plate instead (Nagasai et al. 2022).

WAAM offers several advantages over other additive manufacturing techniques. One major advantage is its high deposition rate, which ranges up to 6 kg/h. This high deposition rate enables the construction of large components in a relatively short amount of time. Components can be produced within a single workday, providing a significant time advantage compared to techniques like SLM, which typically operate at around 0.1 kg/h and thus much slower deposition rates. (IvánTabernero et al. 2018)

Another advantage of WAAM is its capability to construct large components with almost no limitations on part size. The production volume is only constrained by the working range of the kinematics employed. For example, in the case of an articulated-arm robot, the range is defined by its maximum reach. This means that WAAM has the potential to create components of various sizes without compromising its effectiveness (Li et al. 2019).

However, it is important to note that WAAM components may have some inherent defects. These include residual stresses, voids and deformations that persist after the production process, as well as relatively low geometric precision and modest surface quality (Wu et al. 2018). These limitations should be taken into consideration when utilizing WAAM for manufacturing purposes.

Figure 2.3 shows a schematic representation of the WAAM process. In this process, a wire is fed trough the gas metal arc welding (GMAW) torch to supply a continuous stream of material. The wire is then subjected to high heat generated by an electric arc. The wire is melted and then deposited onto a substrate plate. The substrate plate serves as the foundation or base on which the material is built. As the molten wire is deposited, it solidifies and fuses with the previous layers, gradually building up the desired object.

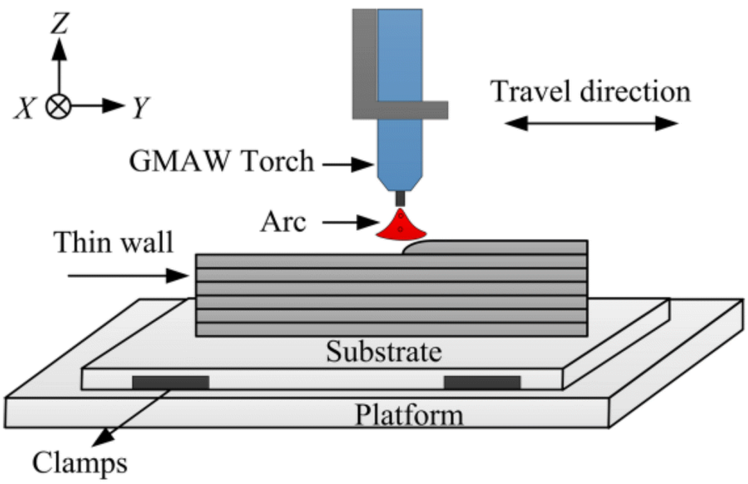

Figure 2.3: Schematic representation of WAAM (*Chaurasia* 2021)

Figure 2.4 shows a part produced by WAAM with the addition of a post processing step. The rough surface finish is clearly visible on the non post processed side of the part.

Figure 2.4: Part produced by WAAM with post machining (*Lortek* 2023)

Cold Metal Transfer

Cold Metal Transfer (CMT) welding is a sophisticated process that merges the advantages of multiple welding techniques (DUTRA et al. 2015). It functions based on the principle of controlled short-circuiting, wherein the welding torch generates a short circuit between the wire and the workpiece. This resulting electric arc triggers the melting of the tip of the wire and subsequent detachment. The detachment is assisted by a retraction of the wire. This process is generating a sequence of droplets that are transferred to the weld pool with high precision (Selvi et al. 2018; Srinivasan et al. 2022). This process provides superior heat control with lower heat input than conventional methods. The controlled arc and droplet transfer reduce the risk of overheating and distortion due to internal stresses, making it suitable for thinner materials and heat-sensitive applications (Scotti et al. 2020). Additionally, this process minimizes spatter formation, resulting in cleaner and smoother welds and reducing the requirement for post-weld cleaning (Srinivasan et al. 2022). CMT welding is ideal for applications that require the highest weld quality which includes structural fabrication and automotive manufacturing (Cong et al. 2016). For dependable weld quality, CMT welding typically integrates advanced process control systems, which utilize adaptive control and real-time monitoring to consistently adjust welding parameters based on sensor feedback. This enhances the precision and dependability (Pickin and Young 2006).

A CMT cycle consists of three phases (Selvi et al. 2018):
1st - pulse phase: A high current pulse leads to the ignition of the arc, which melts the wire electrode. A droplet begins to form at the tip of the wire. The wire is moved forward in the direction of the workpiece.
2nd - arc phase: The arc is kept burning at a lower current. This prevents the melt droplet from detaching prematurely and transferring to the workpiece.
3rd - short-circuit phase: As soon as the wire comes into contact with the substrate, the voltage drops to 0 V and the wire feeder is signaled to withdraw the wire. This supports the droplet detachment from the wire into the molten bath.

Figure 2.5 shows the three Phases of a CMT cycle. The voltage is constant in the first two phases and drops to zero in the short circuit phase. The spike of current is clearly visible in the first phase, which is also the shortest.

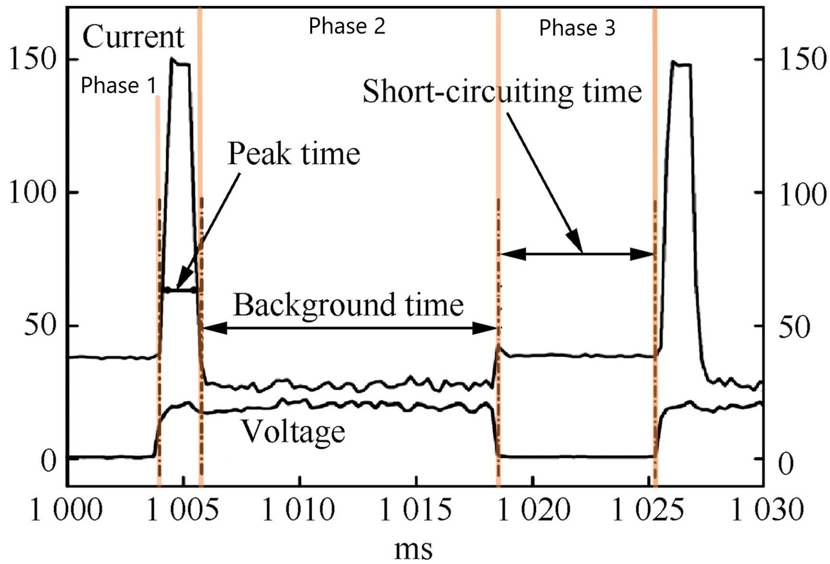

Figure 2.5: Current and Voltage wave forms of a CMT process (*Selvi* 2018)

Figure 2.6 shows the clearly distinct parts in a CMT cycle. At first an electric arc is formed and melts the wire. After a short circuit is established the wire retracts and detaches from the molten droplet. After that the cycle restarts.

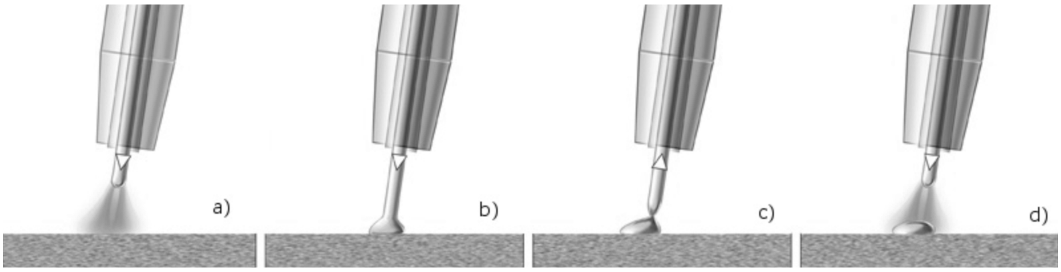

Figure 2.6: Individual sections of a CMT cycle (*Dalton* 2023)

In summary, WAAM and CMT are highly sophisticated processes that enable the creation of additively manufactured parts with specifically designed parameters. CMT achieves precise welds with low heat input and minimal spatter. It is ideal for thinner materials and applications requiring high weld quality. Advanced process control systems can enhance the reliability of CMT welding (PICKIN et al. 2011; RAHUL et al. 2018).

2.1.3 Industrial Robots

Industrial robots are advanced machines designed to perform various tasks in manufacturing and industrial settings. They come in different types, each with its own set of capabilities and advantages. They are crucial to modern manufacturing and automation, transforming production methods and repetitive task performance across diverse industries. Since their inception in the mid-20th century, these machines have undergone significant advancements, evolving into highly adaptive and sophisticated devices that promote productivity, accuracy, and safety within manufacturing processes (JI and WANG 2019). At their core, industrial robots are programmable machines designed to execute tasks with a high degree of accuracy and efficiency. They can carry out repetitive actions consistently, which enhances productivity and reduces the risk of human error (SICILIANO and KHATIB 2016).

One common type of industrial robots are the articulated robots. These robots have rotary joints that allow them to move like a human arm, with multiple links and joints. They can perform a wide range of different tasks, such as welding, material handling, quality control or assembly operations (HANAFUSA et al. 1981; JAIN et al. 2019). Another type is the Cartesian robot, also known as gantry robots. These robots move along three linear axes (X, Y, and Z) to perform tasks. They are commonly used for pick-and-place operations or in applications that require precise positioning (KIM and TSAI 2003). SCARA robots, shown in figure 2.7, are designed for fast and precise movements in assembly operations. They have a selective compliance assembly robot arm that allows them to move quickly while maintaining accuracy (DAS and CANAN DÜLGER 2005). Delta robots, shown in figure 2.8, robots are used for high-speed pick and place applications, such as packaging or sorting. They are known for their rapid movements and high throughput (Bonev 2001). Collaborative robots, or cobots, are designed to work safely alongside humans. They have built-in safety features, such as force sensors or vision systems, that allow them to interact with humans without causing harm. Cobots are often used in tasks that require human-robot collaboration, such as assembly (Liu et al. 2022).

Figure 2.7: SCARA robot (*Epson* 2023)

Figure 2.8: Delta robot (*Weiss* 2023)

Industrial robots are based on articulated robots and have a wide range of applications across various industries. Depending on the attached tool, they can perform tasks like fastening, welding, or soldering components together. These robots are also commonly used for material handling tasks in warehouses or production lines. Inspection tasks can be automated with robots equipped with sensors or cameras, allowing them to analyze products for defects or perform quality control checks (Hägele et al. 2016).

Industrial robots offer several benefits in comparison to manual labor. Firstly, they increase productivity by working continuously, without breaks or fatigue. This leads to higher production rates and shorter cycle times. Additionally, robots can perform tasks with high precision and accuracy, reducing errors and defects and thereby improving product quality (Kubela et al. 2016). Safety is another important aspect of industrial robots. They are designed to handle dangerous or hazardous tasks, keeping human workers safe. Robots can work in environments with high temperatures, toxic substances, or heavy loads, minimizing the risk of injury to humans (Heyer 2010). While the initial investment in industrial robots can be high, they offer long-term cost savings. Robots can reduce labor costs by automating repetitive tasks and increasing efficiency. They also offer flexibility, as they can be reprogrammed or reconfigured to perform different tasks, allowing for greater adaptability in manufacturing processes (Jung and Lim 2020).

When comparing industrial robots to CNC machines, there are a few notable disadvantages for industrial robots. Firstly, industrial robots generally have lower positional accuracy and repeatability compared to CNC machines. CNC machines are purpose-built for precise machining operations and can achieve high levels of accuracy and repeatability (WANG et al. 2023). Secondly, industrial robots typically have a longer cycle time compared to CNC machines for similar tasks. The complex movements and computations involved in robot control can result in slower overall operation speeds, which may not be ideal for high-volume production environments (JOSHI et al. 2021). Additionally, industrial robots can be more complex to program and set up than CNC machines. CNC machines follow a predefined set of instructions, whereas programming industrial robots often requires more advanced programming skills and can be time-consuming (YE 2022). Lastly, industrial robots may have limitations when it comes to handling heavy loads or performing heavy-duty machining operations. CNC machines are specifically designed for heavy-duty cutting, milling, and drilling tasks, whereas industrial robots are better suited for lighter material handling and assembly operations (WU et al. 2022). These differences should be considered when deciding between industrial robots and CNC machines for specific manufacturing applications.

Industrial robots can be programmed using different methods. One common method is using a teach pendant, where operators manually move the robot to record positions and actions. Offline programming is another approach, where programs are created and simulated on a computer before being transferred to the robot. Sensor-based programming allows robots to respond to sensor inputs or interact with the environment (HEIMANN and GUHL 2020).

Serial kinematics is a widely used configuration in industrial robots, where the robot arm is constructed as a sequential chain of joints and links. Each joint provides one DoF, enabling the robot to move and position its end-effector in a controlled manner. The joints can be of various types, including revolute, prismatic, spherical, and cylindrical, providing rotational, linear, and combined movements. The motion of the robot arm is controlled using forward kinematics and inverse kinematics. Forward kinematics calculates the position and orientation of the end-effector based on the joint angles, while inverse kinematics determines the joint angles required to achieve the desired end-effector pose (SINGH, KUKSHAL, et al. 2021).

Figure 2.9 shows the schematic design of a 6-DoF industrial robot with a spindle and force sensor that is used for machining.

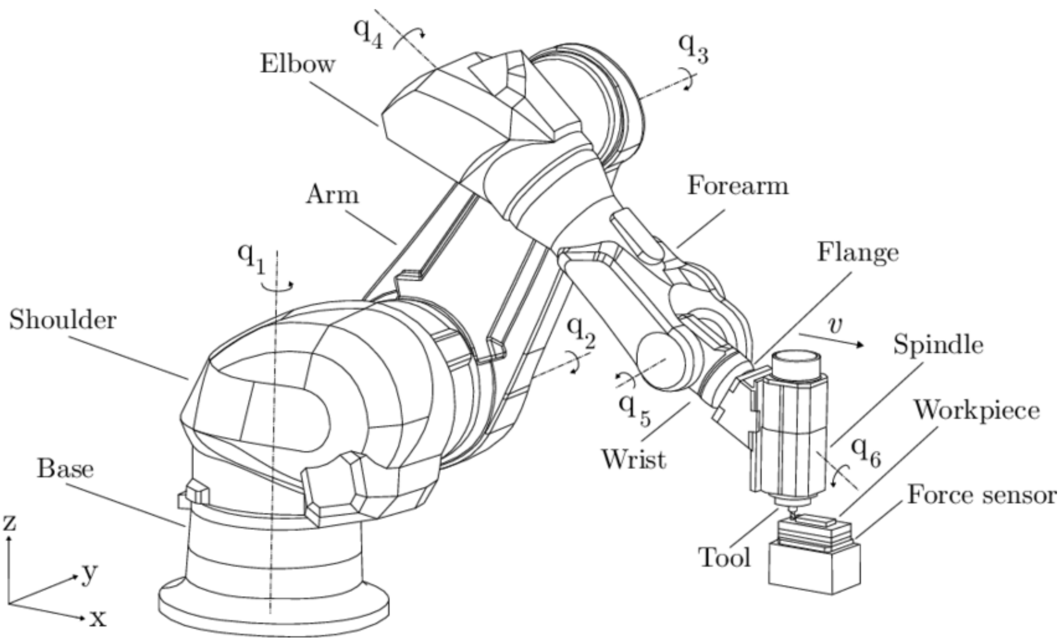

Figure 2.9: 6-DoF industrial robot (*Huynh et al.* 2018)

In summary, the robots performance relies on sophisticated control algorithms and feedback systems that allow them to adapt to dynamic conditions, adjust movements in real-time, and maintain a consistently high level of accuracy (LIN et al. 2023). This improves both the quality of the final product and the safety of the manufacturing process, as robots can navigate complex paths without risking collisions or accidents (BOSSCHER and HEDMAN 2011). As this technology continues to advance, industrial robots will play an even more prominent role in shaping the future of manufacturing and automation (DOMAE 2019)

Redundancy in robotic systems

Industrial robots with redundant DoFs are robotic systems that have been designed with more DoFs than are necessary for a specific task (WANG et al. 2022). These extra DoFs allows the robots to perform additional joint movements or configurations beyond what is required for defined movement or manipulation.

The primary advantage of these redundant systems is their increased flexibility and adaptability (DUONG 2021). Robots with more DoFs can access a wider range of positions and orientations, making it possible for them to complete complex tasks in constrained environments that would have been difficult or impossible otherwise. With this added flexibility, they can avoid obstacles and work around them without disrupting their duties. In industrial settings, redundant manipulators provide significant advantages. Their additional DoFs enable them to improve accessibility to hard-to-reach areas and enhance overall operational capabilities (SHI et al. 2021). Redundancy can take on many different forms in robotic systems. One option is to increase the number of joints in the serial kinematics of an articulated industrial robot (MILENKOVIC 2021).

Another approach to redundancy is the addition of a rotary tilt table, which is commonly used in WAAM in combination with a 6-DoF robot (Yuan et al. 2020). This combined system enables the robot to manipulate the workpiece from various angles, enhancing the manufacturing process. Furthermore, the inclusion of a linear axis that the robot base can traverse on is yet another form of redundant DoF. This additional linear motion provides the robot with extended reach and the capability to access a larger workspace, making it suitable for tasks that require movement along a specific axis (Boscariol and Richiedei 2019). Additionally, redundancy can also be observed when using a generic 6-DoF system for operations that only necessitate 5 or fewer DoFs (for example, milling or WAAM) (Hanafusa et al. 1981; Wang et al. 2022).

Figure 2.10 shows two industrial robots from the manufacturer KUKA GmbH that are placed on a linear axis. This enables the robots to use the additional and redundant DoF to optimize the process. Multiple robots can be positioned on one linear unit. Figure 2.11 shows how a 7-DoF robot can have multiple poses reaching the same position. In this case, only six DoF are necessary to achieve the position, while one DoF can be defined manually.

Figure 2.10: Industrial robots with an additional linear axis (*KUKA* 2023)

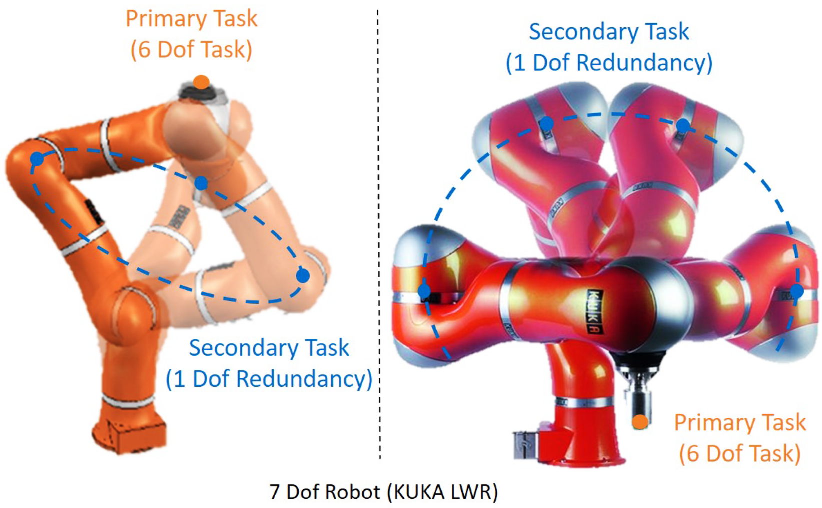

Figure 2.11: 7-DoF robot (*Hagane* 2022)

In summary, redundancy in robotic systems can be achieved through various means, such as increasing joint numbers, incorporating rotary tilt tables, including linear axes, or using a higher DoF system for tasks that demand fewer DoFs. These redundant features enhance the capabilities and versatility of the robot, enabling it to perform a wide range of complex tasks efficiently.

While redundancy in industrial robots can provide increased flexibility and adaptability, it also comes with certain disadvantages. One major drawback is the increased complexity and cost associated with redundant systems (HALEVI et al. 2011). The addition of extra joints, axes, or mechanisms adds to the overall complexity of the robot, requiring more sophisticated control algorithms and hardware (DUONG 2021). This complexity not only increases the initial cost of the robot but also adds to the maintenance and troubleshooting efforts to maintain the system (AHANGAR et al. 2019). Additionally, the presence of redundant DoFs can make the robot more susceptible to mechanical failures as more components are involved. This can result in increased downtime and even higher maintenance costs. Moreover, the increased complexity of redundant systems can make programming and calibration more challenging, requiring specialized skills and expertise (ERDŐS et al. 2016). Therefore, while redundancy can offer advantages in certain scenarios, careful consideration must be given to the cost, complexity, and maintenance implications before implementing it in industrial robotics applications.

Continuous-path mode

In the context of industrial robotics, continuous paths without abrupt direction or velocity changes of a tool play a crucial role in achieving smooth movements of robotic arms along a defined trajectory (JIA et al. 2018). This ensures that the robot can execute complex tasks and movements with accuracy and efficiency. By incorporating continuous path mode into industrial robot programming, manufacturers can optimize production processes and improve the quality of manufactured products (ZHANG et al. 2020). Constant velocity of a tool is especially important in applications like WAAM where the quality of the layer is directly dependent on the feed rate (LI, CHEN, et al. 2018). In CNC machining, discontinuities in velocity, acceleration, and jerk result in non-optimal surface finishes (SUN and ALTINTAS 2021).

Continuous path mode refers to a mode of operation in high-speed robotics as well as CNC machines where the goal is to achieve a smooth and uninterrupted movement of the machine along a toolpath. In this mode, the machine is expected to follow a path without any sudden changes in velocity, acceleration, or curvature. The purpose of continuous path mode is to minimize jerk spikes, machine vibrations, and other undesirable effects that can occur when there are discontinuities in the toolpath (JIA et al. 2018; YANG and YUEN 2017).

Figure 2.12 gives a visual example of a contouring toolpath that is defined with a constant velocity. To maintain a constant velocity along sharp corners or small radii, significant deceleration and acceleration may be needed.

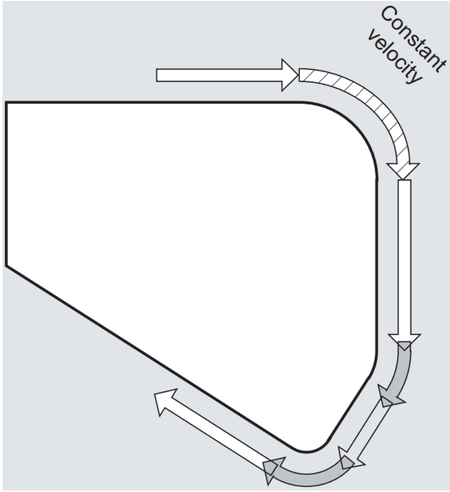

Figure 2.12: Desired path with constant velocity (*SINUMERIK* 2023)

Figure 2.13 shows how specific G-code commands of the SINUMERIK 840D influence the targeted feedrate. N1 to N12 are the individual G-code lines defining the coordinates with the corresponding orientation, also called waypoints, of the tool center point (TCP). When using the G60 command, the points are reached exactly, but the feedrate is reducing to 0 at every waypoint. When implementing the G64 (continuous pathmode) command, the feedrate can be held at the desired value but also requires *LookAhead*-deceleration to maintain precision.

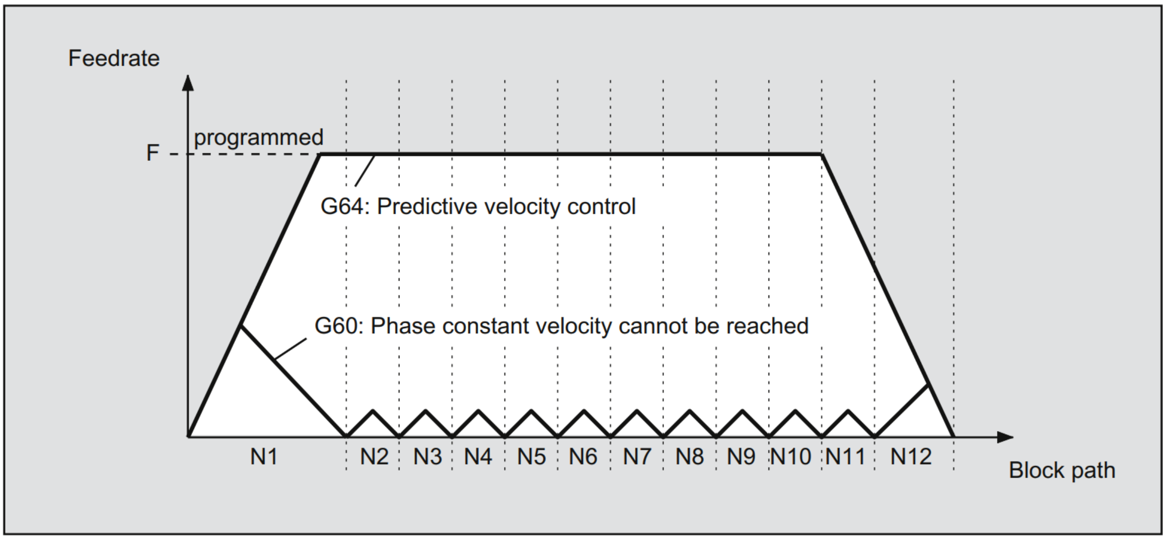

Figure 2.13: Influence of G-Code commands regarding feedrate compliance (*SINUMERIK* 2023)

The SINUMERIK 840D offer more commands to specify how much deviation is acceptable. Figure 2.14 shows how the G-code command G641 ADIS=0.5 is influencing the programmed contour. The rounding of the path begins no more than 0.5 mm before the programmed end of the contour and must finish 0.5 mm after the end of the corner point.

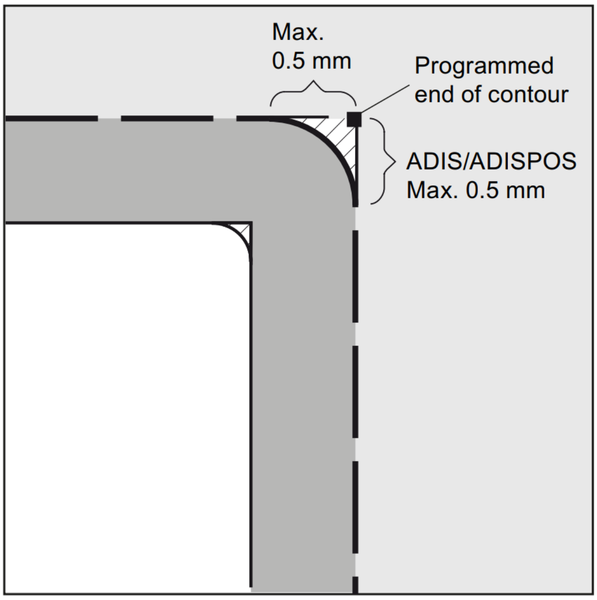

Figure 2.14: Predetermined deviation of the programmed and executed path (*SINUMERIK* 2023)

It is also possible to define the precision criterion globally instead of individually at every coordinate. For that the commands G601 and G602 can be utilized. Figure 2.15 shows how these two commands influence the executed trajectory. In this case, two different tolerances, according to the axis-specific tolerance limits, allow the tool to deviate from the programmed path.

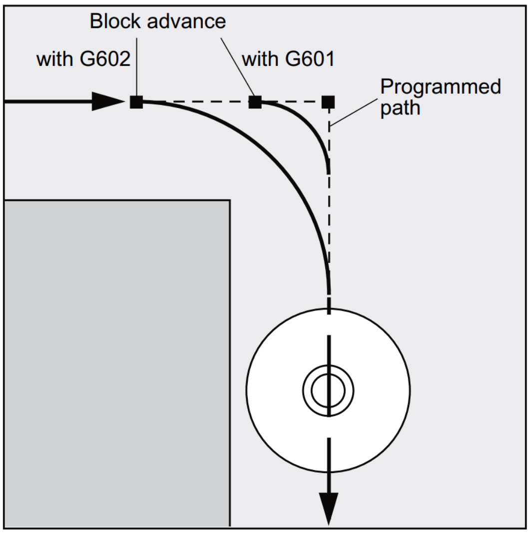

Figure 2.15: Influence of commands G601 and G602 (*SINUMERIK* 2023)

Continuous-path mode in CNC machining is a crucial aspect when it comes to processing parts with rapidly varied geometric features. These types of components, often found in high-end equipment, pose challenges due to their intricate structures and strict dimensional requirements. The presence of rapidly varied geometric features, coupled with the continuous-path running characteristic, gives rise to trajectory errors during the machining process, which severely hampers the overall machining accuracy of such parts (SHAHZADEH et al. 2018). This becomes even more critical in high-speed machining scenarios, where existing studies struggle to effectively reduce this error without compromising machining efficiency (LI, ZHANG, et al. 2018).

In CNC machines, toolpaths are typically composed of lines and arcs (LIU et al. 2020). At the transition points between these elements, careful consideration is required to ensure that the physical limits of the machine are not exceeded. For example, when the machine is moving at a constant feedrate, a sudden change in velocity can occur when two successive non-tangent linear moves meet. This can lead to undesirable effects on the machine and the quality of the cut (BOUJELBENE et al. 2004). Similar issues arise at transitions between lines and arcs or between two arcs, where curvature discontinuities need to be addressed.

Many path smoothing methods have been proposed in the literature, but most of them are limited to linear toolpaths. However, in high-speed CNC machines and industrial robots, the toolpaths often consist of both lines and arcs. Therefore, there is a need for a path smoothing method that can handle both line-to-line transitions and transitions involving arcs (SHAHZADEH et al. 2018). These errors are caused by factors such as servo lag, dynamics mismatch, external disturbances, and more.

To address this issue, various estimation and compensation methods have been proposed for reducing trajectory error. These approaches can be divided into contouring-error estimation and contouring-error reduction approaches (JIA et al. 2018). These approaches include the "Moving frame based method", "Analytical method", "Generalized method" or "Servo-tuning approach". It is important to note that these methods for contouring-error estimation and reduction, only offer relative significance. Each algorithm has its own optimal range of applications and may outperform other methods within that range. Additionally, it is important to note that not every approach can be implemented on every system.

Another approach for achieving continuous path mode is by using biclothoid fillets. These fillets are used for corner smoothing and can be fitted between two arcs or a line and an arc. The main advantage of using biclothoid fillets is that they result in a smoother curvature profile compared to other methods, such as Bezier fillets. Especially with tight tolerance values, only a few biclothoid fillets are needed compared to Bezier fillets. Additionally, the biclothoid approach is more suitable in regards to the jerk and acceleration limits of the driving units. This smoother curvature profile allows for higher feedrates and shorter cycle times, ultimately improving the overall performance of the CNC machine (SHAHZADEH et al. 2018).

2.2 Computer-Aided Manufacturing

CAM is a technology that uses computer software to automate and optimize manufacturing processes. It involves the use of computer systems to control and operate machinery, such as CNC machines, robots, and 3D printers. CAM software can generate tool paths and instructions for machines based on CAD models, allowing for precise and efficient production. By reducing manual labor, CAM helps improve productivity, accuracy, and consistency in manufacturing. It is widely used in industries like aerospace, automotive, and electronics to streamline production (Bi 2021).

2.2.1 CAM Software

CAM software enables manufacturers to generate toolpaths and machining instructions for a variety of manufacturing processes, including milling, turning, drilling, and 3D printing (Kumar et al. 2019). It takes into account factors such as material properties, tool capabilities, and manufacturing constraints to generate the most efficient and accurate instructions for the machines. CAM software can also simulate the machining process to detect any potential collisions or issues before actual production begins, saving time and resources (Bui et al. 2019).

One of the key features of CAM software is its ability to optimize the machining process. It can automatically optimize toolpaths to minimize machining time, reduce material waste, and improve surface finish. By analyzing the geometry of the part, the software can determine the most efficient toolpath strategies, such as contouring, pocketing, or adaptive machining. It can also optimize tool selection, toolpath sequencing, and cutting parameters to achieve the best possible results (Kyratsis et al. 2020). Furthermore, CAM software often integrates with other manufacturing software systems, such as computer-aided engineering (CAE) and enterprise resource planning (ERP) systems (Ramazanov et al. 2020). This integration enables seamless data exchange, improves collaboration between different departments, and ensures that the manufacturing process is aligned with the overall production goals (Kadam et al. 2023). With features such as optimization, simulation, multi-axis machining, and integration with other systems, CAM software empowers manufacturers to stay competitive in today's fast-paced and complex manufacturing environment (Kappmeyer and Novovic 2021).

Figure 2.16 shows the interface of Siemens NX, a CAM/CAD software that can be used to design parts and generate machine-specific instructions for manufacturing.

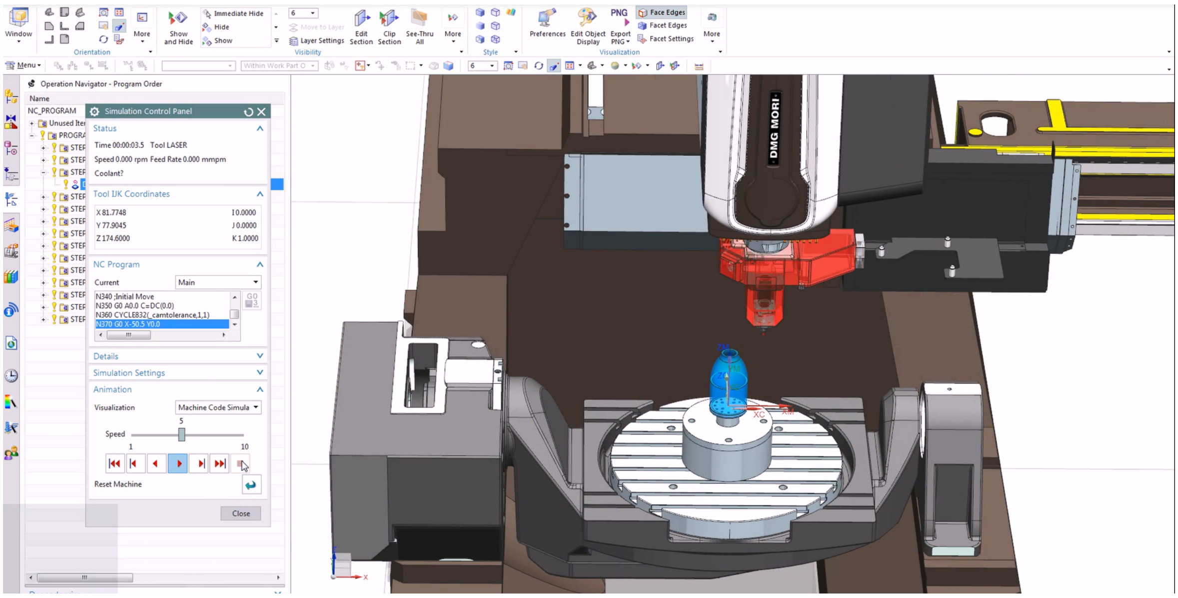

Figure 2.16: Interface of Siemens NX (*NX Manufacturing* 2015)

2.2.2 Path Planning

Path planning is a crucial features of CAM. It involves establishing the most effective toolpaths for machining operations, guaranteeing efficient and precise production (BRECHER and LOHSE 2013). It involves determining the optimal sequence of movements for the machining tool to follow while producing a part. It considers factors such as geometry, tool capabilities, machining constraints, and desired parameters. Its goal is to minimize machining time, reduce waste, and improve the finished product (XU et al. 2015). CAM software employs algorithms and mathematical models to determine the tool's position and orientation on the toolpath. Additionally, factors such as cutting direction, feed rate, and tool engagement need to be taken into account (TUNC and STODDART 2017).

Adaptive machining is a critical part of path planning and generation. It enables the CAM software to adjust the toolpath and cutting parameters in real-time based on material properties, tool wear, and other factors. This constant monitoring and adaptation ensure precise and dependable outcomes, even in difficult manufacturing conditions (LIU et al. 2017).

Multi-axis machining is an advanced function of CAM software, ideal for intricate cuts and shapes on complex geometries. By allowing the tool to move simultaneously along multiple axes, it delivers greater precision and accuracy during the machining of curved surfaces, free-form shapes, or parts with undercuts (TAKEUCHI 2014).

CAM software typically includes simulation tools that enable users to visualize and verify the toolpath prior to production. These simulations can detect potential collisions or errors that may occur during machining (DUBOVSKA et al. 2014).

Figure 2.17 shows three different path trajectories for planar milling operations. Depending on the area of application, different paths can be optimal. In generic 3D-printing as well as in WAAM multiple different infill methods, similar to the planar milling operations, can be used to build up and fill the desired geometry.

Figure 2.17: Three exemplary tool paths for iso-planar milling (*DSCarver* 2018)

2.3 Optimization Algorithms

Optimization algorithms are computational methods used to find the best possible solution to a problem within a given set of constraints. These algorithms aim to minimize or maximize an objective function by iteratively adjusting the values of decision variables (Sivanandam and Deepa 2007). They are widely used in various fields, including engineering, operations research, finance, and machine learning, to optimize resource allocation, scheduling, parameter tuning, and other complex tasks. For the problem described in Chapter 1.2 optimization algorithms can be used for determining optimal constraint for the redundant DoFs while considering the defined objective, like reduction of direction changes or energy optimization.

Optimization algorithms are computational techniques employed to identify the optimal solution or set of solutions for a given problem. There are several types of optimization algorithms, each exhibiting a unique methodology and characteristics. Gradient-based optimization algorithms, like gradient descent, update the solution iteratively by following the direction of the steepest ascent or descent of the objective function (Ruder 2017). These algorithms are efficient for convex optimization problems where the objective function is smooth and has a unique global minimum or maximum.

Another type of optimization algorithm is the evolutionary algorithm, which is inspired by biological evolution. Evolutionary algorithms employ mutation, crossover, and selection to progressively shape a population of solutions over time. These techniques are especially applicable to resolving intricate optimization problems characterized by non-linear and non-convex objective functions. By reading a wider range of the search space, evolutionary algorithms can uncover tier-one solutions that draw near to the global optimum, although they may necessitate enhanced computational resources (Bäck and Schwefel 1993).

Genetic algorithms are evolutionary algorithms that use genetic operators, like crossover and mutation, to evolve solutions in a population. They can handle various types of optimization problems. Genetic algorithms are particularly effective for multi-objective optimization problems. They generate a set of solutions called the Pareto front, which represents the trade-off between conflicting objectives (KATOCH et al. 2021; LAMBORA et al. 2019).

Particle swarm optimization (PSO) is a metaheuristic optimization algorithm based on the collective behavior of a particle swarm. In PSO, each particle represents a potential solution, and it moves through the search space to discover the optimal solution by exchanging information with other particles. This cooperative behavior enables the algorithm to efficiently converge to better solutions. PSO is especially beneficial for continuous optimization problems that have numerous local optima (BÄCK and SCHWEFEL 1993).

In recent years, there has been an increasing interest in metaheuristic optimization algorithms. Examples of such algorithms are ant colony optimization, differential evolution, and harmony search, which draw inspiration from natural phenomena or human behavior. These general-purpose algorithms can be applied to various optimization problems and provide efficient and flexible approaches to finding optimal solutions (YANG 2011).

Optimization algorithms prove to be significant resources for uncovering optimal solutions to intricate issues. Optimization algorithms effectively fine-tune objectives, meet requirements, and refine decision-making processes across a broad spectrum of industries. The algorithm choice relies on the problem's characteristics, the available computational resources, and the desired balance between solution quality and computational efficiency.

2.4 Comparison of the State of the Art

In the following, a literature analysis is performed regarding the optimization of various process parameters. The focus lies on manufacturing systems with redundant DoFs, specifically for tasks such as milling and WAAM. The main focus lies on the parameters: singularity avoidance, joint accelerations and jerk, stiffness and energy use. In cases where no literature is available that incorporates redundant DoFs, non-redundant systems are analyzed. Additional parameters like transfer time, precision, and maximum load capacity can also be analyzed but are omitted from the detailed analysis due to the limitations of scope.

2.4.1 Singularity Avoidance

As mentioned in Chapter 1.2, singularities occur when the robot manipulator loses control or achieves limited mobility due to certain configurations (MALYSHEV et al. 2022). This results in the loss of a DoF or makes the system highly sensitive to small changes (MILENKOVIC 2021; ZHAO et al. 2021). Figure 2.18 shows how the 5th joint needs to rotate significantly when moving along a straight line in Cartesian space. When an additional velocity boundary condition is set that defines the feed rate of that path, the rotation is very difficult to perform as the motor joints cannot keep up with the required angular acceleration. This movement significantly increases energy consumption and increases wear on the joints.

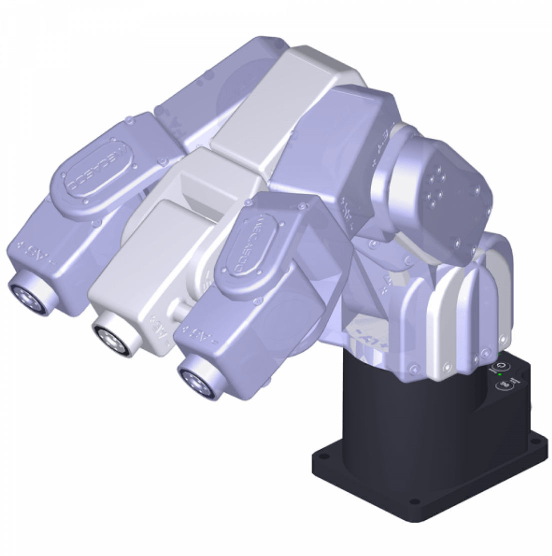

Figure 2.18: Passing trough a wrist singularity (*Mecademic* 2023)

Due to the infinite possible solutions for the inverse kinematics of redundant manipulators, it is exceptionally challenging to predict and prevent the occurrence of singularity configurations during motion planning (SHI et al. 2021).

In tasks that involve functional redundancy, as where the manipulator has more DoF than required for the task, the general projection method cannot be applied (WEI et al. 2014). Robotic industrial welding processes often have functional redundancy due to the presence of symmetry axes when using generic 6-DoF industrial robots. Different approaches have been proposed to solve functional redundancy, including adding a virtual joint to the manipulator or using the twist decomposition approach (TWA).

Most of the research is limited to the mathematical analysis of singularities and does not consider the industrial implementation of the proposed algorithms in an industrial setting. The manipulability measure and maximization of Jacobian minors are commonly used methods to avoid singularities. Other methods, such as condition number and singular value decomposition, can also be used (STEVENSON et al. 2002). Another mathematical analysis performs a differentiation between non-recoverable singularities and configurations where through self-motion recovery into a non-singular configuration is possible (BEDROSSIAN 2002).

Another approach proposes a kinetostatic performance index for evaluating the quality of robotic postures, which includes singularity avoidance and joint limit consideration (HUO and BARON 2008). This method is also transferable to applications like milling. A parameter called "condition number" and "manipulability" are introduced, which are used to calculate the "kinetostatic performance index". The presented method can increase the distance from singularities and lower the maximum rotation velocity of the fourth joint. One disadvantage of the proposed method is the manual selection of a parameter. This parameter is responsible for avoiding joint limits and minimizing joint velocities. Manual fine-tuning of that parameter is required for optimal performance.

Further approaches are proposing roll motion around the tool's symmetry axis to counter the loss of a DoF at the singularity. Paths with varying tool roll or fixed roll angles can be chosen, with considerations for tool elevation changes. Selecting paths with a fixed roll angle simplifies implementation for existing robot controllers (MILENKOVIC 2021).

Another approach uses the non-square Jacobi matrix and, after analysis, derives a simplified version through the selection of coordinate systems and primary transformation. By using block matrix analysis, the singularity conditions of the articulated robot are determined. A singular configuration avoidance algorithm is used to avoid singular patterns through constraining redundant DoF (SHI et al. 2021).

Neural networks and other machine learning approaches are commonly used to solve the issue of inverse kinematics. In this case, the optimization variable is not only limited to singularity avoidance but can also be focused on precision or optimization of feed rate (WEI et al. 2014).

2.4.2 Optimization of Joint Accelerations and Jerk

Jerk and acceleration control are critical because high values can wear out the robot structure and significantly stimulate its resonance frequencies. Vibrations caused by non-smooth trajectories can harm the robot's actuators and produce substantial deviations when completing tasks like trajectory tracking. Furthermore, low-jerk trajectories can be accomplished more quickly and precisely (GASPARETTO and ZANOTTO 2010).

One recently published approach uses an adaptive greedy algorithm to generate the jerk-optimized trajectory with discrete time constraints. The proposed algorithm improves the trajectory in an iterative routine after obtaining an initial trajectory by a graph-search method (DAI et al. 2020). A further method proposes a sequential quadratic programming method. The results show that optimal time-jerk trajectories with traveling time constraints can be obtained (JIANG et al. 2017).

Another method is proposing a method of reconstructing the path by a sequence of via-points that define the positions and orientations of the robot's end-effector. Unlike most minimum-jerk trajectory planning techniques, this algorithm does not force an execution time beforehand and takes into account constraints such as upper bounds on velocity, acceleration, and jerk. The algorithm uses a hybrid objective function that balances execution time and smoothness of the trajectory. The output of the algorithm is a vector of time intervals between consecutive via-points that minimizes the objective function (GASPARETTO and ZANOTTO 2010).

A further method is using an algorithm for adjusting the increments of the generalized coordinate vector. By using a pseudo-inverse of the Jacobi matrix and a Taylor's expansion, the robot's acceleration and jerk can be calculated. Results show that when the end effector is closer to the center of the robot, joint jerk increases. It is also shown that if trajectories are designed on the OXZ plane and directed away from the robot's center, the jerk decreases (DUONG 2021).

2.4.3 Optimization of Stiffens

Stiffness plays a crucial role in machining with industrial robots. It refers to the ability of a machine or structure to resist deformation under an applied load. In the context of machining, stiffness directly affects the accuracy, precision, and overall performance of the robot. A high level of stiffness ensures that the robot remains stable and rigid during machining operations, minimizing unwanted vibrations, deflections, and inaccuracies (WU et al. 2022). This is particularly important when dealing with high-speed or heavy-duty machining tasks, as any lack of stiffness can result in poor surface finish, dimensional inaccuracies, and reduced tool life.

A recent publication is evaluating the stiffness of a robot using a newly defined performance index, which is maximized to optimize the robot's posture. The problem is solved using a discretization search algorithm, taking into account joint limits, singularity avoidance, and trajectory smoothness. Each joint of the robot is modeled as a linear torsion spring, which is transferred into a stiffness matrix. This method is applied to a 6-DoF robot that is used for a milling operation. The goal of this method is to set the redundant angle in such a way that stiffness is maximized. Simulations and experiments on an industrial robot validate the performance index and optimization algorithm, demonstrating improved machining accuracy using this method (XIONG et al. 2019).

Another approach is working with a dynamic model to reduce the chatter in a milling operation with a 6-DoF robot. By considering the frequency response function, the maximum possible cutting depth, without the occurrence of chatter can be determined. The cutting depth is a function of the redundant DoF. In this case, the redundant DoF is the rotation around the axis of the spindle. An experimental analysis of a full-slot cut is performed. The results show that a significant reduction in chatter can be achieved by setting the redundant DoF to the optimal value (WANG et al. 2022).

A further publication performs a comparative study of robot pose optimization using static and dynamic stiffness models. The results suggest that the static stiffness model can achieve close to optimal results for pose selection for tasks where the process forces do not approach the resonant frequencies of the robot. It is also discussed that static and dynamic stiffness-based optimizations cannot reduce the deflections of the cutting tool to a range smaller than the robot's repeatability (CVITANIC et al. 2020).

There are many more methods, like finite element analysis, matrix structure analysis, and virtual joint modeling. To enhance stiffness models, further investigation needs to be conducted. The current state of the art shows a need for standardization in stiffness modeling, as there is currently no universally accepted procedure for establishing such models. Developing a modeling process with standard principles, evaluation indicators, and measuring techniques can simplify the selection and application of modeling methods. Additionally, the application of machine learning techniques, such as artificial neural networks, can be explored for stiffness modeling. Processing experimental data using machine learning algorithms can yield high-precision stiffness models (WU et al. 2022).

2.4.4 Optimization of Energy use

Energy-efficient usage of industrial robots is essential for achieving cost savings and sustainable manufacturing processes. Manufacturers can achieve this by implementing strategies such as optimizing robot movement paths, reducing idle time, and using energy-efficient components, resulting in significant reductions in energy consumption of their robotic systems. Incorporating advanced algorithms enables robots to adapt to changing conditions and operate at their most efficient levels, optimizing energy usage (UHLMANN et al. 2016).

One paper analyzed the different methods at different development stages of a production environment in regards to energy optimization. The results show that operating speed and payload strongly influence power consumption, and reducing it can be achieved through optimizing speed, reducing weight, and smoothing motion (PARYANTO et al. 2015).

Further analysis in a different publication shows that in a setting where a 6-DoF is used to perform a 5-DoF task, energy savings of up to 20.8% can be expected. The proposed method uses the yaw angle as an optimization variable that can be set to a value in a certain range (BOSCARIOL et al. 2020).

Another publication analyzes the general energy consumption of an industrial robot. The results show that cooling and movement speed have the most significant impact on energy consumption. The axis drives are responsible for 23% of the energy consumption. Based on this result, it is shown that optimizing the robot's movement in regards to optimal movement will significantly reduce its energy usage (UHLMANN et al. 2016).

2.4.5 Summary

Setting the appropriate process parameters directly impacts the performance and efficiency of a production system. By carefully fine-tuning parameters such as singularity avoidance, joint accelerations, and jerks, the system can operate smoothly, minimizing wear on the structure while achieving precise trajectory tracking. Moreover, optimizing energy usage through the adjustment of parameters related to movement speed not only contributes to environmental sustainability but also leads to economic benefits by reducing long-term operational costs. Additionally, the consideration of parameters like stiffness and joint limits ensures the safety of both the manufacturing system and its operators. The optimization of stiffness, for instance, enables the maximization of the system's performance and the attainment of improved machining accuracy. In conclusion, the careful selection and optimization of process parameters play a significant role in achieving optimal performance, efficiency, safety, and utilization of manufacturing systems, thereby contributing to overall operational success.

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Disclaimer

I hereby declare that this thesis is entirely the result of my own work except where otherwise indicated. I have only used the resources given in the list of references.

Garching, March 15, 2024????????????????????????????

(Signature)