Institute for Machine Tools and Industrial Management (iwb)
TUM School of Engineering and Design
Technical University of Munich

Methodical Approach for Analyzing Process Parameters and Optimizing Boundary Conditions in Mutli-Axis Robot Programs

Methodischer Ansatz zur Analyse von Prozessparametern und Optimierung von Randbedingungen in Mutli-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
Institute for Machine Tools and Industrial Management (iwb)

Submitted by Jan Nalivaika
Lerchenauerstrasse 10
80809 Munich

Submitted on March 15, 2024 in Garching

Acknowledgment

I would like to take this opportunity to express my heartfelt appreciation to my two supervisors, Marius Breuer and Ludwig Siebert, for their exceptional guidance and unwavering support throughout the entire duration of my master's thesis. Their expertise, dedication, and willingness to share their knowledge have been instrumental in shaping the direction and quality of this research. Their valuable insights and constructive feedback have significantly contributed to the development of this work. I am truly grateful for their availability, as they were always approachable and ready to assist whenever I encountered challenges or needed clarification. Their prompt response and timely feedback were incredibly valuable in ensuring the smooth progress of this thesis. I am deeply thankful for their remarkable contributions and for being outstanding mentors throughout this journey.

Scope of Work

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

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

Author:	Jan Nalivaika	**Supervisor:**	Ludwig Siebert
Issue:	02.10.2023	**Submission:**	29.03.2024

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, and 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:

Through the supervision of B.Sc. Jan Nalivaika intellectual property of the *iwb* is incorporated in this work. Publication of the work or transfer to third parties requires the permission of the chair holder. I agree to the archiving of the work in the library of the *iwb*, which is only accessible to *iwb* staff, as inventory and in the digital student research project database of the *iwb* as a PDF document.

Garching, 29.03.2024 WHAT DATE GOES HERE ???

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

Abstract

Place your abstract here.

Zusammenfassung

Hier könnte Ihre Kurzzusammenfassung stehen.ROS

Contents

List of Abbreviations

ROS	Robot Operating System

Chapter 1

Introduction

1.1 Motivation

In the age of "Industrie 4.0", advanced technologies like digital twins, have greatly transformed industrial manufacturing [1]. 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 efficient manufacturing [2]. 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 [3, 4].
Computer-Aided Manufacturing (CAM) has been introduced as a crucial tool to improve productivity and accuracy in creating customized products [5]. CAM systems automate and optimize tasks such as machining, welding, and assembly [6]. 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 [7]. These capabilities play a significant role in achieving a carbon-neutral production process [8]. 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 [9].

Manufacturing machines are the backbone of modern industrial processes [10]. 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, reducing human error and ensuring consistency [11].
Industrial robots are a dominant part in the area of manufacturing as they can perform multi-axis movements that are needed to fulfill the customers wishes for individualized products [12]. They are cheaper to acquire and more flexible compared to CNC milling machines, but have their own set of disadvantages [13]. One of the most important advantages is its wide adaptability. They allow for quick reconfiguration to produce different components or products, promoting flexibility in manufacturing [14]. Further, advancements in robotics

and artificial intelligence (AI) have broadened their capabilities, enabling tasks that were once deemed too complex or hazardous for humans [15].
Achieving efficiency and 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 [9, 16]. As the companies that work with industrial robots can place a strong emphasis on energy reduction, cycle-time minimization, or precision, optimizing these parameters is essential. CAM enables the simulation of the planned process, thus adapting any boundary conditions to fit the selected goals [9, 17–19]. 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 (DoF) offer significant advantages in terms of flexibility and adaptability [20]. One example of a system with redundancy is a 6-DoF industrial robot with a rotary tilt table, which brings the system to eight DoF. However, these systems also present various conflict points that need to be carefully managed to ensure optimal performance [21, 22].

One of the critical challenges in manufacturing systems with redundant DoF is singularity avoidance [22]. Singularities occur when the robot manipulator loses control or achieves limited mobility due to certain configurations [23]. These configurations result in the loss of a DoF or make the system highly sensitive to small changes, leading to unstable or unpredictable behavior [24, 25]. Limiting the possible positions by adding artificial constraints can help to avoid this problem [26].

One significant aspect of manufacturing systems with redundant DoF 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 [27]. 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 [28]. Therefore, advanced control algorithms and motion planning techniques are necessary to optimize joint motion and minimize conflicts in joint acceleration and jerk [27, 29].

Extension control is another critical aspect that needs to be addressed in systems with redundant DoF. Redundant DoF can provide additional extension capabilities to industrial robots, allowing them to reach difficult-to-access areas [27]. However, managing and controlling the extension can be challenging, particularly when precise positioning or maintaining stability is required [30]. The robot must accurately determine the appropriate position for each joint to avoid unnecessary overextension 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 [31]. 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 DoF must be carefully considered to ensure the desired level of system rigidity [22, 32].

Precision is a crucial element in manufacturing systems, closely tied to its stiffness. The robot needs to have precise control over the movement of each joint to achieve the desired accuracy of position in the manufacturing process. Nevertheless, achieving and maintaining high accuracy and repeatability can be difficult due to the increased complexity and sensitivity to various factors [27]. 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 [33, 34]. Mechanical stress, decreased precision, and increased energy consumption can result from abrupt and frequent direction changes [35].

Furthermore, effectively coordinating the movement of multiple joints to execute rapid direction changes can prove to be a difficult and computationally intensive task [36]. Poor direction changes can result in prolonged and unnecessary movement times, ultimately hampering the overall productivity of the manufacturing process [37]. 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 DoF effectively [21].

Energy use is also a significant concern in manufacturing systems employing redundant DoF [38]. 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 energy management strategies are necessary to mitigate the increased power demand [21, 39].

While redundant DoF may introduce potential conflicts and require special attention, they can also significantly enhance performance in manufacturing systems [40]. 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 DoF, manufacturing systems can enhance their performance, increase efficiency, and exhibit greater flexibility in handling diverse tasks [21].

Currently, there is no integrated system that can evaluate a computed tool path based on the chosen objective, such as minimizing movement or maximizing stiffness, in conjunction with available CAM systems. 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.

1.3 Objective

The definition of the redundant constraints, mentioned in chapter 1.2, does not affect the relative tool path as generated by the CAM software. As such, a methodical approach to optimize these constraints without altering the toolpath 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. 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 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, 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 methods 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.

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 degrees of freedom.

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 [41]. Subtractive manufacturing involves removing material from a workpiece to shape it into the desired form [42]. This is commonly achieved through techniques like cutting, drilling, milling, or grinding. On the other hand, additive manufacturing, 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 [43]. Both subtractive and additive manufacturing play crucial roles in various industries, revolutionizing production methods and offering new possibilities for customization and innovation [44, 45].

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 [46]. This approach entails the removal of material from a workpiece, resulting in the formation of a desired shape or product [47]. In contrast to additive manufacturing techniques, like 3D printing, where material is applied layer by layer, subtractive manufacturing always relies on material that is removed [48].

Subtractive manufacturing involves various techniques such as milling, turning, drilling, and grinding that are mostly performed by using CNC machines [49]. Such machines are programmed to precisely control the cutting tool movement to clear material from the workpiece based on a predetermined design [50].

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 [51, 52]. 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 computer-aided design (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 [53].

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 degrees of freedom are along the X, Y, and Z axes. In a 5-axis machine, two additional degrees of freedom 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 [54].

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 [55]. 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 alternative to produce a multitude of parts [56].

One of the disadvantages of the process is the possibly long cycle time. Particularly for intricate and large-volume designs, the process can result in significant material waste [57]. Furthermore, it may not be appropriate for high hardness or brittle materials, which can lead to excessive tool wear or breakage [58]. 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.

One 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 [59]. 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 [60].

Several factors contribute to tool vibration in CNC machining. One of the primary factors is 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 material removal rates and minimizing tool vibration to ensure optimal machining outcomes [61].

The tool holder and spindle system also influence tool vibration. A rigid and stable tool holder and spindle are necessary to minimize vibrations and maintain accuracy during machining [62]. Any play or misalignment in these components can contribute to tool vibration.

In conclusion, tool vibration is a common challenge in CNC machining that can negatively impact part quality. Thus, it is paramount to ensure stiffness for high-precision operations. Chapter 2.1.3 gives a more in-depth look regarding the stiffens in machining operations executed with industrial robots.

Figure 2.1 shows the basic design of a CNC machine. In this design, 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 in the Z direction. This vertical movement of the spindle enables it to perform various machining operations at different depths.

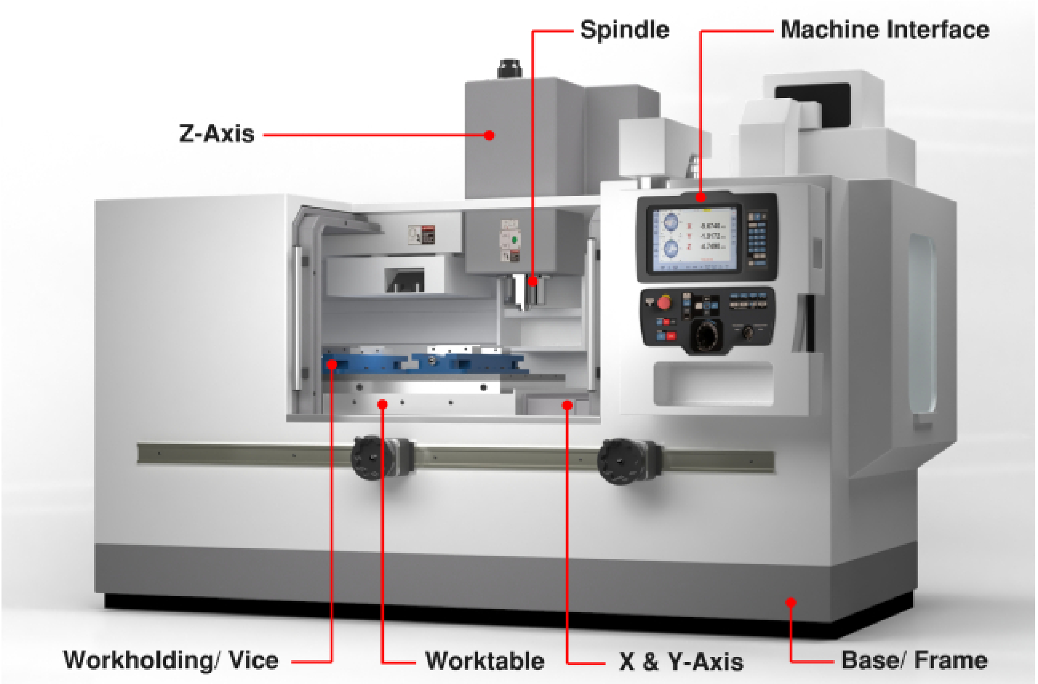


Figure 2.1: 3-Axis CNC Machine [63]

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. By selecting the appropriate program, operators can control the movements and actions of the CNC machine to achieve the desired part.

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 B 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 B 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. Additionally, a tool magazine is included that allows for tool changes. In this way, a roughing and finishing operation can be performed without having to change the tool manually.

The inclusion of these two additional degrees of freedom in the 5-axis CNC machine significantly expands the range of operations that can be performed. It enables the machine to handle more complex and sophisticated machining tasks, such as multi-sided machining, contouring, and simultaneous machining on multiple surfaces. This increased flexibility and versatility make the 5-axis CNC machine a valuable tool in industries that require high precision and intricate part production.

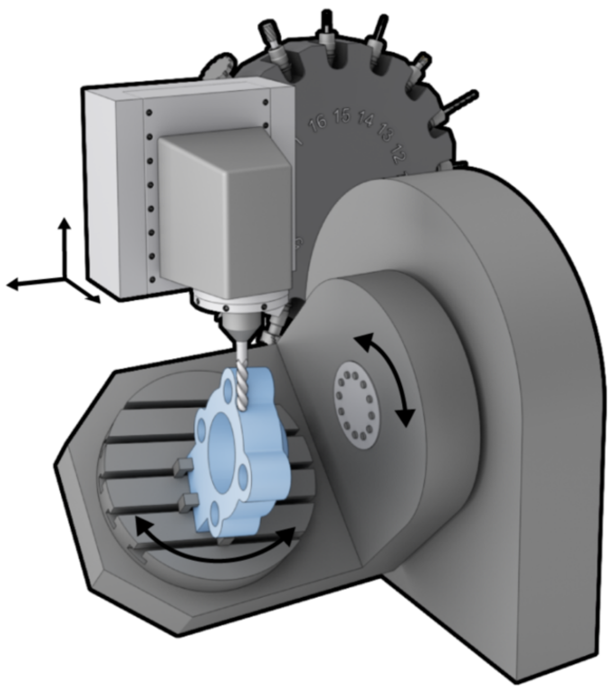


Figure 2.2: 5-Axis CNC Machine [64]

2.1.2 Additive Manufacturing

AM processes involve the conversion of CAD files into physical objects by building them layer by layer. This layering approach offers several advantages. Firstly, it allows for the creation of complex geometries that would be extremely challenging or impossible to produce using traditional manufacturing methods [65]. The ability to fabricate intricate structures with internal cavities, undercuts, and overhangs opens up new possibilities in engineering and design [48].

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 [66]. 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 [67, 68].

The compatibility of AM with a wide range of materials is another significant advantage [69]. 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 [70].

The design freedom offered by AM is a significant option. Traditional manufacturing 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 [71].

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 [72]. 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 [43].

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 [72]. This reduces transportation costs, lowers carbon emissions, and enables on-demand manufacturing, leading to shorter lead times and increased sustainability [73].

Figure 2.3 shows a commercially available 3D printer. The base plate has the ability to move along the Y axis, which allows for horizontal movement of the printed object. On the other hand, the print head can move along the X and Z axes. The X-axis movement controls the horizontal positioning of the print head, while the Z-axis movement controls the vertical positioning. This combination of movements in the X and Z axes enables the print head to accurately deposit layers of material to create the desired 3D object.

Figure 2.3: 3D Printer [74]

Wire Arc Additive Manufacturing

Wire Arc Additive Manufacturing (WAAM) is a specific type of additive manufacturing process which is part of Directed Energy Deposition (DED) processes [75]. 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 [76]. In the case of WAAM, an electric arc is used to generate the necessary energy for melting. In the most basic form, this process is utilizing standard welding technology, such as gas-shielded metal arc welding, in combination with precise spatial movement of the welding torch [77]. This process places multiple weld seams over each other and thus forms the workpiece layer by layer.

WAAM offers several advantages over other additive manufacturing techniques. One major advantage is its high deposition rate, which ranges up to 6kg/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 0.1kg/h and thus much slower deposition rates [78].

Another advantage of WAAM is its capability to construct large components without 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 [79].

However, it is important to note that WAAM components may have some inherent defects. These include residual stresses and deformations that persist after the production process, as well as relatively low geometric precision and modest surface quality. These limitations should be taken into consideration when utilizing WAAM for manufacturing purposes [80].

Figure 2.4 shows a schematic representation of a 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 3D object.

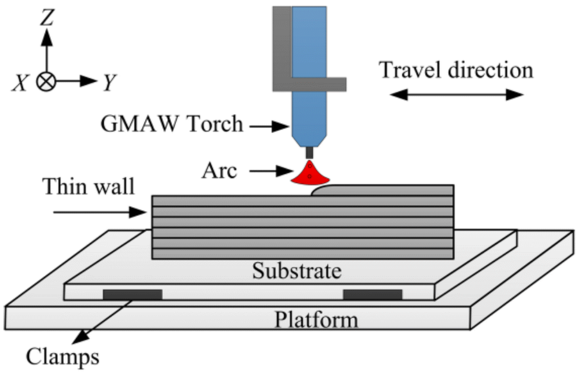


Figure 2.4: Schematic representation of WAAM [81]

Figure 2.5 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 2.5: Part produced by WAAM with post machining [82]

WAAM-Process and Cold Metal Transfer

The operating principle of WAAM involves the generation of an arc through electrical discharge between an feed-wire and the workpiece. This arc transfers energy to the workpiece, causing melting in the fusion zone [83]. 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 [77]. To ensure a continuous weld seam, a wire feed system must be employed [84].

The industrial manufacturing of components using WAAM involves a kinematic system that allows movement of the welding torch. This can be achieved using robot-configurations or gantry systems [85]. Alternatively, a spatially fixed welding torch, combined with robotic kinematics or rotary-tilt table, can be used to move the component [86].

Cold Metal Transfer (CMT) welding is a sophisticated process that merges the advantages of multiple welding techniques [87]. 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 short circuit 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 [88, 89].

CMT welding provides superior heat control with lower heat input than conventional methods. The controlled arc and droplet transfer reduce the risk of overheating and distortion, making it suitable for thinner materials and heat-sensitive applications [90]. The process minimizes spatter formation, resulting in cleaner and smoother welds and reducing the requirement for post-weld cleaning [89]. CMT welding is ideal for applications that require the highest weld quality which includes structural fabrication and automotive manufacturing [91].

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 of the welding process [92].

A CMT cycle consists of three phases [88]:
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 early and from detaching prematurely and transferring to the workpiece.
3d - 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 2.6 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.

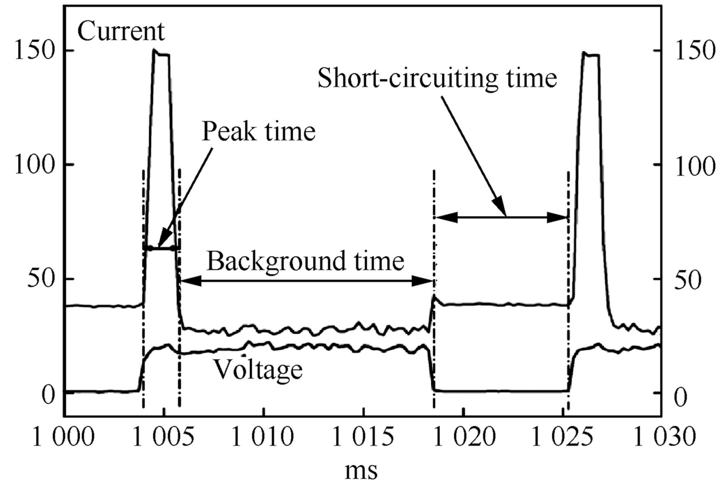


Figure 2.6: Current and Voltage wave forms of a CMT process [88]

Figure 2.7 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.

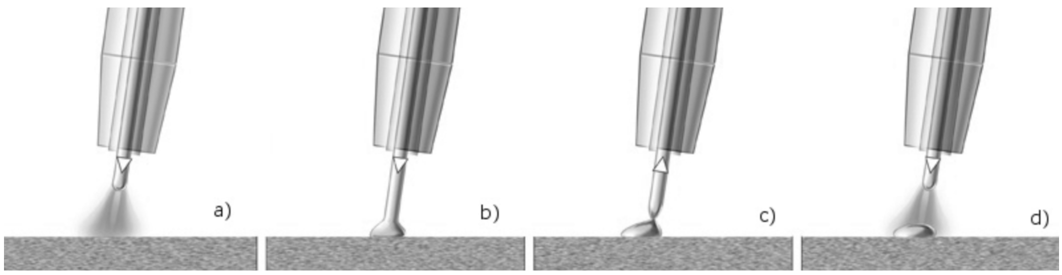


Figure 2.7: Individual sections of a CMT cycle [93]

In summary, WAAM and CMT are highly sophisticated processes that enable the creation of 3D printed metal 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 [94, 95].

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 [96]. 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 [97].

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 tasks, such as welding, material handling, or assembly operations [98, 99]. 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 [100]. SCARA robots, on the other hand, 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 [101]. Delta 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 [102]. 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 or inspection operations [103].

Figure 2.8 shows a SCARA and Delta Robot.

Figure 2.8: SCARA and Delta Robot

Industrial robots are based on articulated robots and have a wide range of applications across various industries. They can be used for assembly operations, where they can perform tasks like fastening, welding, or soldering components together. These robots are also commonly used for material handling tasks, such as lifting, moving, and stacking materials in warehouses or production lines. Inspection tasks can be automated with robots equipped with sensors or cameras, allowing them to inspect products for defects or perform quality control checks [104].

Industrial robots offer several benefits. 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 [105]. 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 [106]. 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 [107].

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 [46]. 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 [108]. 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 [109]. 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 [110]. 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 [111].

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 [112].

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 [113]. 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 [114]. As technology continues to advance, industrial robots will play an even more prominent role in shaping the future of manufacturing and automation [115]

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

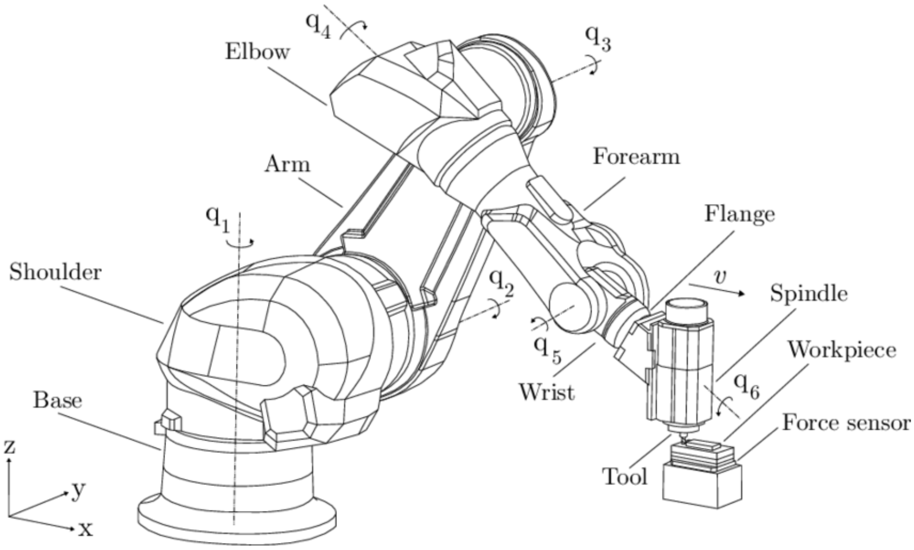


Figure 2.9: 6-DoF industrial Robot [116]

Redundancy in robotic systems

Industrial robots with redundant degrees of freedom are robotic systems that have been designed with more degrees of freedom (DOF) than are necessary for a specific task [22]. This extra DOF allows the robots to perform additional joint movements or configurations beyond what is required for basic movement or manipulation.

The primary advantage of these redundant robots is their increased flexibility and adaptability [27]. Robots with more DOF 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 degrees of freedom enable them to improve accessibility to hard-to-reach areas and enhance overall operational capabilities [32].

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 robot [25]. 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 [117]. 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 [39].

Additionally, redundancy can also be observed when using a generic 6-DoF system for operations that only necessitate 5 or fewer DoF (for example, milling or WAAM) [22, 98]. The system possesses more flexibility than required for the specific task and allows for adaptability and versatility, thus accommodating different operations without the need for reconfiguring the robot.

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 DoF. These redundant features enhance the capabilities and versatility of the robot, enabling it to perform a wide range of complex tasks efficiently.

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 [118]

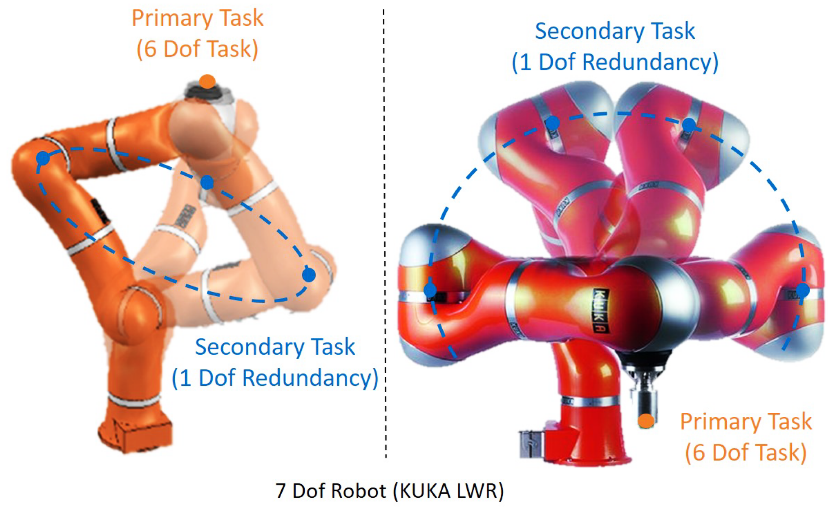


Figure 2.11: 7 DoF robot [119]

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 [120]. The addition of extra joints, axes, or mechanisms adds to the overall complexity of the robot, requiring more sophisticated control algorithms and hardware [27]. This complexity not only increases the initial cost of the robot but also adds to the maintenance and troubleshooting efforts [121]. Additionally, the presence of redundant DoF can make the robot more susceptible to mechanical failures as more components are involved. This can result in increased downtime and higher maintenance costs. Moreover, the increased complexity of redundant systems can make programming and calibration more challenging, requiring specialized skills and expertise [122]. 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 precise and smooth movements of robotic arms along a defined trajectory [11]. 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 [123]. 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 [124]. In CNC machining, discontinuities in velocity, acceleration, and jerk result in non-optimal surface finishes [125].

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 [11, 126].

Figure 2.12 shows where the smooth-path-requirement comes into conflict with the tool path, which is based on the part geometry. Sharp corners and small radii can require significant acceleration to maintain a constant velocity.

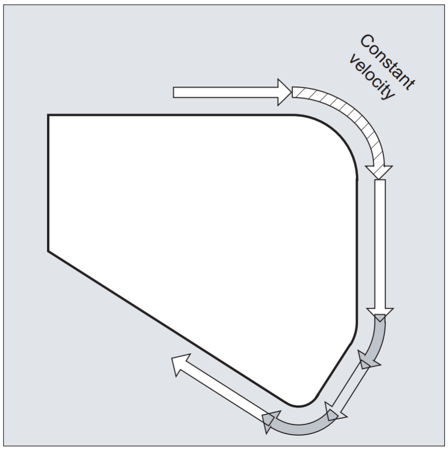


Figure 2.12: Desired path with constant velocity [127]

Figure 2.13 shows how specific G-code commands of the SINUMERIK 840D influence the targeted feedrate. When using the G60 command, the points are reached exactly, but the feedrate is reducing to 0 at every waypoint. When implementing the G64 command, the feedrate can be held at the desired value.

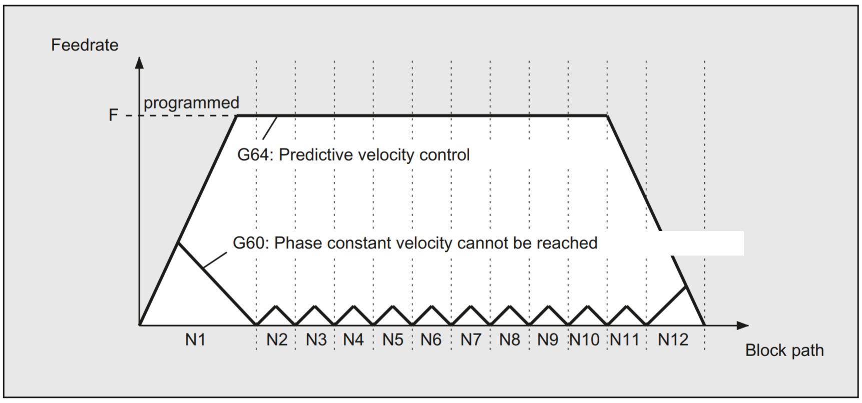


Figure 2.13: Influence of G-Code commands regarding feedrate compliance [127]

Figure 2.14 shows how the G-code command G641 ADIS=0.5 of the SINUMERIK 840D is influencing the programmed contour. The rounding of the path begins no more than 0.5 mm before the programmed end of the block and must finish 0.5 mm after the end of the block.

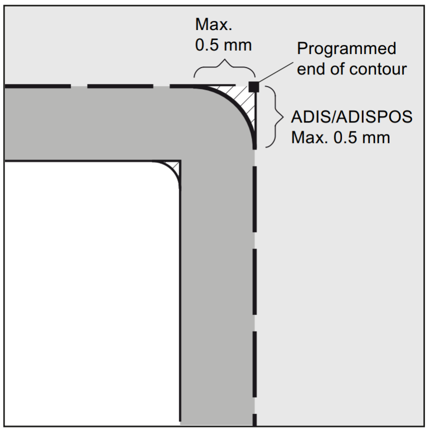


Figure 2.14: Predetermined deviation of the programmed and executed path [127]

Figure 2.15 shows how commands G601 and 602 influence the executed trajectory. In this case, two different tolerance limits allow the tool to deviate from the programmed path.

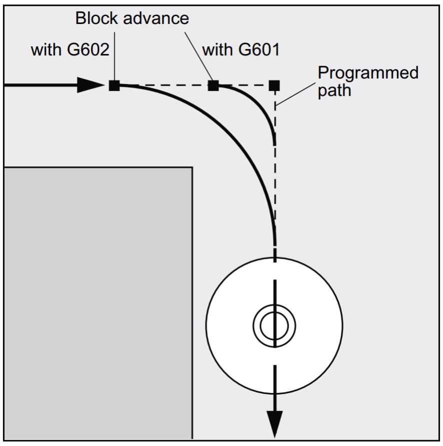


Figure 2.15: Influence of commands G601 and G602 [127]

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 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 [128]. This becomes even more critical in high-speed machining scenarios, where existing studies struggle to effectively reduce this error without compromising machining efficiency [129].

In CNC machines, toolpaths are typically composed of lines and arcs [130]. 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 [131]. Similar issues arise at transitions between lines and arcs or between two arcs, where curvature discontinuities need to be addressed.

Contouring errors are caused by factors such as servo lag, dynamics mismatch, external disturbances, and more. Reducing contouring errors is essential for improving the performance of CNC motion systems and achieving high-speed and high-precision machining [11].

To overcome these challenges and achieve a smooth and continuous toolpath, path smoothing techniques are necessary. 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 [128].

To address this issue and enhance both processing efficiency and precision, 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 [11]. These approaches include the "Moving frame based method", "Analytical method", "Generalized method" or "Servo-tuning approach". While this review paper compares the representative algorithms commonly used for contouring-error estimation and reduction, it is important to note that the comparison results 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 [128].

G-code

Information about G-code here or too much ?

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 Computer-Aided Design (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 and reduce costs [132].

2.2.1 CAM Software

CAM software is a type of computer software used to automate and optimize the manufacturing process. CAM software takes the design data from computer-aided design (CAD) software and converts it into instructions that control machines and tools to produce the desired product [132]. It plays a critical role in modern manufacturing, helping to streamline production, improve efficiency, and reduce errors.

CAM software enables manufacturers to generate toolpaths and machining instructions for a variety of manufacturing processes, including milling, turning, drilling, and 3D printing [133]. 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 [134].

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 [17].

It also offers advanced features such as multi-axis machining and support for complex geometries. It can generate toolpaths for machines with multiple axes of motion, allowing for more intricate and precise machining operations. It can handle complex geometries, including freeform surfaces and curved profiles, and generate toolpaths that accurately follow the desired shape [135].

Furthermore, CAM software often integrates with other manufacturing software systems, such as computer-aided engineering (CAE) and enterprise resource planning (ERP) systems [136]. This integration enables seamless data exchange, improves collaboration between different departments, and ensures that the manufacturing process is aligned with the overall production goals [137].

CAM software is a crucial tool for modern manufacturing. It automates and optimizes the manufacturing process, generating toolpaths and machining instructions based on CAD data. It enables manufacturers to improve efficiency, reduce errors, and achieve higher-quality products. 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 [138].

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.

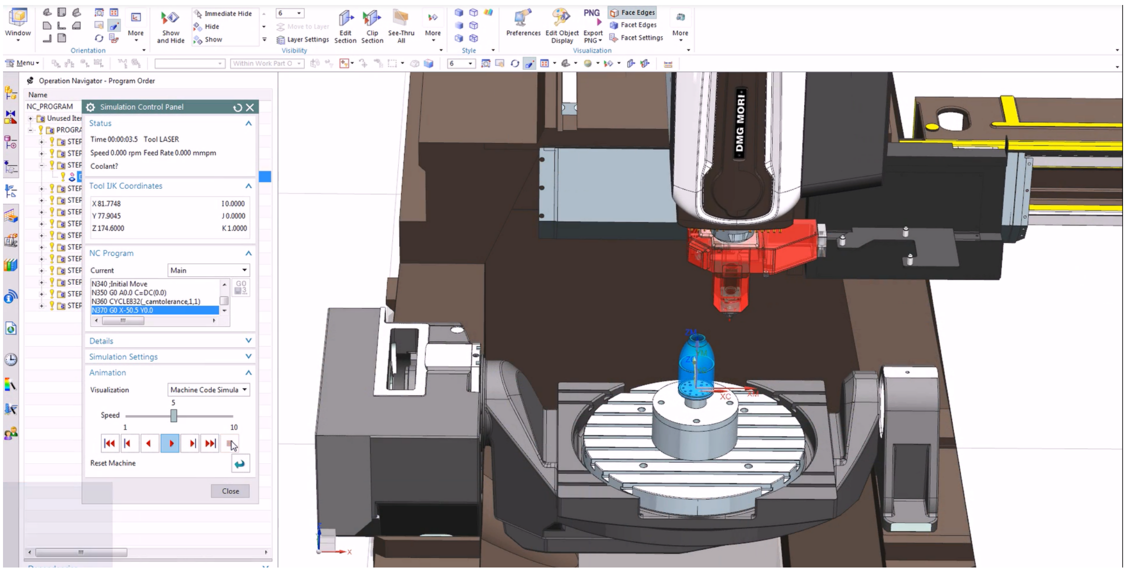


Figure 2.16: Interface of Siemens NX [139]

2.2.2 Path Planning

Path planning and generation are crucial features of CAM software. They involve establishing the most effective toolpaths for machining operations, guaranteeing efficient and precise production [140].

Path planning involves determining the optimal sequence of movements for the machining tool to follow while producing a component. It considers factors such as part geometry, tool capabilities, machining constraints, and desired parameters. Its goal is to minimize machining time, reduce waste, and improve the finished product [141]. 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 [142].

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 [143].

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 [144].

Simulation is vital in planning and generating paths for this process. CAM software typically includes simulation tools that enable users to visualize and verify the toolpath prior to production. These simulations can detect and resolve potential collisions, interference, or errors that may occur during machining, leading to cost savings and increased safety [7].

Figure 2.17 shows three different path trajectories for planar milling operations. Depending on the area of application, different paths can be optimal.

Figure 2.17: Three exemplary tool paths for iso-planar milling [145]

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 [146]. 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 1.2 optimization algorithms can be used for determining optimal parameters for the redundant degrees of freedom 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 [147]. 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 [148].

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 [149, 150].

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 nearby 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 [148].

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 [151].

Optimization algorithms prove to be significant resources for uncovering optimal solutions to intricate issues. Be it via gradient-based means, evolutionary algorithms, metaheuristics, or other customized mechanisms. 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 DoF, specifically for tasks such as milling and WAAM. In cases where no literature is available that incorporates redundant DoF, non-redundant systems are analyzed. Table 2.1 summarizes the analyzed parameters.

Singularity avoidance [152]	Joint accelerations [35]
Joint jerks [35]	Stiffness [153]
Energy use [154]	

Table 2.1: Areas of influence of boundary conditions and process parameters

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 [155–157]. Direction changes in the joint are briefly mentioned in [158] but not discussed in detail in any other publication.

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 [23]. This results in the loss of a DoF or makes the system highly sensitive to small changes [24, 25]. Image 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 is unnecessary movement that increases energy consumption and adds unnecessary wear to the joints.

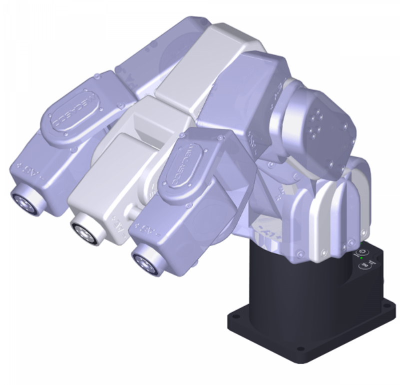


Figure 2.18: Passing trough a wrist singularity [159]

Due to the numerous 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 [32].

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 [160]. 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 [161]. Another mathematical analysis performs a differentiation between non-recoverable singularities and configurations where through self-motion recovery into a nonsingular configuration is possible [162]

Another approach proposes a kinetostatic performance index for evaluating the quality of robotic postures, which includes singularity avoidance and joint limit consideration [152]. 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 degree of freedom 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 [25].

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 [32].

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 [160].

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 [35].

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 [163]. A further method proposes a sequential quadratic programming method. The results show that optimal time-jerk trajectories with traveling time constraints can be obtained [164].

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 [35].

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 [27].

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 [110]. 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 [31].

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 degree of freedom. In this case, the redundant degree of freedom 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 degree of freedom to the optimal value [165].

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 [153].

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 [110].

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 [19].

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 [154].

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 [21].

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 cycle time will significantly reduce its energy usage [19].

2.4.5 Summery

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.

Chapter 3

Methodology

3.1 Introduction

The proposed method aims to provide a framework for optimizing various parameters of an industrial robot toward a specified objective. By effectively utilizing the redundant degrees of freedom mentioned in Chapter 1.3, this method is applicable to robotic milling operations and WAAM processes. The successful implementation of this methodology improves the robot's overall performance and efficiency, leading to increased productivity in industrial operations. The methodology is broken down into two parts. First, an evaluation of process parameters for a specific tool path with set boundary conditions, and second, an optimization of those boundary conditions to optimize the specific process parameters.

3.2 General Methodology for Process Analysis and Evaluation

3.2.1 General Methodology

The flowchart in figure 3.1 shows the interdependence of a tool path, the used manufacturing machine, the material, and set boundary conditions. The machine defines general parameters like total working volume, DoF, maximum feed rates, and manufacturing process (additive or subtractive). It can be a 6-axis CNC machine or an 8-DoF industrial robot. The part is referred to as the finished geometry as designed in CAD. The material is a user-defined element from which the part should be manufactured. The elements "Machine", "Part" and "Material" directly influence the toolpath that is necessary for manufacturing. The machine, for example, defines if the spindle or the work piece itself needs to be tilted while machining to achieve the desired geometric features. Further elements like available end-mills, desired depth of cut, machining strategy and operation sequence are regarded as adjacent parameters.

As the tool path is only a relative movement in regards to the work piece, the user is required to define further parameters before starting the manufacturing process. One example is the positioning of the raw stock material in the machine itself and defining the coordinate system that is used as a reference for the tool center point (TCP). These boundary conditions have to be in accordance with the machine's capabilities and can require extensive knowledge about the machine as well as the performed process.

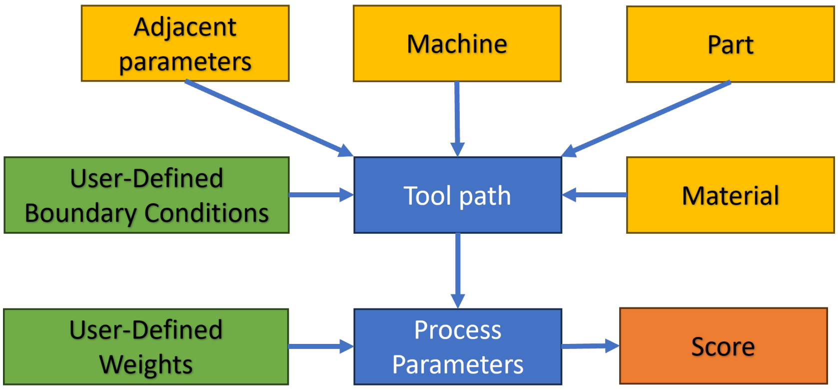


Figure 3.1: Interdependence of various parameters

One of the other parameters that needs to be defined in the "User-Defined Boundary Conditions" is the positioning or constraining of redundant DoF. One of the simplest cases to illustrate this constraining, is when using a 6-DoF robot for milling operations. In milling, the TCP position is defined by three coordinates, namely X, Y, and Z, as well as the rotation around the X and Y axes. The rotation around the Z-axis needs to be defined manually, as the spindle is rotationally symmetric around that axis. This constraint ensures that the robot maintains a specified pose while performing milling operations. The rotation around the Z axis can, in theory, be set to any arbitrary value but can influence the overall process parameters significantly. In practical applications, this rotation value is limited due to factors like cable routing or joint limits. The same limitations come into play in WAAM where the wire feed system cobmined with the torch position limit the possible orientation.

After the constraints are set and the tool path is generated, various process parameters can be analyzed. Some of the more prominent parameters are the total angular travel of a specific joint or the total angular acceleration. In addition to these numerical values, the user can define a specific importance for the analyzed process parameters and, with a weighting of all available process parameters, calculate an overall score of the determined tool path.

In the following, the elements "Adjacent parameters" and "Material" are omitted as they do not directly impact the optimization of a manufacturing process, as explained in Chapter 1.3. They are hard constraints that define the possible tool path and are not directly related to the redundant DoF. Nonetheless, it is important to note that these adjacent parameters can still offer a significant improvement in areas like cycle time or surface finish of the manufactured part.

3.2.2 Process Parameters

Table 3.1 presents a comprehensive overview of the various process parameters that can be derived from a tool path with defined boundary conditions that is executed by an industrial robot.

Process Parameter	Numerical Form
Angular position of each joint	Time-series
Angular velocity of each joint	Time-series
Angular acceleration of each joint	Time-series
Angular jerk of each joint	Time-series
Direction changes of each joint	Scalar value
Total travel of each joint	Scalar value
TCP coordinates (X,Y,Z)	Time-series
TCP velocity (X,Y,Z)	Time-series
TCP acceleration (X,Y,Z)	Time-series
Continuous energy usage	Time-series
Total energy usage	Scalar value
Reachability index	Binary value / Time-series
Singularity Analysis	Scalar value / Time-series
Torch orientation	Time-series

Table 3.1: Process parameter and their numerical form

One of the first key parameters is the joint position, which is typically recorded as a one-dimensional array containing the rotational position or extension values of each rotary or linear joint at every time step. This information serves as a basis for determining subsequent parameters such as velocity, acceleration, and jerk. These parameters are important to analyze so that it can be ensured that the joints are not overly strained in the manufacturing process and their service life can be extended as much as possible.

In order to prolong the lifespan of an industrial robot, it is crucial to consider the load on individual joints. One important indicator of joint load is the number of direction changes that a joint undergoes during its operation. High-frequency rotation changes can result in significant degradation and loss of precision during manufacturing processes. This process parameter, known as the number of direction changes, is a scalar value that can be derived from the angular position of each joint. By further analyzing the joint position data, the total travel of a joint can be determined by taking the integral of the joint velocity over time.

Additionally, it can be analyzed whether a velocity change always occurs at the same position and thus introduces wear at the same tooth flank. This results in significant local wear and shortens the lifespan of the joints.

Programs or tool paths that require less total joint travel are generally more desirable. By minimizing the number of direction changes and optimizing the joint travel, the stress and wear on the robot joints can be reduced, thereby extending the overall lifespan of the robot system.

By employing a forward kinematics approach or extracting it directly from the G-code, it becomes possible to determine the position (X Y Z position) and orientation (rotation) of the TCP (Tool Center Point). Additionally, the acceleration and jerk of the TCP can be calculated by taking the respective derivatives with respect to time. These derived parameters, along with the joint positions, are all stored in the form of arrays that capture the temporal changes in their respective values. These parameters can be used to determine how many times a robot will deviate from the proposed tool path and how much deviation in the continuous path mode can be expected.

Estimating the energy usage in industrial robot applications is another crucial aspect that is becoming more important in the current manufacturing environment. One option to accurately estimate energy consumption is to perform a multi-body simulation. For that, it is essential to have a correct 3D model that includes information about the weight and its distribution of the robot joints. Another option is to employ machine learning (ML) approaches or any other intermediate analysis.

Furthermore, in cases where the industrial robot is utilized for WAAM, the power required for welding can be extracted from the G-code by analyzing the duration for which the welding torch remains active. The continuous energy similarly to the other parameters mentioned earlier, is also represented in the form of an array to capture the variations over time.

Total energy usage, measured in kWh, is a key parameter that can be measured directly during the manufacturing process. It provides valuable insights into the overall energy consumption of the industrial robot system. This parameter can be obtained by monitoring the energy usage in real-time or by integrating the time-series data of the continuous energy consumption. By analyzing energy usage, manufacturers can identify energy-intensive processes or operations, optimize energy consumption, and implement strategies to reduce overall energy consumption, leading to cost savings and environmental benefits.

The reachability index is a binary parameter used to determine the feasibility of executing a program in an industrial robot system. This index indicates whether all the necessary points defined in the tool path are inside the working volume of the robot and can be reached by the robot's TCP. This parameter helps ensure that the robot can physically access all the required positions in the work area. If any point is found to be outside the reachable workspace, it indicates a need for adjustments. Additional factors like cable routing can also influence reachability, even though the endpoints lie inside the working volume of the robot. Wire-feed systems or optical fiber used to transmit a laser can only tolerate a set bending degree. When specifically analyzing the orientation regarding the cable routing, the reachability index can take the form of a time-series that records the deviation of the bending angle of a cable from the optimal angle.

The singularity analysis parameter can be represented either as a time-series or as a single numerical value. It is based on the smallest eigenvalue of the Jacobian matrix, which is calculated using the robot's current configuration. This parameter can be stored in array form, capturing the changes in singularity analysis over time. Alternatively, only the smallest eigenvalue encountered during the entire tool path can be recorded. The analysis of the singularity time-series can be used to optimize non-optimal poses, ensuring that the robot avoids singular configurations that may lead to reduced performance or unexpected behavior.

Torch orientation is a critical parameter in WAAM. It monitors the tilt angle of the welding torch during the process. To achieve optimal performance, it is essential that the material deposition process always occurs in the direction of gravity. When the welding head is positioned upside down, it represents a worst-case scenario where the welding process takes place against the force of gravity. When the tilt angle significantly deviates from the gravity vector, maintaining the stability of the molten metal pool becomes more difficult, potentially leading to defects like sagging.

To ensure the torch orientation is properly monitored, a time-series is used to record the deviation of the torch angle from the gravity vector. Analyzing this information helps identify any deviations or issues that may affect the quality of the deposited material.

Figure 3.2 visualizes how the different parameters are interconnected. It is clearly visible that all parameters can be derived from the angular position of the joints. This is a clear indicator of the importance of that information. The angular position data provides essential information for analyzing and optimizing the performance of the robot system. By monitoring and analyzing the joint positions, the user can gain insights into various aspects of the robot's operation and make informed decisions to optimize productivity.

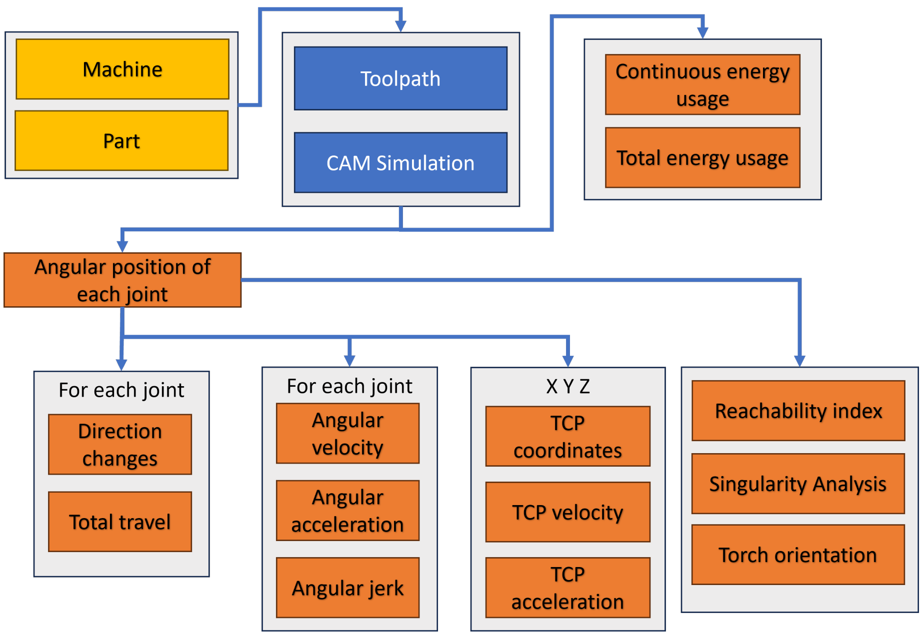


Figure 3.2: Parameter Flowchart

3.3 User-Defined Weights and Score Calculation

3.3.1 Local Rating and Global Score

To assess if a tool path with its boundary conditions is optimal or offers the possibility for improvement, a score or rating value is required that takes the process parameters and their importance into account.

Determining the relative importance of different parameters can involve subjective judgments, expert knowledge, and consideration of specific manufacturing constraints. For example, in some cases, minimizing joint jerk may be the primary objective, while in others, energy usage may take precedence.

To quantify the performance of a tool path, the user can assign weights or importance factors to each parameter based on their specific requirements. These weights can reflect the relative significance of each parameter in achieving the desired optimum. A weighted sum or scoring method can then be used to evaluate and compare the same tool paths with different constraints based on the aggregated scores of the individual parameters.

It's important to note that the subjective weighing of parameters can vary between different manufacturing scenarios and requires continuous evaluation and adjustment based on changing priorities or goals.

The score of a tool path with its boundary conditions is calculated as shown in table 3.2. Each process parameter can take a local rating in the range 0-100. 0 being the least optimal, while 100 represents the optimal best-case solution. This value is multiplied by the importance factor and returns the local score. All local scores are summed up and result in the overall global score of that specific tool path with corresponding boundary conditions and that specific importance assignment. The sum of all defined importance values must add up to 1 so that the most optimal boundary conditions lead to a global score of 100.

Process Parameters	Local rating	Importance	Local score
Process Parameter 1	74	0.5	37
Process Parameter 2	34	0.1	3.4
Process Parameter 3	65	0.1	6.5
Process Parameter 4	22	0.3	6.6
Global Score			53,5

Table 3.2: Calculation of a tool path score

3.3.2 Local Rating Calculation

Calculating a local rating is not a straight-forward approach. The first problem is that based on a singular value like "direction changes," it is not possible to determine a local rating as it is not clear if that value is close to optimal or far from it. The solution to this problem is to calculate the tool path with different boundary conditions or constraints, like rotation around the C-axis, and compare the different results. Figure 3.3 shows how a local score can be calculated by means of variation. Each variation leads to a different number of direction changes in joint 1. The local score is calculated by essentially applying a Min-Max scaler.

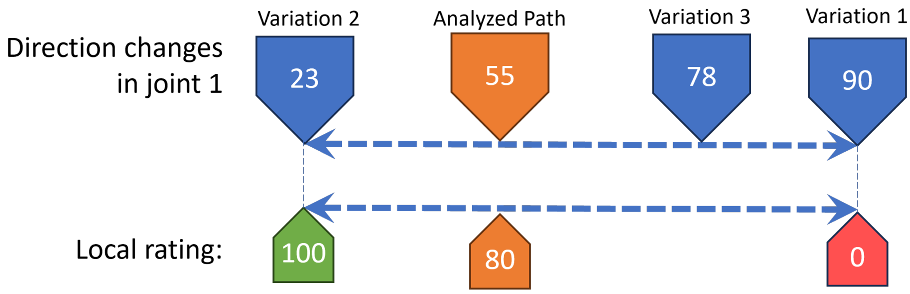


Figure 3.3: Calculation of the local score trough variation

It is important to note that performing more variations before calculating the local sore will increase the accuracy of this approach. If only a few variations are performed, it is possible that only variations with similar outcomes will be found, which can skew the result significantly.

Another factor that needs to be analyzed is whether the variations in the boundary result in local scores that exceed a certain standard deviation. Figure 3.4, shows how a local score of 66 is calculated despite the presence of very small absolute differences. In this case, the standard deviation is only 0.37. Figure 3.5 demonstrates how the same local score of 66 is calculated even though the absolute differences are significantly higher. Here, the standard deviation is 22.36. Only if the standard deviation exceeds a set threshold should the local score be used as input for the global score. In cases where the standard deviation criteria is not met, the corresponding process parameter should be omitted from the global score calculation.

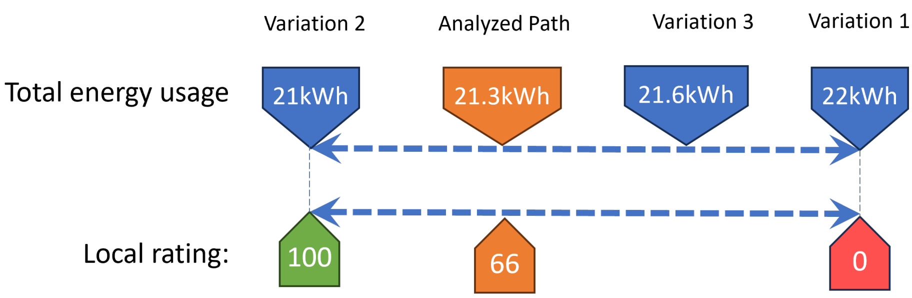


Figure 3.4: Variation with low standard deviation

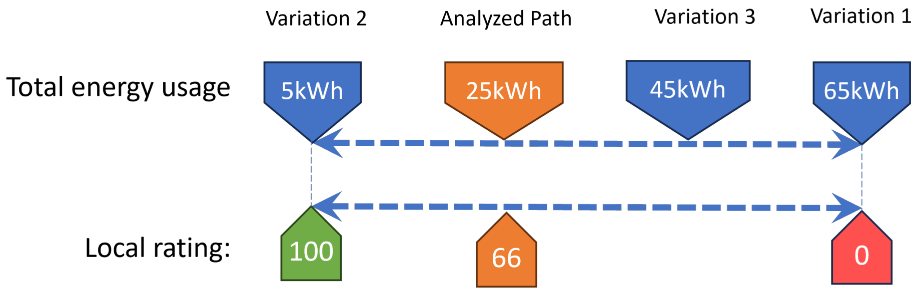


Figure 3.5: Variation with high standard deviation

3.3.3 Information Extraction form Time-Series Data

It is important to note that for a local score computation, as mentioned in Chapter 3.3.2, a time-series needs to be transformed into a scalar value. This can either be done by directly transforming the time-series like, for example, summing up all values or performing a subsequent analysis. As each time-series is capturing different physical phenomena, each one requires an individual process for transforming into a scalar value.

3.4 Information from Angular Position

The angular position of a joint by itself does not provide much information from which much qualitative analysis can be performed. But by adding information, like a temporal component, it can serve as a significant information source.

Figure 3.6 visualizes what information needs to be added to enhance the information content of process parameters that are directly related to the angular position of joints.

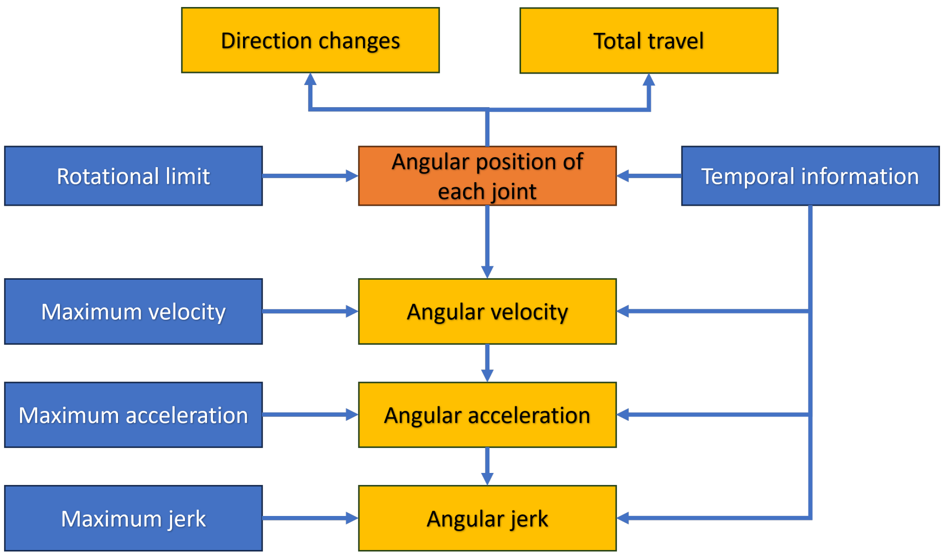
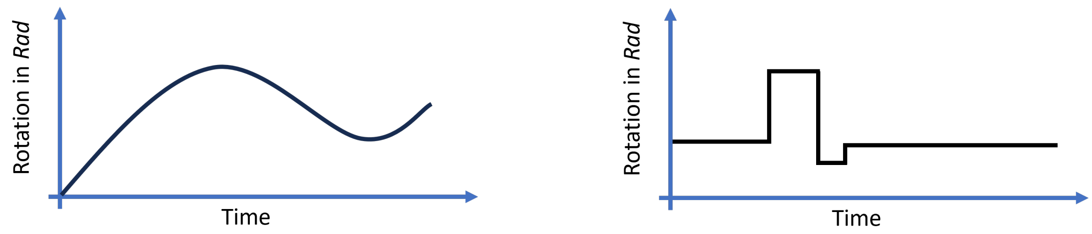


Figure 3.6: Additional Information for angular position of each joint

The first additional piece of required information is the temporal element, which specifies the time when a joint is supposed to be in what rotational position. This information can either be recorded in equidistant time steps as shown in figure 3.7 on the left or adapted to only record the change of position as shown on the right. Recording only the change of position is not optimal as it does not correspond to the physical system, where the position cannot significantly change from one time step to the next. Additionally, it is not defined with which rotational velocity the joint needs to change position. On the other hand, continuous recording in small equidistant time steps can result in significantly more recorded values and thus, a longer time-series.

Figure 3.7 shows the rotational position of a rotary joint in radians recorded with equidistant steps as well as a time-series where only the destination positions and the associate times are recorded.



Rad:	0	0.2	0.4	0.5	0.4	0.3	0.2	0.3	0.4
Time:	0s	0.1s	0.2s	0.3s	0.4s	0.5s	0.6s	0.7s	0.8s

Rad:	0.3	0.5	0.25	0.3	0.3
Time:	0s	0.2s	0.3s	0.35s	1s

Figure 3.7: Two option for recording the joint position in a time-series

3.4.1 Total Joint Travel and Direction Changes

Parameters that can be analyzed without any additional information are the number of direction changes as well as the total travel of a joint. The total travel is easily obtained by subtracting the position from two adjacent recorded points and summing up the absolute value. Additionally, more information can be extracted by summing up, for example, the clockwise and anti-clockwise rotations individually. By combining the absolute values of these, the total travel of that joint is calculated.

Figure 3.8 gives a visual representation of how the total travel can be calculated. Summing up the length of the green arrows results in the total forward rotation, while the sum of the length of the orange arrows is the backward rotation.

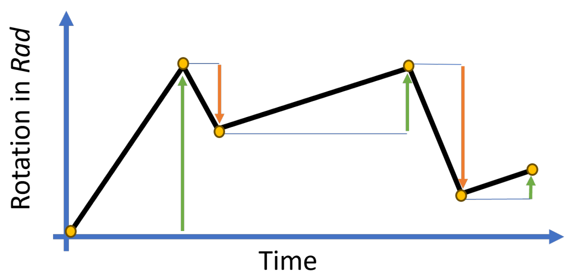


Figure 3.8: Summing up the rotation in the clockwise and anti-clockwise direction

The number of direction changes is a parameter that can also be determined by just analyzing the joint position without having the temporal information. This value can be determined by finding all points where the position before and after is either smaller or larger. But this method is not applicable to points where multiple positions are recorded at the same value right after each other.

The solution to that problem is to introduce a tracking value that indicates if the previous change in direction of two adjacent positions was either up or down. If the direction of two positions is different from the tracking value, the direction change counter is incremented by 1. If the direction is the same as the previous points or neutral, which means that two positions were identical, the direction change counter and tracking values are not changed.

Figure 3.9 gives a visual representation of where the direction-change-counter is incremented.

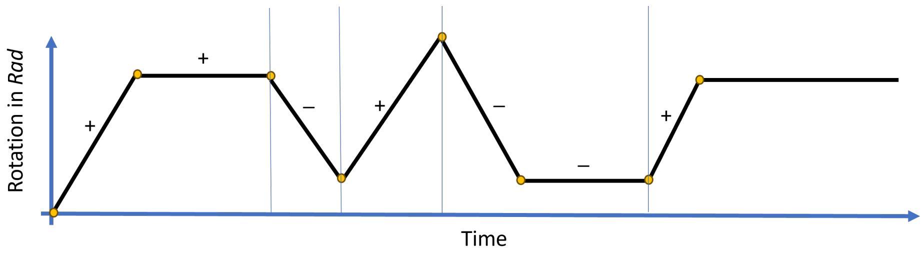


Figure 3.9: Calculating direction changes from a time-series

The counter of the direction changes and total travel of each joint are the values that are then transformed into a local sore as explained in Chapter 3.3.2 and then multiplied with an importance factor to result in the local score. The direction changes can either be summed up over all joints or specifically grouped.

Table 3.3 gives an example of how a global score can be calculated based only on the number of direction changes and total travel. In this example, the highest importance is assigned to the direction changes of joint 1. Direction changes in joints 2 to 6 are grouped together. Further, the total travel in joint 4 is also explicitly weighted, while the total travel of the other joints is grouped together. It is important to note that only the local score is multiplied by the importance factor, not the actual counted direction changes or total travel. This is why the values lie in an interval between 0 and 100. As the direction changes in joint 1 have a high local score and a high importance factor, the overall global score is also very high. This again indicates the significance of setting the imortance factor in accordance with the desired outcome.

Process Parameters	Local rating	Importance	Local score
Direction changes in joint 1	95	0.7	66.5
Direction changes in joint 2-6	45	0.1	4.5
Total travel in joint 4	34	0.1	3.4
Total travel in joint 1-3 and 5-6	46	0.1	4.6
Global Score			79

Table 3.3: Calculation of a score regarding only direction changes and total travel

In some cases, it is not possible to reduce the number of direction changes by adapting the boundary conditions. But having the same number of direction changes does not make two time-series identical. Figure 3.10 shows how two time-series have the same number of direction changes but have significantly different characteristics. To differentiate these cases, a value corresponding to the standard deviation can be employed. Tool paths that result in frequent and temporally close-positioned direction changes are generally not advisable.

This factor can be combined with the direction changes to form one parameter. This is done by dividing the direction changes by the standard deviation before calculating the local score by means of variation. Few direction changes with a high variance will lead to a low number, which is opposed by many direction changes with a low variance.

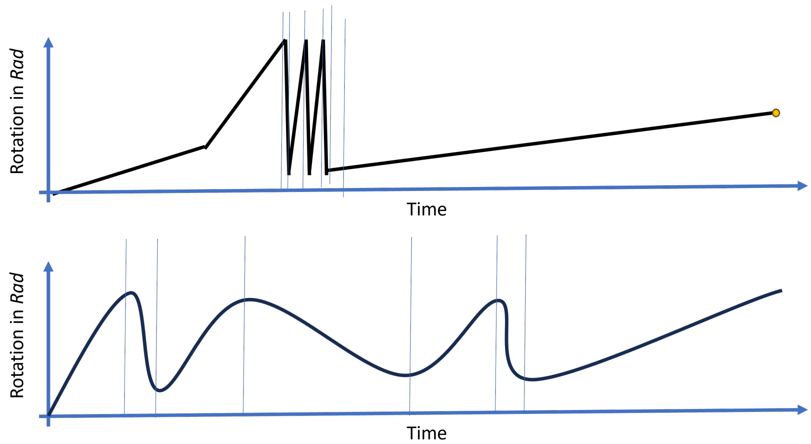


Figure 3.10: Two Time-Series with equal number of direction changes but different characteristics

3.4.2 Rotation Limits

Further, a simple analysis regarding the rotational limits can be performed, for which two different values need to be known. The first one is the physical limit that a joint can not exceed. Trying to drive the robot joint past that point can result in significant damage. The second value are possible soft limits that exist to prevent the joint from over-rotation into its physical limits. To validate if any rotational positions come close to the limits or are exceeded, a simple comparison of all the values can be made. If necessary, additional limits can be defined in cases where it is known that a joint is most stable in a specific range. After a tool path with set boundary conditions is defined, the joint angles can be analyzed and a simple comparison can be made. If the joint positions exceed the soft limits or deviate too much from their desired orientation, a "No-Go" exception is issued. The analysis of the rotation limits does not contribute to the calculation of the global score but rather serves as a validity analysis to determine if the movement necessary for the toolpath is physically possible.

3.4.3 Velocity, Acceleration and Jerk of the Joints

To specifically analyze the rotational velocity, acceleration and jerk of the joints, a time derivative needs to be performed. After that, simple comparisons of the time-series values are enough to determine whether the maximum capabilities of the motor driving the joint are exceeded.

Figure 3.11 shows how the velocity aspect can be transformed into a scalar value that can be used for a local score calculation. First, the joint velocity is obtained by taking a time derivative of the joint position. Then it is analyzed for how long the absolute velocity exceeded a certain threshold value. In the example, the threshold is set at 80%. Further, it is possible to add multiple thresholds and weigh them exponentially in relation to each other. The combined result is then used as a local score.

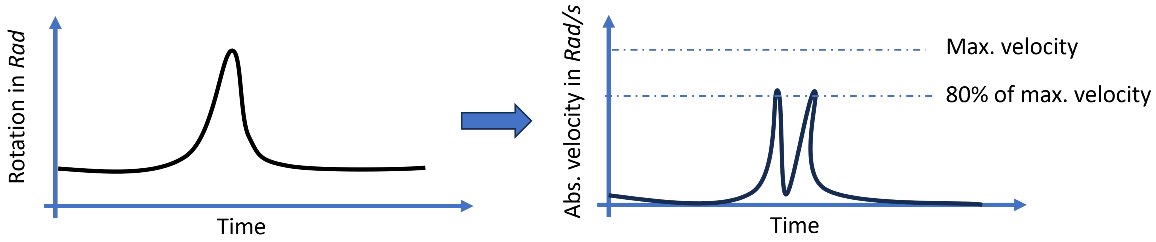


Figure 3.11: Calculating velocity from the joint position over time

It is also possible to define if a short but significant peak over the threshold values is more desirable than a constant but small overstep. Figure 3.12 gives a visualization of these two cases.

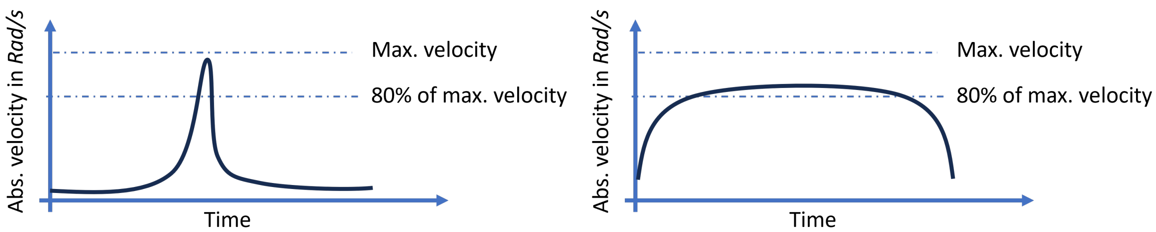


Figure 3.12: Overstepping the threshold value

In the former case, where peaks are more desirable, it is enough to count the time-steps where the threshold was overstepped. If the avoidance of limits is the first priority, it must be analyzed how close the velocity, acceleration, and jerk came to the maximum limit. The simplest case however, is to just simply square all values and sum them up. By employing this method, no threshold boundaries have to be defined, and high peaks will influence the resulting value more than small constant values.

In the case that the velocity exceeds the maximum velocity, a "No-Go" exception must be thrown as that movement is not possible. The same rating principle is applicable to acceleration and jerk. The derivative of the velocity returns the acceleration, and the next derivative returns the jerk. Individual limits and thresholds can be set to calculate how optimal the robot's movement is. In cases where the maximum acceleration or jerk is exceeded, a "No-Go" error is also thrown.

Table 3.4 shows the calculation of a global score with a weighting that prefers low acceleration in joint 2 and accepts high velocity in all joints. The acceleration in joint 1 and 3-6 are also of low importance. The jerk is completely omitted from the rating.

Process Parameters	Local rating	Importance	Local score
Velocity in Joints 1-6	45	0.1	4.5
Accelerations in Joint 2	90	0.8	72
Accelerations in Joint 1 and 3-6	15	0.1	1.5
Jerk in joints 1-6	4	0	0
Global Score			78

Table 3.4: Calculation of a score regarding only velocity, acceleration and jerk

3.5 TCP Coordinates, Velocity and Acceleration

As mentioned in Chapter 3.2.2, with the help of a forward kinematics approach it is possible to determine the X-Y-Z coordinates and orientation of the TCP. Alternatively this information can also be directly extracted from the G-code.

By calculating the time derivative of the positions, the velocity of the TCP can be determined, and subsequently, the acceleration can be obtained as well. These two parameters play a crucial role in milling applications, particularly when the goal is to fabricate precise corners. It is important to note that both robotic systems and CNC machines have limitations on their acceleration capabilities. As highlighted in Chapter 2.1.3, these limitations result in slight deviations occurring in the path, especially at corners. These deviations occur due to the inability of the systems to instantaneously change their velocity or direction. Consequently, the path followed by the TCP will not be perfectly smooth and will exhibit minor variations in the corners.

To quantitatively analyze the magnitude and frequency of these deviations, it is crucial to examine the endpoints of the linear toolpath as defined in the G-code. When the endpoints are aligned, it indicates that no deviation from the desired toolpath is expected. However, when there is a misalignment between the endpoints, it indicates that a deviation is expected.

Figure 3.13 gives a visual example of the position in th X-Y plane that the robot needs to pass. The expected deviation is shown in red.

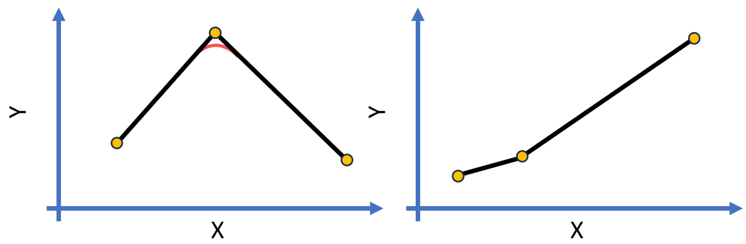


Figure 3.13: Deviation of of the TCP from the actual toolpath

To obtain a qualitative estimate of the total deviation, it is necessary to analyze the individual velocity vectors that characterize the toolpath. When the velocity vectors are perfectly aligned, it indicates that no deviation is expected. However, as the angle between two consecutive velocity vectors increases, the deviation also increases.

To quantitatively represent this information, the sine of each angle can be calculated and summed. An angle of 0 or 180 degrees will return 0, while an angle of 90 degrees will return 1. This scalar value provides an indication of the overall magnitude of the expected deviation.

Furthermore, it is essential to consider the magnitude or speed of the velocity vectors. In the case of sharp corners with high velocities, the deviation is expected to be more significant compared to corners with lower velocities. To account for this, the result obtained from the sine calculation can be multiplied by the smaller of the two velocities.

This analysis is helpful for the operator to define more optimal machining strategies but is not related to the optimization with the redundant DoF.

In the context of WAAM, the acceleration of the welding torch can have a significant impact on the process. This is particularly true when using CMT technology, which involves wire retraction, as discussed in Chapter 2.1.2. A sharp acceleration of the welding torch can lead to unintended drop detachment and imprecise drop placement. This phenomenon can negatively affect the quality and accuracy of the additive manufacturing process, resulting in defects and deviations from the desired geometry.

However, it is important to note that this issue, similar to the deviation in the toolpath as discussed earlier, is not something that can be directly optimized by simply setting specific boundary conditions.

THIS WHOLE PARAGRAPH IS USELESS !!

THIS WHOLE PARAGRAPH IS USELESS !!

THIS WHOLE PARAGRAPH IS USELESS !!

3.6 Energy Usage

Energy usage is one of the most important factors in manufacturing today. By carefully selecting optimal boundary conditions, the robot can avoid unnecessary and energy-intensive movements. The energy usage can be analyzed in two different ways. First, there is the continuous energy analysis where each movement can be attribute to a specific energy consumption. Secondly, there is to option for considering the overall energy requirement spanning the entire manufacturing process. This provides a holistic perspective on energy utilization.

3.6.1 Continuous Energy-Usage

One of the simplest approaches to track energy consumption is by monitoring the velocity and acceleration of individual joints. The energy demand can be divided into two parts: the rotation of a joint with a set velocity and the acceleration of the joint.

To calculate the energy consumption of each joint, the time-series of joint velocity can be multiplied by an average energy consumption value for that specific joint. The same principle applies to the time-series of joint acceleration. By summing up these resulting time-series, an energy consumption time-series for each joint can be obtained. Adding up the time-series of all joints gives the overall energy consumption of the robot. Table 3.5 gives exemplary values for the scaling factors.

Joint Nr.	Velocity Scaling in $\frac{\text{kWh}}{\text{m/sec}}$	Acceleration Scaling in $\frac{\text{kWh}}{\text{m/sec}^2}$
Joint 1	0.1	0.5
Joint 2	0.4	0.3
Joint 3	0.3	0.2
...	...	...

Table 3.5: Average scaling factors for energy calculations

The main advantage of this approach lies in its simplicity. However, its main drawback is the potential inaccuracy due to working with an average scaling value. If this value is calculated by averaging all possible positions, but only a few are actually traversed by the robot, significant differences may arise.

To overcome these limitations, more sophisticated approaches are required. For instance, implementing multi-body simulations in the CAM software allows for a direct analysis of the precise amount of energy needed for a robot to transition between poses. This method necessitates accurate modeling of weight distribution but yields highly precise results. However, it's important to note that this implementation may require significant computation time.

Another option to consider is utilizing a ML approach for calculating energy consumption during transitions between discrete poses. By employing a supervised learning technique, where the input data includes the current pose (joint positions and velocities) as well as the target pose, an ML model can be trained to predict the energy required for each transition. This approach offers the advantage of leveraging ML algorithms to provide accurate energy consumption estimates in a more efficient manner. However, it is important to acknowledge that generating high-quality training data and training the ML model can be time-intensive processes. Figure 3.14 shows the three mentioned options with their main requirements. It is important to note that these examples do not covet all possibilities to solve this problem.

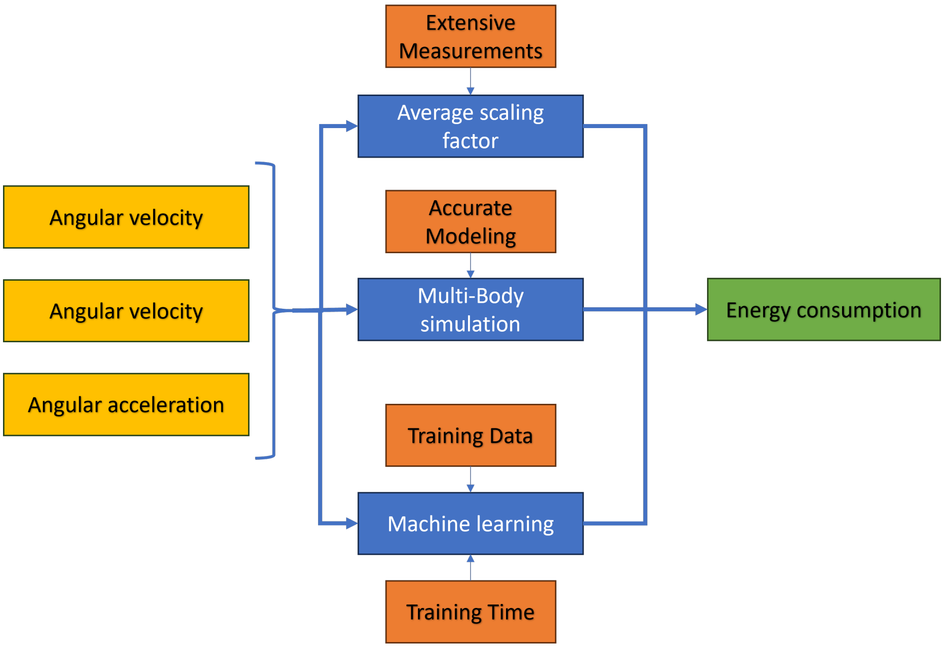


Figure 3.14: Exemplary methods for energy usage calculations

After the time-series for the energy consumption is obtained, it is possible to find peaks and relate them to specific movements. Based on the optimization goal, it is also possible to set analogue threshold values as mentioned in chapter 3.5, to optimize for a constant energy consumption.

WAMM GCODE

3.6.2 Total Energy-Usage

When the objective is to obtain a single scalar value for energy consumption, the same processes described in the previous chapter can be employed, and the values from the time series can be summed up.

However, in cases where the temporal information in energy consumption is considered irrelevant, alternative machine learning approaches can be implemented. For instance, Recurrent Neural Networks (RNNs) can be utilized, which have the ability to take a whole time series as input and return a scalar value representing the total energy consumption. RNNs are capable of capturing dependencies and patterns in sequential data, making them suitable for modeling the energy consumption over time. By training an RNN model using a time series dataset, it can learn to predict the total energy consumption based on the given input. But just as with most ML approaches, this method requires significant upfront effort and time for generating training data and training itself.

3.7 Reach, Singularities, Torch Orientation

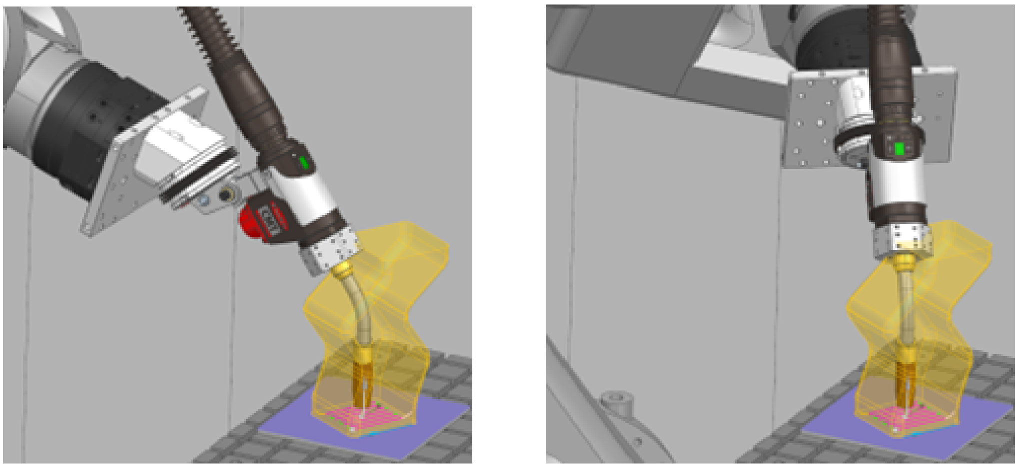
In the following, the robot poses with respect to reach, singularity avoidance, and torch orientation is discussed. These are essential factors in ensuring successful and efficient robotic operations.

3.7.1 Reach

As mentioned in Chapter 3.2.2, the analysis of the reachability index can be done in multiple formats. The first format involves a simple analysis to determine if all the points that the robot needs to traverse, lie within its work volume without any collisions occurring with itself or exceeding the hard joint limits. This aspect is closely related to the joint limits, as discussed in Chapter 3.4.2. Further it is necessary to analyze that no collision of the robot with the piecework occurs. Ensuring that the robot's joint configurations are within the specified limits is crucial for maintaining reachability and avoiding any potential collisions or constraints during its operation. If all these parameters are met, a binary index can be used to indicate the feasibility that signifies the program's safety to execute. This index however, can not be used for optimizing the robots movement as the parameters that influence this index are mostly defined by the G-Code.

When utilizing a robotic system with a specific tool, such as a spindle for milling or a welding torch for WAAM, it is crucial to consider the boundary conditions associated with that tool. In many cases, the spindle and welding torch come with cables that provide power from an external power supply. These cables have an optimal orientation where bending and wear are minimized. By positioning the cables in an optimal orientation, the robotic system can operate efficiently and effectively without any interference or limitations due to cable movement or any potential damage or wear caused by excessive bending or twisting.

Figure 3.15 visualizes the rotation around the C-axis of the welding torch. Each of the rotations strains the wire differently.

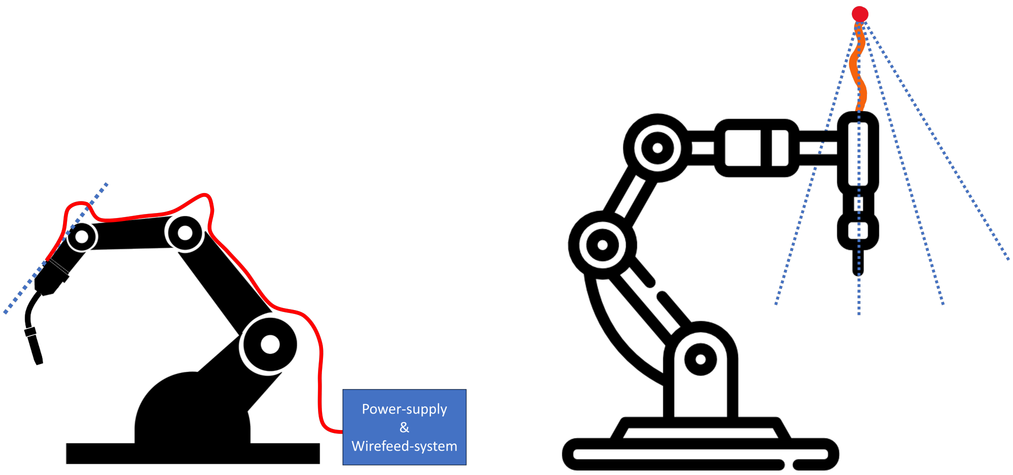


(a) No rotation **(b)** 30 degree rotation

Figure 3.15: Rotation around the C-axis of a welding torch

To determine how optimal the pose of the robot is for the cables it is necessary to know additional parameters. In some cases, the cable routing is preferably in a certain orientation along a vector in space and can be translated parallel in direction of that vector. in this case that angle between the planes of the base coordinate system of the robot is constant.

In other cases it is most optimal for the routing to bo directed towards a specific point in space. This can for example a mounting point of the cables on a wall.



(a) XXX **(b)** XX

Figure 3.16: ss

3.7.2 Singularities

3.7.3 Torch Orientation

3.8 Summery for Boundary Condition Evaluation

3.9 General Methodology for Process Optimization

3.9.1 Without NX

3.9.2 With NX

Chapter 4

Implementation and Validation

The first step involves constructing a basic model that captures the kinematics and dynamics of an industrial robot. To test the method in a simple case, the first tests are performed on a 6-DoF model. After validation on this simple model, additional redundant degrees of freedom are introduced. After that, the method is connected to CAM software to be tested in more complex scenarios.

Once the basic mathematical model is established, various optimization algorithms are implemented to determine the optimal values for each parameter associated with the redundant degrees of freedom. These methods and optimization algorithms can consider the industrial robot's specific objectives and constraints, like energy consumption or joint accelerations.

The validation process entails conducting real-world tests and simulations to evaluate optimized parameter performance and verify the effectiveness of the proposed methodology.

4.1 Implementation

4.2 Testing and Validation

4.3 Analysis and Discussion of the results

4.3.1 Analysis

4.3.2 Discussion

Chapter 5

Conclusion

5.1 Summary

5.2 Outlook

Cycle time

Stiffness value

Collision index

Man kann im Ausblick zeigen, dass ein Bauteil-Verschieben auch eine Verbesserung bringen kann, aber das ist erstmal nicht der Fokus

ML for best case calculations – Oultook?)

Chapter 6

Appendix

List of Figures

List of Tables

Bibliography

[1] Singh, M., Fuenmayor, E., Hinchy, E., Qiao, Y., Murray, N., and Devine, D. "Digital Twin: Origin to Future". In: *Applied System Innovation* 4.2 (2021), p. 36. ISSN: 2571-5577. DOI: 10.3390/asi4020036. URL: https://www.mdpi.com/2571-5577/4/2/36.

[2] Ghobakhloo, M. "Industry 4.0, digitization, and opportunities for sustainability". In: *Journal of Cleaner Production* 252 (2020), p. 119869. ISSN: 0959-6526. DOI: 10.1016/j.jclepro.2019.119869. URL: https://www.sciencedirect.com/science/article/pii/s0959652619347390.

[3] Bibby, L. and Dehe, B. "Defining and assessing industry 4.0 maturity levels – case of the defence sector". In: *Production Planning & Control* 29.12 (2018), pp. 1030–1043. DOI: 10.1080/09537287.2018.1503355.

[4] Simonis, K., Gloy, Y.-S., and Gries, T. "INDUSTRIE 4.0 - Automation in weft knitting technology". In: *IOP Conference Series: Materials Science and Engineering* 141.1 (2016), p. 012014. ISSN: 1757-899X. DOI: 10.1088/1757-899X/141/1/012014. URL: https://iopscience.iop.org/article/10.1088/1757-899x/141/1/012014/meta.

[5] Feldhausen, T., Heinrich, L., Saleeby, K., Burl, A., Post, B., MacDonald, E., Saldana, C., and Love, L. "Review of Computer-Aided Manufacturing (CAM) strategies for hybrid directed energy deposition". In: *Additive Manufacturing* 56 (2022), p. 102900. ISSN: 2214-8604. DOI: 10.1016/j.addma.2022.102900.

[6] Lalit Narayan, K., Mallikarjuna Rao, K., and Sarcar, M. M. M. *Computer aided design and manufacturing*. Second printing. Delhi: PHI Learning Private Limited, 2013. ISBN: 9788120333420.

[7] Dubovska, R., Jambor, J., and Majerik, J. "Implementation of CAD/CAM System CATIA V5 in Simulation of CNC Machining Process". In: *1877-7058* 69 (2014), pp. 638–645. ISSN: 1877-7058. DOI: 10.1016/j.proeng.2014.03.037. URL: https://www.sciencedirect.com/science/article/pii/s1877705814002835.

[8] Saxena, P., Stavropoulos, P., Kechagias, J., and Salonitis, K. "Sustainability Assessment for Manufacturing Operations". In: *Energies* 13.11 (2020), p. 2730. ISSN: 1996-1073. DOI: 10.3390/en13112730. URL: https://www.mdpi.com/1996-1073/13/11/2730.

[9] Pan, Z., Polden, J., Larkin, N., van Duin, S., and Norrish, J. “Recent progress on programming methods for industrial robots”. In: *Robotics and Computer-Integrated Manufacturing* 28.2 (2012), pp. 87–94. ISSN: 0736-5845. DOI: 10.1016/j.rcim.2011.08.004. URL: https://www.sciencedirect.com/science/article/pii/s0736584511001001.

[10] Bi, Z. and Wang, X. *Computer aided design and manufacturing*. 1st edition. Wiley-ASME press series. Hoboken, New Jersey and West Sussex, England: Wiley and ASME Press, 2020. ISBN: 9781119534211.

[11] Jia, Z.-y., Ma, J.-w., Song, D.-n., Wang, F.-j., and Liu, W. “A review of contouring-error reduction method in multi-axis CNC machining”. In: *International Journal of Machine Tools and Manufacture* 125 (2018), pp. 34–54. ISSN: 0890-6955. DOI: 10.1016/j.ijmachtools.2017.10.008.

[12] Sherwani, F., Asad, M. M., and Ibrahim, B. “Collaborative Robots and Industrial Revolution 4.0 (IR 4.0)”. In: *2020 International Conference on Emerging Trends in Smart Technologies (ICETST)*. IEEE, 2020. DOI: 10.1109/icetst49965.2020.9080724.

[13] Iglesias, I., Sebastián, M. A., and Ares, J. E. “Overview of the State of Robotic Machining: Current Situation and Future Potential”. In: *1877-7058* 132 (2015), pp. 911–917. ISSN: 1877-7058. DOI: 10.1016/j.proeng.2015.12.577. URL: https://www.sciencedirect.com/science/article/pii/s1877705815044896.

[14] Billard, A. and Kragic, D. “Trends and challenges in robot manipulation”. In: *Science* 364.6446 (2019). DOI: 10.1126/science.aat8414.

[15] Goel, R. and Gupta, P. “Robotics and Industry 4.0”. In: *A Roadmap to Industry 4.0: Smart Production, Sharp Business and Sustainable Development*. Springer, Cham, 2020, pp. 157–169. DOI: 10.1007/978-3-030-14544-6{\textunderscore}9. URL: https://link.springer.com/chapter/10.1007/978-3-030-14544-6_9.

[16] Gadaleta, M., Pellicciari, M., and Berselli, G. “Optimization of the energy consumption of industrial robots for automatic code generation”. In: *Robotics and Computer-Integrated Manufacturing* 57 (2019), pp. 452–464. ISSN: 0736-5845. DOI: 10.1016/j.rcim.2018.12.020. URL: https://www.sciencedirect.com/science/article/pii/s0736584518301856.

[17] Kyratsis, P., Kakoulis, K., and Markopoulos, A. P. “Advances in CAD/CAM/CAE Technologies”. In: *Machines* 8.1 (2020), p. 13. ISSN: 2075-1702. DOI: 10.3390/machines8010013. URL: https://www.mdpi.com/2075-1702/8/1/13/htm.

[18] Maiti, C. K. *Introducing technology computer-aided design (TCAD): Fundamentals, simulations and applications*. Temasek Boulevard, Singapore: Pan Stanford Publishing, 2017. ISBN: 9789814745529.

[19] Uhlmann, E., Reinkober, S., and Hollerbach, T. “Energy Efficient Usage of Industrial Robots for Machining Processes”. In: *2212-8271* 48 (2016), pp. 206–211. ISSN: 2212-8271. DOI: 10.1016/j.procir.2016.03.241. URL: https://www.sciencedirect.com/science/article/pii/s2212827116305303.

[20] Anjum, Z., Samo, S., Nighat, A., Nisa, A. U., Soomro, M. A., and Alayi, R. "Design and Modeling of 9 Degrees of Freedom Redundant Robotic Manipulator". In: *Journal of Robotics and Control (JRC)* 3.6 (2022), pp. 800–808. ISSN: 2715-5056. DOI: 10.18196/jrc.v3i6.15958. URL: https://journal.umy.ac.id/index.php/jrc/article/view/15958.

[21] Boscariol, P., Caracciolo, R., Richiedei, D., and Trevisani, A. "Energy Optimization of Functionally Redundant Robots through Motion Design". In: *Applied Sciences* 10.9 (2020), p. 3022. DOI: 10.3390/app10093022.

[22] Liu, Y., Wang, L., Yu, Y., Zhang, J., and Shu, B. "Optimization of redundant degree of freedom in robot milling considering chatter stability". In: (2022). DOI: 10.21203/rs.3.rs-1360661/v1. URL: https://www.researchsquare.com/article/rs-1360661/latest.

[23] Malyshev, D. I., Rybak, L. A., Pisarenko, A. S., and Cherkasov, V. V. "Analysis of the Singularities Influence on the Forward Kinematics Solution and the Geometry of the Workspace of the Gough-Stewart Platform". In: *Advances in Service and Industrial Robotics*. Ed. by Müller, A. and Brandstötter, M. Vol. 120. Mechanisms and Machine Science. Cham: Springer International Publishing and Imprint: Springer, 2022, pp. 60–67. ISBN: 978-3-031-04869-2. DOI: 10.1007/978-3-031-04870-8{\textunderscore}8.

[24] Zhao, H., Zhang, B., Yin, X., Zhang, Z., Xia, Q., and Zhang, F. "Singularity Analysis and Singularity Avoidance Trajectory Planning for Industrial Robots". In: *2021 China Automation Congress (CAC)*. IEEE, 2021. DOI: 10.1109/cac53003.2021.9727497.

[25] Milenkovic, P. "Wrist singularity avoidance with a robot end-effector adding an oblique, redundant axis". In: *Mechanism and Machine Theory* 162 (2021), p. 104355. ISSN: 0094-114X. DOI: 10.1016/j.mechmachtheory.2021.104355. URL: https://www.sciencedirect.com/science/article/pii/s0094114x21001130.

[26] Faria, C., Ferreira, F., Erlhagen, W., Monteiro, S., and Bicho, E. "Position-based kinematics for 7-DoF serial manipulators with global configuration control, joint limit and singularity avoidance". In: *Mechanism and Machine Theory* 121 (2018), pp. 317–334. ISSN: 0094-114X. DOI: 10.1016/j.mechmachtheory.2017.10.025. URL: https://www.sciencedirect.com/science/article/pii/s0094114x17306559.

[27] Duong, X. B. "On the Effect of the End-effector Point Trajectory on the Joint Jerk of the Redundant Manipulators". In: *Journal of Applied and Computational Mechanics* 7.3 (2021), pp. 1575–1582. ISSN: 2383-4536. DOI: 10.22055/jacm.2021.35350.2635. URL: https://jacm.scu.ac.ir/article_16660.html.

[28] R.V. Dubey, J.A. Euler, and S.M. Babcock. *Robotics and Automation, 5th IEEE International Conference on, 1988: Proceedings*. Los Alamitos: IEEE Computer Society Press, 1988. ISBN: 0818608528. URL: http://ieeexplore.ieee.org/servlet/opac?punumber=202.

[29] Valente, A., Baraldo, S., and Carpanzano, E. “Smooth trajectory generation for industrial robots performing high precision assembly processes”. In: *CIRP Annals* 66.1 (2017), pp. 17–20. ISSN: 00078506. DOI: 10.1016/j.cirp.2017.04.105. URL: https://www.sciencedirect.com/science/article/pii/s0007850617301051.

[30] Lin, J., Ye, C., Yang, J., Zhao, H., Ding, H., and Luo, M. “Contour error-based optimization of the end-effector pose of a 6 degree-of-freedom serial robot in milling operation”. In: *Robotics and Computer-Integrated Manufacturing* 73 (2022), p. 102257. ISSN: 0736-5845. DOI: 10.1016/j.rcim.2021.102257. URL: https://www.sciencedirect.com/science/article/pii/s073658452100137x.

[31] Xiong, G., Ding, Y., and Zhu, L. “Stiffness-based pose optimization of an industrial robot for five-axis milling”. In: *Robotics and Computer-Integrated Manufacturing* 55 (2019), pp. 19–28. ISSN: 0736-5845. DOI: 10.1016/j.rcim.2018.07.001. URL: https://www.sciencedirect.com/science/article/pii/s0736584517304556.

[32] Shi, X., Guo, Y., Chen, X., Chen, Z., and Yang, Z. “Kinematics and Singularity Analysis of a 7-DOF Redundant Manipulator”. In: *Sensors* 21.21 (2021), p. 7257. ISSN: 1424-8220. DOI: 10.3390/s21217257. URL: https://www.mdpi.com/1424-8220/21/21/7257.

[33] Huynh, H. N., Assadi, H., Rivière-Lorphèvre, E., Verlinden, O., and Ahmadi, K. “Modelling the dynamics of industrial robots for milling operations”. In: *Robotics and Computer-Integrated Manufacturing* 61 (2020), p. 101852. ISSN: 0736-5845. DOI: 10.1016/j.rcim.2019.101852. URL: https://www.sciencedirect.com/science/article/pii/s0736584519301784.

[34] Chen-Gang, Li-Tong, Chu-Ming, Xuan, J.-Q., and Xu, S.-H. “Review on kinematics calibration technology of serial robots”. In: *International Journal of Precision Engineering and Manufacturing* 15.8 (2014), pp. 1759–1774. ISSN: 2005-4602. DOI: 10.1007/s12541-014-0528-1. URL: https://link.springer.com/article/10.1007/s12541-014-0528-1.

[35] Gasparetto, A. and Zanotto, V. “Optimal trajectory planning for industrial robots”. In: *Advances in Engineering Software* 41.4 (2010), pp. 548–556. ISSN: 0965-9978. DOI: 10.1016/j.advengsoft.2009.11.001. URL: https://www.sciencedirect.com/science/article/pii/s0965997809002464.

[36] Vande Weghe, M., Ferguson, D., and Srinivasa, S. S. “Randomized path planning for redundant manipulators without inverse kinematics”. In: *2007 7th IEEE-RAS International Conference on Humanoid Robots*. IEEE, 2007. DOI: 10.1109/ichr.2007.4813913.

[37] Reiter, A., Muller, A., and Gattringer, H. “Inverse kinematics in minimum-time trajectory planning for kinematically redundant manipulators”. In: *IECON 2016 - 42nd Annual Conference of the IEEE Industrial Electronics Society*. IEEE, 2016. DOI: 10.1109/iecon.2016.7793436.

[38] Doan, N. C. N., Tao, P. Y., and Lin, W. "Optimal redundancy resolution for robotic arc welding using modified particle swarm optimization". In: *2016 IEEE International Conference on Advanced Intelligent Mechatronics (AIM)*. IEEE, 2016. DOI: 10.1109/aim.2016.7576826.

[39] Boscariol, P. and Richiedei, D. "Energy Saving in Redundant Robotic Cells: Optimal Trajectory Planning". In: Springer, Cham, 2019, pp. 268–275. DOI: 10.1007/978-3-030-00365-4{\textunderscore}32. URL: https://link.springer.com/chapter/10.1007/978-3-030-00365-4_32.

[40] Ayten, K. K., Sahinkaya, M. N., and Dumlu, A. "Optimum Trajectory Generation for Redundant/Hyper-Redundant Manipulators". In: *IFAC-PapersOnLine* 49.21 (2016), pp. 493–500. ISSN: 2405-8963. DOI: 10.1016/j.ifacol.2016.10.651. URL: https://www.sciencedirect.com/science/article/pii/s2405896316322637.

[41] Iqbal, A., Zhao, G., Suhaimi, H., He, N., Hussain, G., and Zhao, W. "Readiness of subtractive and additive manufacturing and their sustainable amalgamation from the perspective of Industry 4.0: a comprehensive review". In: *The International Journal of Advanced Manufacturing Technology* 111.9-10 (2020), pp. 2475–2498. ISSN: 1433-3015. DOI: 10.1007/s00170-020-06287-6. URL: https://link.springer.com/article/10.1007/s00170-020-06287-6.

[42] Watson, J. K. and Taminger, K. M. B. "A decision-support model for selecting additive manufacturing versus subtractive manufacturing based on energy consumption". In: *Journal of Cleaner Production* 176 (2015), pp. 1316–1322. ISSN: 0959-6526. DOI: 10.1016/j.jclepro.2015.12.009. URL: https://www.sciencedirect.com/science/article/pii/s0959652615018247.

[43] Dilberoglu, U. M., Gharehpapagh, B., Yaman, U., and Dolen, M. "The Role of Additive Manufacturing in the Era of Industry 4.0". In: *Procedia Manufacturing* 11 (2017), pp. 545–554. ISSN: 2351-9789. DOI: 10.1016/j.promfg.2017.07.148. URL: https://www.sciencedirect.com/science/article/pii/s2351978917303529.

[44] Bandyopadhyay, A. *Additive Manufacturing, Second Edition*. 2nd ed. Milton: Taylor & Francis Group, 2020. ISBN: 9780429881022.

[45] van Le, T., Paris, H., and Mandil, G. "Environmental impact assessment of an innovative strategy based on an additive and subtractive manufacturing combination". In: *Journal of Cleaner Production* 164 (2017), pp. 508–523. ISSN: 0959-6526. DOI: 10.1016/j.jclepro.2017.06.204. URL: https://www.sciencedirect.com/science/article/pii/s0959652617313732.

[46] Wang, W., Guo, Q., Yang, Z., Jiang, Y., and Xu, J. "A state-of-the-art review on robotic milling of complex parts with high efficiency and precision". In: *Robotics and Computer-Integrated Manufacturing* 79 (2023), p. 102436. ISSN: 0736-5845. DOI: 10.1016/j.rcim.2022.102436. URL: https://www.sciencedirect.com/science/article/pii/s073658452200120x.

[47] Calleja, A., Bo, P., González, H., Bartoň, M., and López de Lacalle, Luis Norberto. "Highly accurate 5-axis flank CNC machining with conical tools". In: *The International Journal of Advanced Manufacturing Technology* 97.5-8 (2018), pp. 1605–1615. ISSN: 1433-3015. DOI: 10.1007/s00170-018-2033-7. URL: https://link.springer.com/article/10.1007/s00170-018-2033-7.

[48] Abdulhameed, O., Al-Ahmari, A., Ameen, W., and Mian, S. H. "Additive manufacturing: Challenges, trends, and applications". In: *Advances in Mechanical Engineering* 11.2 (2019). DOI: 10.1177/1687814018822880.

[49] Kumar, K., Ranjan, C., and Davim, J. P. *CNC Programming for Machining*. 1st ed. 2020. Materials Forming, Machining and Tribology. Cham: Springer International Publishing and Imprint: Springer, 2020. ISBN: 978-3-030-41278-4. DOI: 10.1007/978-3-030-41279-1.

[50] Amanullah, A., Murshiduzzaman, Saleh, T., and Khan, R. "Design and Development of a Hybrid Machine Combining Rapid Prototyping and CNC Milling Operation". In: *1877-7058* 184 (2017), pp. 163–170. ISSN: 1877-7058. DOI: 10.1016/j.proeng.2017.04.081.

[51] Tomaz, I., Gupta, M. K., and Pimenov, D. Y. "Subtractive Manufacturing of Different Composites". In: *Additive and Subtractive Manufacturing of Composites*. Springer, Singapore, 2021, pp. 137–165. DOI: 10.1007/978-981-16-3184-9{\textunderscore}6. URL: https://link.springer.com/chapter/10.1007/978-981-16-3184-9_6.

[52] Yang, B., Zhang, G., Ran, Y., and Yu, H. "Kinematic modeling and machining precision analysis of multi-axis CNC machine tools based on screw theory". In: *Mechanism and Machine Theory* 140 (2019), pp. 538–552. ISSN: 0094-114X. DOI: 10.1016/j.mechmachtheory.2019.06.021. URL: https://www.sciencedirect.com/science/article/pii/s0094114x19307992.

[53] Nee, A. Y. C. *Handbook of Manufacturing Engineering and Technology*. 1st ed. 2015. London: Springer London and Imprint: Springer, 2015. ISBN: 978-1-4471-4669-8. DOI: 10.1007/978-1-4471-4670-4.

[54] Tien, D. H., Duc, Q. T., Van, T. N., Nguyen, N.-T., Do Duc, T., and Duy, T. N. "Online monitoring and multi-objective optimisation of technological parameters in high-speed milling process". In: *The International Journal of Advanced Manufacturing Technology* 112.9-10 (2021), pp. 2461–2483. ISSN: 1433-3015. DOI: 10.1007/s00170-020-06444-x. URL: https://link.springer.com/article/10.1007/s00170-020-06444-x.

[55] Jayawardane, H., Davies, I. J., Gamage, J. R., John, M., and Biswas, W. K. "Sustainability perspectives – a review of additive and subtractive manufacturing". In: *Sustainable Manufacturing and Service Economics* 2 (2023), p. 100015. ISSN: 2667-3444. DOI: 10.1016/j.smse.2023.100015.

[56] Gu, X. and Koren, Y. "Manufacturing system architecture for cost-effective mass-individualization". In: *Manufacturing Letters* 16 (2018), pp. 44–48. ISSN: 2213-8463. DOI: 10.1016/j.mfglet.2018.04.002. URL: https://www.sciencedirect.com/science/article/pii/s2213846317300974.

[57] Faludi, J., Bayley, C., Bhogal, S., and Iribarne, M. "Comparing environmental impacts of additive manufacturing vs traditional machining via life-cycle assessment". In: *Rapid Prototyping Journal* 21.1 (2015), pp. 14–33. DOI: 10.1108/RPJ-07-2013-0067. URL: https://www.emerald.com/insight/content/doi/10.1108/rpj-07-2013-0067/full/pdf.

[58] Hesser, D. F. and Markert, B. "Tool wear monitoring of a retrofitted CNC milling machine using artificial neural networks". In: *Manufacturing Letters* 19 (2019), pp. 1–4. ISSN: 2213-8463. DOI: 10.1016/j.mfglet.2018.11.001. URL: https://www.sciencedirect.com/science/article/pii/s2213846318301524.

[59] YUE, C., GAO, H., LIU, X., LIANG, S. Y., and Wang, L. "A review of chatter vibration research in milling". In: *1000-9361* 32.2 (2019), pp. 215–242. ISSN: 1000-9361. DOI: 10.1016/j.cja.2018.11.007. URL: https://www.sciencedirect.com/science/article/pii/s1000936119300147.

[60] Aslan, D. and Altintas, Y. "On-line chatter detection in milling using drive motor current commands extracted from CNC". In: *International Journal of Machine Tools and Manufacture* 132 (2018), pp. 64–80. ISSN: 0890-6955. DOI: 10.1016/j.ijmachtools.2018.04.007. URL: https://www.sciencedirect.com/science/article/pii/s0890695518300841.

[61] Giorgio Bort, C. M., Leonesio, M., and Bosetti, P. "A model-based adaptive controller for chatter mitigation and productivity enhancement in CNC milling machines". In: *Robotics and Computer-Integrated Manufacturing* 40 (2016), pp. 34–43. ISSN: 0736-5845. DOI: 10.1016/j.rcim.2016.01.006. URL: https://www.sciencedirect.com/science/article/pii/s0736584516300242.

[62] Wan, S., Li, X., Su, W., Yuan, J., Hong, J., and Jin, X. "Active damping of milling chatter vibration via a novel spindle system with an integrated electromagnetic actuator". In: *Precision Engineering* 57 (2019), pp. 203–210. ISSN: 0141-6359. DOI: 10.1016/j.precisioneng.2019.04.007. URL: https://www.sciencedirect.com/science/article/pii/s0141635918307931.

[63] CNC Masters - Just another WordPress site. *CNC Machine Buyer's Guide: Types, Uses, Price, & Definitions: Last access: 30.10.2023*. 2022. URL: https://www.cncmasters.com/cnc-machine-buyers-guide/.

[64] *5-axis milling: Last access: 30.10.2023*. URL: https://www.manufacturingguide.com/en/5-axis-milling.

[65] Prakash, K. S., Nancharaih, T., and Rao, V. S. "Additive Manufacturing Techniques in Manufacturing -An Overview". In: *Materials Today: Proceedings* 5.2 (2018), pp. 3873–3882. ISSN: 2214-7853. DOI: 10.1016/j.matpr.2017.11.642. URL: https://www.sciencedirect.com/science/article/pii/s2214785317329152.

[66] Wickramasinghe, S., Do, T., and Tran, P. “FDM-Based 3D Printing of Polymer and Associated Composite: A Review on Mechanical Properties, Defects and Treatments”. In: *Polymers* 12.7 (2020), p. 1529. ISSN: 2073-4360. DOI: 10.3390/polym12071529. URL: https://www.mdpi.com/2073-4360/12/7/1529.

[67] Wang, J., Goyanes, A., Gaisford, S., and Basit, A. W. “Stereolithographic (SLA) 3D printing of oral modified-release dosage forms”. In: *International Journal of Pharmaceutics* 503.1-2 (2016), pp. 207–212. ISSN: 0378-5173. DOI: 10.1016/j.ijpharm.2016.03.016. URL: https://www.sciencedirect.com/science/article/pii/s0378517316302150.

[68] Meier, C., Penny, R. W., Zou, Y., Gibbs, J. S., and Hart, A. J. “THERMOPHYSICAL PHENOMENA IN METAL ADDITIVE MANUFACTURING BY SELECTIVE LASER MELTING: FUNDAMENTALS, MODELING, SIMULATION, AND EXPERIMENTATION”. In: *Annual Review of Heat Transfer* 20.1 (2017), pp. 241–316. ISSN: 1049-0787. DOI: 10.1615/AnnualRevHeatTransfer.2018019042. URL: https://www.dl.begellhouse.com/references/5756967540dd1b03,562e7b3835dec96e,0860d4f32b9f248d.html.

[69] Bose, S., Ke, D., Sahasrabudhe, H., and Bandyopadhyay, A. “Additive manufacturing of biomaterials”. In: *Progress in materials science* 93 (2018), pp. 45–111. ISSN: 0079-6425. DOI: 10.1016/j.pmatsci.2017.08.003.

[70] Attaran, M. “The rise of 3-D printing: The advantages of additive manufacturing over traditional manufacturing”. In: *Business Horizons* 60.5 (2017), pp. 677–688. ISSN: 0007-6813. DOI: 10.1016/j.bushor.2017.05.011. URL: https://www.sciencedirect.com/science/article/pii/s0007681317300897.

[71] Plocher, J. and Panesar, A. “Review on design and structural optimisation in additive manufacturing: Towards next-generation lightweight structures”. In: *Materials & Design* 183 (2019), p. 108164. ISSN: 02641275. DOI: 10.1016/j.matdes.2019.108164.

[72] Jandyal, A., Chaturvedi, I., Wazir, I., Raina, A., and Ul Haq, M. I. “3D printing – A review of processes, materials and applications in industry 4.0”. In: *2666-4127* 3 (2022), pp. 33–42. ISSN: 2666-4127. DOI: 10.1016/j.susoc.2021.09.004. URL: https://www.sciencedirect.com/science/article/pii/s2666412721000441.

[73] Haleem, A. and Javaid, M. “Additive Manufacturing Applications in Industry 4.0: A Review”. In: *Journal of Industrial Integration and Management* 04.04 (2019), p. 1930001. ISSN: 2424-8622. DOI: 10.1142/S2424862219300011.

[74] *AnkerMake M5C 3D-Drucker + 2kg Filament: Last access: 30.10.2023*. URL: https://www.ankermake.com/eu-de/products/m5c-3d-printer-2kg-filament?variant=45837302694176&discount=WS24DEM5C.

[75] Svetlizky, D., Das, M., Zheng, B., Vyatskikh, A. L., Bose, S., Bandyopadhyay, A., Schoenung, J. M., Lavernia, E. J., and Eliaz, N. “Directed energy deposition (DED) additive manufacturing: Physical characteristics, defects, challenges and applications”. In: *Materials Today* 49 (2021), pp. 271–295. ISSN: 1369-7021. DOI: 10.1016/j.mattod.2021.03.020. URL: https://www.sciencedirect.com/science/article/pii/s1369702121001139.

[76] *DIN EN ISO/ASTM 52900:2022-03, Additive Fertigung_- Grundlagen_- Terminologie (ISO/ASTM 52900:2021); Deutsche Fassung EN_ISO/ASTM 52900:2021*. Berlin. DOI: 10.31030/3290011.

[77] Cunningham, C. R., Flynn, J. M., Shokrani, A., Dhokia, V., and Newman, S. T. "Invited review article: Strategies and processes for high quality wire arc additive manufacturing". In: *Additive Manufacturing* 22 (2018), pp. 672–686. ISSN: 2214-8604. DOI: 10.1016/j.addma.2018.06.020. URL: https://www.sciencedirect.com/science/article/pii/s2214860418303920.

[78] IvánTabernero, Paskual, A., Álvarez, P., and Suárez, A. "Study on Arc Welding Processes for High Deposition Rate Additive Manufacturing". In: *2212-8271* 68 (2018), pp. 358–362. ISSN: 2212-8271. DOI: 10.1016/j.procir.2017.12.095. URL: https://www.sciencedirect.com/science/article/pii/s2212827117310363.

[79] Li, J. Z., Alkahari, M. R., Rosli, N. A. B., Hasan, R., Sudin, M. N., and Ramli, F. R. "Review of Wire Arc Additive Manufacturing for 3D Metal Printing". In: *International Journal of Automation Technology* 13.3 (2019), pp. 346–353. ISSN: 1883-8022. DOI: 10.20965/ijat.2019.p0346. URL: https://www.jstage.jst.go.jp/article/ijat/13/3/13_346/_article/-char/ja/.

[80] Wu, B., Pan, Z., Ding, D., Cuiuri, D., Li, H., Xu, J., and Norrish, J. "A review of the wire arc additive manufacturing of metals: properties, defects and quality improvement". In: *Journal of Manufacturing Processes* 35 (2018), pp. 127–139. ISSN: 1526-6125. DOI: 10.1016/j.jmapro.2018.08.001. URL: https://www.sciencedirect.com/science/article/pii/s1526612518310739.

[81] Chaurasia, M. and Sinha, M. K., eds. *Investigations on Process Parameters of Wire Arc Additive Manufacturing (WAAM): A Review*. 2021. DOI: 10.1007/978-981-15-8542-5{\textunderscore}74.

[82] *Fabricación aditiva en metales - WAAM | Lortek: Last access: 30.10.2023*. URL: https://www.lortek.es/en/technological-areas/metal-additive-manufacturing/waam.

[83] Ou, W., Mukherjee, T., Knapp, G. L., Wei, Y., and DebRoy, T. "Fusion zone geometries, cooling rates and solidification parameters during wire arc additive manufacturing". In: *International Journal of Heat and Mass Transfer* 127 (2018), pp. 1084–1094. ISSN: 0017-9310. DOI: 10.1016/j.ijheatmasstransfer.2018.08.111. URL: https://www.sciencedirect.com/science/article/pii/s0017931018323974.

[84] Ding, D., Pan, Z., Cuiuri, D., and Li, H. "Wire-feed additive manufacturing of metal components: technologies, developments and future interests". In: *The International Journal of Advanced Manufacturing Technology* 81.1-4 (2015), pp. 465–481. ISSN: 1433-3015. DOI: 10.1007/s00170-015-7077-3. URL: https://link.springer.com/article/10.1007/s00170-015-7077-3.

[85] Schmitz, M., Wiartalla, J., Gelfgren, M., Mann, S., Corves, B., and Hüsing, M. "A Robot-Centered Path-Planning Algorithm for Multidirectional Additive Manufacturing for WAAM Processes and Pure Object Manipulation". In: *Applied Sciences* 11.13 (2021), p. 5759. DOI: 10.3390/app11135759. URL: https://www.mdpi.com/2076-3417/11/13/5759.

[86] Nagasai, B. P., Malarvizhi, S., and Balasubramanian, V. "Effect of welding processes on mechanical and metallurgical characteristics of carbon steel cylindrical components made by wire arc additive manufacturing (WAAM) technique". In: *CIRP Journal of Manufacturing Science and Technology* 36 (2022), pp. 100–116. ISSN: 1755-5817. DOI: 10.1016/j.cirpj.2021.11.005. URL: https://www.sciencedirect.com/science/article/pii/s1755581721001887.

[87] Dutra, J. C., Gonçalves e Silva, R. H., and Marques, C. "Melting and welding power characteristics of MIG–CMT versus conventional MIG for aluminium 5183". In: *Welding International* 29.3 (2015), pp. 181–186. DOI: 10.1080/09507116.2014.932974.

[88] Selvi, S., Vishvaksenan, A., and Rajasekar, E. "Cold metal transfer (CMT) technology - An overview". In: *2214-9147* 14.1 (2018), pp. 28–44. ISSN: 2214-9147. DOI: 10.1016/j.dt.2017.08.002. URL: https://www.sciencedirect.com/science/article/pii/s2214914717301022.

[89] Srinivasan, D., Sevvel, P., John Solomon, I., and Tanushkumaar, P. "A review on Cold Metal Transfer (CMT) technology of welding". In: *Materials Today: Proceedings* 64 (2022), pp. 108–115. ISSN: 2214-7853. DOI: 10.1016/j.matpr.2022.04.016. URL: https://www.sciencedirect.com/science/article/pii/s2214785322021289.

[90] Scotti, F. M., Teixeira, F. R., Da Silva, L. J., Araújo, D. B. de, Reis, R. P., and Scotti, A. "Thermal management in WAAM through the CMT Advanced process and an active cooling technique". In: *Journal of Manufacturing Processes* 57 (2020), pp. 23–35. ISSN: 1526-6125. DOI: 10.1016/j.jmapro.2020.06.007. URL: https://www.sciencedirect.com/science/article/pii/s1526612520303807.

[91] Cong, B., Ouyang, R., Qi, B., and Ding, J. "Influence of Cold Metal Transfer Process and Its Heat Input on Weld Bead Geometry and Porosity of Aluminum-Copper Alloy Welds". In: *Rare Metal Materials and Engineering* 45.3 (2016), pp. 606–611. ISSN: 1875-5372. DOI: 10.1016/S1875-5372(16)30080-7. URL: https://www.sciencedirect.com/science/article/pii/s1875537216300807.

[92] Pickin, C. G. and Young, K. "Evaluation of cold metal transfer (CMT) process for welding aluminium alloy". In: *Science and Technology of Welding and Joining* 11.5 (2006), pp. 583–585. DOI: 10.1179/174329306X120886.

[93] Dalton, R. *Imaging CMT Welding with a Weld Camera: Last access: 30.10.2023*. URL: https://blog.xiris.com/blog/imaging-cmt-welding-with-a-weld-camera.

[94] Rahul, S. G., Dhivyasri, G., Kavitha, P., Arungalai Vendan, S., Kumar, K. R., Garg, A., and Gao, L. “Model reference adaptive controller for enhancing depth of penetration and bead width during Cold Metal Transfer joining process”. In: *Robotics and Computer-Integrated Manufacturing* 53 (2018), pp. 122–134. ISSN: 0736-5845. DOI: 10.1016/j.rcim.2018.03.013. URL: https://www.sciencedirect.com/science/article/pii/s0736584517304519.

[95] Pickin, C. G., Williams, S. W., and Lunt, M. “Characterisation of the cold metal transfer (CMT) process and its application for low dilution cladding”. In: *Journal of Materials Processing Technology* 211.3 (2011), pp. 496–502. ISSN: 0924-0136. DOI: 10.1016/j.jmatprotec.2010.11.005. URL: https://www.sciencedirect.com/science/article/pii/s0924013610003456.

[96] Ji, W. and Wang, L. “Industrial robotic machining: a review”. In: *The International Journal of Advanced Manufacturing Technology* 103.1-4 (2019), pp. 1239–1255. ISSN: 1433-3015. DOI: 10.1007/s00170-019-03403-z. URL: https://link.springer.com/article/10.1007/s00170-019-03403-z.

[97] Siciliano, B. and Khatib, O. *Springer handbook of robotics: With 1375 figures and 109 tables*. 2nd edition. Berlin and Heidelberg: Springer, 2016. ISBN: 978-3-319-32550-7. DOI: 10.1007/978-3-319-32552-1.

[98] Hanafusa, H., Yoshikawa, T., and Nakamura, Y. “Analysis and Control of Articulated Robot Arms with Redundancy”. In: *IFAC Proceedings Volumes* 14.2 (1981), pp. 1927–1932. ISSN: 1474-6670. DOI: 10.1016/S1474-6670(17)63754-6. URL: https://www.sciencedirect.com/science/article/pii/s1474667017637546.

[99] Jain, R., Nayab Zafar, M., and Mohanta, J. C. “Modeling and Analysis of Articulated Robotic Arm for Material Handling Applications”. In: *IOP Conference Series: Materials Science and Engineering* 691.1 (2019), p. 012010. ISSN: 1757-899X. DOI: 10.1088/1757-899X/691/1/012010. URL: https://iopscience.iop.org/article/10.1088/1757-899x/691/1/012010/meta.

[100] Kim, H. S. and Tsai, L.-W. “Design Optimization of a Cartesian Parallel Manipulator”. In: *Journal of Mechanical Design* 125.1 (2003), pp. 43–51. ISSN: 1050-0472. DOI: 10.1115/1.1543977.

[101] Das, M. T. and Canan Dülger, L. “Mathematical modelling, simulation and experimental verification of a scara robot”. In: *Simulation Modelling Practice and Theory* 13.3 (2005), pp. 257–271. ISSN: 1569-190X. DOI: 10.1016/j.simpat.2004.11.004. URL: https://www.sciencedirect.com/science/article/pii/s1569190x04001200.

[102] Bonev, I. *Delta parallel robot-the story of success*. Newsletter, available at http://www.parallelmic. org, 2001. URL: http://www.robotics.caltech.edu/~jwb/courses/me115/handouts/deltarobothistory.pdf.

[103] Liu, L., Guo, F., Zou, Z., and Duffy, V. G. "Application, Development and Future Opportunities of Collaborative Robots (Cobots) in Manufacturing: A Literature Review". In: *International Journal of Human–Computer Interaction* (2022), pp. 1–18. DOI: 10.1080/10447318.2022.2041907.

[104] Hägele, M., Nilsson, K., Pires, J. N., and Bischoff, R. "Industrial Robotics". In: *Springer Handbook of Robotics*. Springer, Cham, 2016, pp. 1385–1422. DOI: 10.1007/978-3-319-32552-1{\textunderscore}54. URL: https://link.springer.com/chapter/10.1007/978-3-319-32552-1_54.

[105] Kubela, T., Pochyly, A., and Singule, V. "Assessment of industrial robots accuracy in relation to accuracy improvement in machining processes". In: *2016 IEEE International Power Electronics and Motion Control Conference (PEMC)*. IEEE, 2016. DOI: 10.1109/epepemc.2016.7752083.

[106] Heyer, C. "Human-robot interaction and future industrial robotics applications". In: *2010 IEEE/RSJ International Conference on Intelligent Robots and Systems*. IEEE, 2010. DOI: 10.1109/iros.2010.5651294.

[107] Jung, J. H. and Lim, D.-G. "Industrial robots, employment growth, and labor cost: A simultaneous equation analysis". In: *0040-1625* 159 (2020), p. 120202. ISSN: 0040-1625. DOI: 10.1016/j.techfore.2020.120202. URL: https://www.sciencedirect.com/science/article/pii/s0040162520310283.

[108] Joshi, K., Melkote, S. N., Anderson, M., and Chaudhari, R. "Investigation of cycle time behavior in the robotic grinding process". In: *CIRP Journal of Manufacturing Science and Technology* 35 (2021), pp. 315–322. ISSN: 1755-5817. DOI: 10.1016/j.cirpj.2021.06.021. URL: https://www.sciencedirect.com/science/article/pii/s1755581721001139.

[109] Ye, W. "Exploring the Use of Industrial Robots in CNC Machine Tool Programming and Operation Courses". In: *2022 7th International Conference on Mechatronics System and Robots (ICMSR)*. IEEE, 2022. DOI: 10.1109/icmsr2020.2022.00017.

[110] Wu, K., Li, J., Zhao, H., and Zhong, Y. "Review of Industrial Robot Stiffness Identification and Modelling". In: *Applied Sciences* 12.17 (2022), p. 8719. DOI: 10.3390/app12178719. URL: https://www.mdpi.com/2076-3417/12/17/8719.

[111] Heimann, O. and Guhl, J. "Industrial Robot Programming Methods: A Scoping Review". In: *2020 25th IEEE International Conference on Emerging Technologies and Factory Automation (ETFA)*. IEEE, 2020. DOI: 10.1109/etfa46521.2020.9211997.

[112] Singh, R., Kukshal, V., and Yadav, V. S. "A Review on Forward and Inverse Kinematics of Classical Serial Manipulators". In: *Advances in Engineering Design*. Ed. by Rakesh, P. K., Sharma, A. K., and Singh, I. Lecture Notes in Mechanical Engineering. Singapore: Springer Singapore and Imprint: Springer, 2021, pp. 417–428. ISBN: 978-981-33-4017-6. DOI: 10.1007/978-981-33-4018-3{\textunderscore}39.

[113] Lin, Y., Zhao, H., and Ding, H. “Real-time path correction of industrial robots in machining of large-scale components based on model and data hybrid drive”. In: *Robotics and Computer-Integrated Manufacturing* 79 (2023), p. 102447. ISSN: 0736-5845. DOI: 10.1016/j.rcim.2022.102447. URL: https://www.sciencedirect.com/science/article/pii/s0736584522001302.

[114] Bosscher, P. and Hedman, D. “Real–time collision avoidance algorithm for robotic manipulators”. In: *Industrial Robot: An International Journal* 38.2 (2011), pp. 186–197. DOI: 10.1108/01439911111106390. URL: https://www.emerald.com/insight/content/doi/10.1108/01439911111106390/full/pdf.

[115] Domae, Y. “Recent Trends in the Research of Industrial Robots and Future Outlook”. In: *Journal of Robotics and Mechatronics* 31.1 (2019), pp. 57–62. ISSN: 1883-8049. DOI: 10.20965/jrm.2019.p0057. URL: https://www.jstage.jst.go.jp/article/jrobomech/31/1/31_57/_article/-char/ja/.

[116] Huynh Hoai Nam, Edouard Riviere, and Olivier Verlinden. “Multibody modelling of a flexible 6-axis robot dedicated to robotic machining”. In: 2018. URL: https://www.researchgate.net/profile/huynh-hoai-nam/publication/326106790_multibody_modelling_of_a_flexible_6-axis_robot_dedicated_to_robotic_machining.

[117] Yuan, L., Pan, Z., Ding, D., He, F., van Duin, S., Li, H., and Li, W. “Investigation of humping phenomenon for the multi-directional robotic wire and arc additive manufacturing”. In: *Robotics and Computer-Integrated Manufacturing* 63 (2020), p. 101916. ISSN: 0736-5845. DOI: 10.1016/j.rcim.2019.101916. URL: https://www.sciencedirect.com/science/article/pii/s0736584519304260.

[118] “KUKA linear units: Last access: 30.10.2023”. In: (). URL: https://www.kuka.com/en-de/products/robot-systems/robot-periphery/linear-units.

[119] Hagane, S. and Venture, G. “Robotic Manipulator’s Expressive Movements Control Using Kinematic Redundancy”. In: *Machines* 10.12 (2022), p. 1118. ISSN: 2075-1702. DOI: 10.3390/machines10121118.

[120] Halevi, Y., Carpanzano, E., Montalbano, G., and Koren, Y. “Minimum energy control of redundant actuation machine tools”. In: *CIRP Annals* 60.1 (2011), pp. 433–436. ISSN: 00078506. DOI: 10.1016/j.cirp.2011.03.032.

[121] Ahangar, S., Mehrabani, M. V., Pouransari Shorijeh, A., and Masouleh, M. T. “Design a 3-DOF Delta Parallel Robot by One Degree Redundancy along the Conveyor Axis, A Novel Automation Approach”. In: *2019 5th Conference on Knowledge Based Engineering and Innovation (KBEI)*. IEEE, 2019. DOI: 10.1109/kbei.2019.8734975.

[122] Erdős, G., Kovács, A., and Váncza, J. “Optimized joint motion planning for redundant industrial robots”. In: *CIRP Annals* 65.1 (2016), pp. 451–454. ISSN: 00078506. DOI: 10.1016/j.cirp.2016.04.024. URL: https://www.sciencedirect.com/science/article/pii/s0007850616300245.

[123] Zhang, Y., Wang, T., Dong, J., Peng, P., Liu, Y., and Ke, R. "An analytical G3 continuous corner smoothing method with adaptive constraints adjustments for five-axis machine tool". In: *The International Journal of Advanced Manufacturing Technology* 109.3-4 (2020), pp. 1007–1026. ISSN: 1433-3015. DOI: 10.1007/s00170-020-05402-x.

[124] Li, F., Chen, S., Wu, Z., and Yan, Z. "Adaptive process control of wire and arc additive manufacturing for fabricating complex-shaped components". In: *The International Journal of Advanced Manufacturing Technology* 96.1-4 (2018), pp. 871–879. ISSN: 1433-3015. DOI: 10.1007/s00170-018-1590-0. URL: https://link.springer.com/article/10.1007/s00170-018-1590-0.

[125] Sun, S. and Altintas, Y. "A G3 continuous tool path smoothing method for 5-axis CNC machining". In: *CIRP Journal of Manufacturing Science and Technology* 32 (2021), pp. 529–549. ISSN: 1755-5817. DOI: 10.1016/j.cirpj.2020.11.002. URL: https://www.sciencedirect.com/science/article/pii/s1755581720301280.

[126] Yang, J. and Yuen, A. "An analytical local corner smoothing algorithm for five-axis CNC machining". In: *International Journal of Machine Tools and Manufacture* 123 (2017), pp. 22–35. ISSN: 0890-6955. DOI: 10.1016/j.ijmachtools.2017.07.007.

[127] *Continuous-path mode (G64, G641, G642, G643, G644, G645, ADIS, ADISPOS) - SINUMERIK ... - ID: 28705635 - Industry Support Siemens: Last Access: 24/10/2023*. URL: https://support.industry.siemens.com/cs/mdm/28705635?c=19192781067&lc=en-AO.

[128] Shahzadeh, A., Khosravi, A., Robinette, T., and Nahavandi, S. "Smooth path planning using biclothoid fillets for high speed CNC machines". In: *International Journal of Machine Tools and Manufacture* 132 (2018), pp. 36–49. ISSN: 0890-6955. DOI: 10.1016/j.ijmachtools.2018.04.003. URL: https://www.sciencedirect.com/science/article/pii/s0890695518300804.

[129] Li, B., Zhang, H., and Ye, P. "Error constraint optimization for corner smoothing algorithms in high-speed CNC machine tools". In: *The International Journal of Advanced Manufacturing Technology* 99.1-4 (2018), pp. 635–646. ISSN: 1433-3015. DOI: 10.1007/s00170-018-2489-5.

[130] Liu, Y., Wan, M., Qin, X.-B., Xiao, Q.-B., and Zhang, W.-H. "FIR filter-based continuous interpolation of G01 commands with bounded axial and tangential kinematics in industrial five-axis machine tools". In: *International Journal of Mechanical Sciences* 169 (2020), p. 105325. ISSN: 00207403. DOI: 10.1016/j.ijmecsci.2019.105325.

[131] Boujelbene, M., Moisan, A., Tounsi, N., and Brenier, B. "Productivity enhancement in dies and molds manufacturing by the use of C1 continuous tool path". In: *International Journal of Machine Tools and Manufacture* 44.1 (2004), pp. 101–107. ISSN: 0890-6955. DOI: 10.1016/j.ijmachtools.2003.08.005.

[132] Bi, Z. "Computer-Aided Manufacturing (CAM)". In: *Practical Guide to Digital Manufacturing*. Springer, Cham, 2021, pp. 223–320. DOI: 10.1007/978-3-030-70304-2{\textunderscore}4. URL: https://link.springer.com/chapter/10.1007/978-3-030-70304-2_4.

[133] Kumar, L. J., Pandey, P. M., and Wimpenny, D. I., eds. *3D Printing and Additive Manufacturing Technologies*. Springer eBook Collection. Singapore: Springer Singapore, 2019. ISBN: 9789811303050. DOI: 10.1007/978-981-13-0305-0.

[134] Bui, H., Pierson, H. A., Nurre, S. G., and Sullivan, K. M. "Tool Path Planning Optimization for Multi-Tool Additive Manufacturing". In: *2351-9789* 39 (2019), pp. 457–464. ISSN: 2351-9789. DOI: 10.1016/j.promfg.2020.01.389. URL: https://www.sciencedirect.com/science/article/pii/s2351978920304601.

[135] Liang, F., Kang, C., and Fang, F. "A review on tool orientation planning in multi-axis machining". In: *International Journal of Production Research* 59.18 (2021), pp. 5690–5720. DOI: 10.1080/00207543.2020.1786187.

[136] Ramazanov, S., Babenko, V., Honcharenko, O., Moisieieva, N., and Dykan, V. "Integrated Intelligent Information and Analytical System of Management of a Life Cycle of Products of Transport Companies". In: *Journal of Information Technology Management* 12.3 (2020), pp. 26–33. ISSN: 2008-5893. DOI: 10.22059/jitm.2020.76291. URL: https://jitm.ut.ac.ir/article_76291_0.html.

[137] Kadam, O. B., Pirayesh, A., and Fatahi Valilai, O. "Technological Insights of Interoperable Models for Integration of CAD/PLM/PDM and ERP Modules in Engineering Change Management". In: Springer, Cham, 2023, pp. 556–564. DOI: 10.1007/978-3-031-17629-6{\textunderscore}58. URL: https://link.springer.com/chapter/10.1007/978-3-031-17629-6_58.

[138] Kappmeyer, G. and Novovic, D. "Production technology research – Building blocks for competitiveness and solution for future challenges in aerospace component manufacturing". In: *2212-8271* 101 (2021), pp. 62–68. ISSN: 2212-8271. DOI: 10.1016/j.procir.2020.09.189. URL: https://www.sciencedirect.com/science/article/pii/s2212827121006570.

[139] NX Manufacturing. *Hybrid Additive Manufacturing with NX CAM Overview - NX Manufacturing: Last access: 30.10.2023*. 2015. URL: https://blogs.sw.siemens.com/nx-manufacturing/hybrid-additive-manufacturing-with-nx-cam-overview/.

[140] Brecher, C. and Lohse, W. "Evaluation of toolpath quality: User-assisted CAM for complex milling processes". In: *CIRP Journal of Manufacturing Science and Technology* 6.4 (2013), pp. 233–245. ISSN: 1755-5817. DOI: 10.1016/j.cirpj.2013.07.002. URL: https://www.sciencedirect.com/science/article/pii/s1755581713000539.

[141] Xu, T., Chen, Z., Li, J., and Yan, X. "Automatic tool path generation from structuralized machining process integrated with CAD/CAPP/CAM system". In: *The International Journal of Advanced Manufacturing Technology* 80.5-8 (2015), pp. 1097–1111.

ISSN: 1433-3015. DOI: 10.1007/s00170-015-7067-5. URL: https://link.springer.com/article/10.1007/s00170-015-7067-5.

[142] Tunc, L. T. and Stoddart, D. "Tool path pattern and feed direction selection in robotic milling for increased chatter-free material removal rate". In: *The International Journal of Advanced Manufacturing Technology* 89.9-12 (2017), pp. 2907–2918. ISSN: 1433-3015. DOI: 10.1007/s00170-016-9896-2. URL: https://link.springer.com/article/10.1007/s00170-016-9896-2.

[143] Liu, C., Li, Y., and Hao, X. "An adaptive machining approach based on in-process inspection of interim machining states for large-scaled and thin-walled complex parts". In: *The International Journal of Advanced Manufacturing Technology* 90.9-12 (2017), pp. 3119–3128. ISSN: 1433-3015. DOI: 10.1007/s00170-016-9647-4.

[144] Takeuchi, Y. "Current State of the Art of Multi-Axis Control Machine Tools and CAM System". In: *Journal of Robotics and Mechatronics* 26.5 (2014), pp. 529–539. ISSN: 1883-8049. DOI: 10.20965/jrm.2014.p0529. URL: https://www.jstage.jst.go.jp/article/jrobomech/26/5/26_529/_article/-char/ja/.

[145] Zhao, H., Zhang, H., Xin, S., Deng, Y., Tu, C., Wang, W., Cohen-Or, D., and Chen, B. "DSCarver". In: *ACM Transactions on Graphics* 37.4 (2018), pp. 1–14. ISSN: 0730-0301. DOI: 10.1145/3197517.3201338.

[146] Sivanandam, S. N. and Deepa, S. N. "Genetic Algorithm Optimization Problems". In: *Introduction to genetic algorithms*. Ed. by Sivanandam, S. N. and Deepa, S. N. Berlin u.a.: Springer, 2007, pp. 165–209. ISBN: 978-3-540-73189-4. DOI: 10.1007/978-3-540-73190-0{\textunderscore}7.

[147] Ruder, S. *An overview of gradient descent optimization algorithms*. 2017.

[148] Bäck, T. and Schwefel, H.-P. "An Overview of Evolutionary Algorithms for Parameter Optimization". In: *Evolutionary Computation* 1.1 (1993), pp. 1–23. ISSN: 1063-6560. DOI: 10.1162/evco.1993.1.1.1.

[149] Lambora, A., Gupta, K., and Chopra, K. "Genetic Algorithm- A Literature Review". In: *2019 International Conference on Machine Learning, Big Data, Cloud and Parallel Computing (COMITCon)*. IEEE, 2019. DOI: 10.1109/comitcon.2019.8862255.

[150] Katoch, S., Chauhan, S. S., and Kumar, V. "A review on genetic algorithm: past, present, and future". In: *Multimedia Tools and Applications* 80.5 (2021), pp. 8091–8126. ISSN: 1573-7721. DOI: 10.1007/s11042-020-10139-6. URL: https://link.springer.com/article/10.1007/s11042-020-10139-6.

[151] Yang, X.-S. "Metaheuristic Optimization: Algorithm Analysis and Open Problems". In: Springer, Berlin, Heidelberg, 2011, pp. 21–32. DOI: 10.1007/978-3-642-20662-7{\textunderscore}2. URL: https://link.springer.com/chapter/10.1007/978-3-642-20662-7_2.

[152] Huo, L. and Baron, L. "The joint–limits and singularity avoidance in robotic welding". In: *Industrial Robot: An International Journal* 35.5 (2008), pp. 456–464. DOI: 10.1108/01439910810893626. URL: https://www.emerald.com/insight/content/doi/10.1108/01439910810893626/full/pdf.

[153] Cvitanic, T., Nguyen, V., and Melkote, S. N. "Pose optimization in robotic machining using static and dynamic stiffness models". In: *Robotics and Computer-Integrated Manufacturing* 66 (2020), p. 101992. ISSN: 0736-5845. DOI: 10.1016/j.rcim.2020.101992. URL: https://www.sciencedirect.com/science/article/pii/s0736584520302039.

[154] Paryanto, Brossog, M., Bornschlegl, M., and Franke, J. "Reducing the energy consumption of industrial robots in manufacturing systems". In: *The International Journal of Advanced Manufacturing Technology* 78.5-8 (2015), pp. 1315–1328. ISSN: 1433-3015. DOI: 10.1007/s00170-014-6737-z. URL: https://link.springer.com/article/10.1007/s00170-014-6737-z.

[155] Breaz, R. E., Bologa, O., and Racz, S. G. "Selecting industrial robots for milling applications using AHP". In: *1877-0509* 122 (2017), pp. 346–353. ISSN: 1877-0509. DOI: 10.1016/j.procs.2017.11.379. URL: https://www.sciencedirect.com/science/article/pii/s1877050917326224.

[156] Hirzinger, G., Bals, J., Otter, M., and Stelter, J. *The DLR-KUKA Success Story*. Vol. 12. 2005. DOI: 10.1109/MRA.2005.1511865.

[157] Pham, A.-D. and Ahn, H.-J. "High Precision Reducers for Industrial Robots Driving 4th Industrial Revolution: State of Arts, Analysis, Design, Performance Evaluation and Perspective". In: *International Journal of Precision Engineering and Manufacturing-Green Technology* 5.4 (2018), pp. 519–533. ISSN: 2198-0810. DOI: 10.1007/s40684-018-0058-x. URL: https://link.springer.com/article/10.1007/s40684-018-0058-x.

[158] Halbauer, M., Lehmann, C., Stadter, J. P., Berger, U., and Leali, F. "Milling strategies optimized for industrial robots to machine hard materials". In: *2013 IEEE 18th Conference on Emerging Technologies & Factory Automation (ETFA)*. IEEE, 2013. DOI: 10.1109/etfa.2013.6648124.

[159] Mecademic Industrial Robotics. *What are Singularities in a Six-Axis Robot Arm? | Mecademic Robotics: Last access: 02.11.2023*. URL: https://www.mecademic.com/academic_articles/singularities-6-axis-robot-arm/.

[160] Wei, Y., Jian, S., He, S., and Wang, Z. "General approach for inverse kinematics of nR robots". In: *Mechanism and Machine Theory* 75 (2014), pp. 97–106. ISSN: 0094-114X. DOI: 10.1016/j.mechmachtheory.2014.01.008.

[161] Stevenson, R., Shirinzadeh, B., and Alici, G. "Singularity avoidance and aspect maintenance in redundant manipulators". In: (2002), pp. 857–862. DOI: 10.1109/ICARCV.2002.1238536. URL: https://ieeexplore.ieee.org/abstract/document/1238536.

[162] Bedrossian, N. S. "Classification of singular configurations for redundant manipulators". In: *Proceedings, IEEE International Conference on Robotics and Automation*. New York: IEEE, 2002, pp. 818–823. ISBN: 0-8186-9061-5. DOI: 10.1109/ROBOT.1990.126089.

[163] Dai, C., Lefebvre, S., Yu, K.-M., Geraedts, J. M. P., and Wang, C. C. L. "Planning Jerk-Optimized Trajectory With Discrete Time Constraints for Redundant Robots". In: *IEEE Transactions on Automation Science and Engineering* 17.4 (2020), pp. 1711–1724. ISSN: 1545-5955. DOI: 10.1109/TASE.2020.2974771.

[164] Jiang, L., Lu, S., Gu, Y., and Zhao, J. "Time-Jerk Optimal Trajectory Planning for a 7-DOF Redundant Robot Using the Sequential Quadratic Programming Method". In: 2017 (2017), pp. 343–353. DOI: 10.1007/978-3-319-65298-6{\textunderscore}32.

[165] Wang, L., Liu, Y., Yu, Y., Zhang, J., and Shu, B. "Optimization of redundant degree of freedom in robotic milling considering chatter stability". In: *The International Journal of Advanced Manufacturing Technology* 121.11-12 (2022), pp. 8379–8394. ISSN: 1433-3015. DOI: 10.1007/s00170-022-09889-4.

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)