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

TUM

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

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Submitted on	March 15, 2024 in Garching

Acknowledgment

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Scope of Work

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

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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:

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Garching, 29.03.2024 WHAT DATE GOES HERE ??

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

Abstract

Place your abstract here.

Zusammenfassung

Hier könnte Ihre Kurzzusammenfassung stehen.

Contents

Chapter 1

Introduction

1.1 Motivation

In the age of "Industrie 4.0", advanced technologies like digital twins, have greatly transformed industrial manufacturing [38]. 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 [17]. 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 [7, 37].
Computer-Aided Manufacturing (CAM) has been introduced as a crucial tool to improve productivity and accuracy in creating customized products [16]. CAM systems automate and optimize tasks such as machining, welding, and assembly [26]. 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 [14]. These capabilities play a significant role in achieving a carbon-neutral production process [34]. 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 [31].

Manufacturing machines are the backbone of modern industrial processes [6]. 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 [23].
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 [35]. They are cheaper to acquire and more flexible compared to CNC milling machines but have their own set of disadvantages [20]. One advantage is the wide adaptability. They allow for quick reconfiguration to produce different components or products, promoting flexibility in manufacturing [8]. Further, advancements in robotics and artificial intelligence (AI) have broadened their capabilities, enabling tasks that were once deemed too complex or hazardous for humans [18].

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 [31]. 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 [25, 29, 31]. 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 offer significant advantages in terms of flexibility and adaptability [3]. One example of a system with redundant degrees of freedom is a 6-DoF industrial robot with a rotary tilt table, which brings the system to eight degrees of freedom. However, these systems also present various conflict points that need to be carefully managed to ensure optimal performance [9, 28].

One of the critical challenges in manufacturing systems with redundant degrees of freedom is singularity avoidance [28]. Singularities occur when the robot manipulator loses control or achieves limited mobility due to certain configurations [30]. These configurations result in the loss of a degree of freedom or make the system highly sensitive to small changes, leading to unstable or unpredictable behavior [43]. Limiting the possible positions by adding artificial constraints can help to avoid this problem.

One significant conflict point in manufacturing systems with redundant degrees of freedom 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 [15]. 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 [32]. Therefore, advanced control algorithms and motion planning techniques are necessary to optimize joint motion and minimize conflicts in joint acceleration and jerk [15].

Extension control is another critical aspect that needs to be addressed in systems with redundant degrees of freedom. Redundant degrees of freedom can provide additional extension capabilities to industrial robots, allowing them to reach difficult-to-access areas [15]. However, managing and controlling the extension can be challenging, particularly when precise positioning or maintaining stability is required [27]. The robot must accurately determine the appropriate extension for each joint to avoid unnecessary overextension and collisions with the surrounding environment.

Robot orientation also has a significant effect on robot stiffness. A increased number of joints can introduce compliance and reduce overall system stiffness. This can affect precision, accuracy and stability. Robot orientation and its degrees of freedom must be carefully considered to ensure the desired level of stiffness and system rigidity [28, 36].

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 precision in the manufacturing process. Nevertheless, achieving and maintaining high precision can be difficult due to the increased complexity and sensitivity to various factors [15]. Frequent changes in direction in the joints are another factor that affects precision. The present play in the motor joints can add up the inaccuracies and impede the manufacturing process [19].

Mechanical stress, decreased precision, and increased energy consumption can result from abrupt and frequent direction changes.

Furthermore, effectively coordinating the movement of multiple joints to execute rapid direction changes can prove to be a difficult and time-consuming task. Poor direction changes can result in prolonged transfer times, ultimately hampering the overall productivity of the manufacturing process [33]. Minimizing transfer time is crucial for improving production efficiency and throughput. Optimal path planning, motion optimization, and parallel processing techniques can be employed to reduce transfer time while leveraging redundant degrees of freedom effectively [9].

Energy use is also a significant concern in manufacturing systems employing redundant degrees of freedom [13]. 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 [9, 10].

While redundant degrees of freedom may introduce potential conflicts, they can also enhance performance in manufacturing systems [4]. The added degrees of freedom 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 degrees of freedom, manufacturing systems can enhance their performance, increase efficiency, and exhibit greater flexibility in handling diverse tasks [9].

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. 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, 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 a overview of manufacturing technologies, CAM, and various 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 [21]. 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, involves building up layers of material to create an object. This process offers greater design flexibility and the ability to create complex geometries [12]. Both subtractive and additive manufacturing play crucial roles in various industries, revolutionizing production methods and offering new possibilities for customization and innovation [5, 40].

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 [41]. This approach entails the removal of material from a solid block or workpiece, resulting in the formation of a desired shape or product [11]. In contrast to additive manufacturing techniques, like 3D printing, where material is applied layer by layer, subtractive manufacturing always starts from a block of material [1].

Subtractive manufacturing involves various techniques such as milling, turning, drilling, and grinding that are performed using computer numerical control (CNC) machines [24]. Such machines are programmed to control cutting tool movement precisely to clear material from the workpiece based on a predetermined design [2].

The versatility and precision of subtractive manufacturing is one of its significant advantages. A CNC machine can process a diverse array of materials, such as metals, plastics, and composites, with exceptional precision and surface quality, allowing for the creation of intricate

and complex components [39]. 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.

The cutting tools then perform various operations, including drilling holes, creating pockets or slots, and shaping the external contours of the part, by making precise and controlled movements. In a typical 3-axis machine, the degrees of freedom are along the X, Y, and Z axes. Additionally, some machines have advanced abilities like constantly monitor and adjusts the cutting parameters to ensure the most efficient cutting speed, feed rate, and tool engagement while minimizing errors.

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 [22]. 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 tooling.

One of the disadvantages of the process can be time-consuming, particularly for intricate designs, and can result in significant material waste. Furthermore, it may not be appropriate for high hardness or brittle materials, which can lead to excessive tool wear or breakage. In summary, subtractive manufacturing offers a wide range of applications but should be carefully considered for each situation. With the ability to produce intricate shapes with superior precision and surface quality, this technology 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 refers to the unwanted oscillation or movement of the cutting tool during the machining operation. 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.

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.

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. Any excessive play or misalignment in these components can contribute to tool vibration.

To mitigate tool vibration in CNC machining, various strategies can be employed. Optimizing cutting parameters, such as adjusting the cutting speed, feed rate, and depth of cut, can help minimize vibrations. Utilizing appropriate tool geometries, materials, and coatings can also reduce tool vibration. Implementing efficient tool path strategies, such as minimizing sharp changes in direction and avoiding excessive tool engagement, can help maintain stability during machining.

Additionally, using damping techniques, such as through the use of vibration-dampening tool

holders or inserts, can help absorb vibrations and improve machining performance.

Implementing monitoring systems, such as vibration sensors or accelerometers, can provide real-time feedback on tool vibration levels. This data can be used to adjust machining parameters or detect tool wear and prevent potential issues caused by excessive tool vibration.

In conclusion, tool vibration is a common challenge in CNC machining that can negatively impact part quality and machining outcomes. By optimizing cutting parameters, selecting appropriate tooling, employing efficient tool paths, maintaining machine rigidity, using damping techniques, and implementing monitoring systems, tool vibration can be minimized, leading to improved machining results.

2.1.2 Additive Manufacturing

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

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. Stereolithography (SLA) employs a liquid photopolymer resin that is solidified by a UV laser, while Selective Laser Sintering (SLS) uses a high-power laser to selectively fuse powdered materials, such as plastics or metals, layer by layer.

The compatibility of AM with a wide range of materials is another scientific advantage. 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.

The design freedom offered by AM is a significant scientific breakthrough. 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.

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. 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.

AM has a significant impacts across various industries. In aerospace, AM is used to produce lightweight components, reducing fuel consumption and enhancing overall efficiency. In healthcare, AM has revolutionized medical device manufacturing, allowing for the production of patient-specific implants, prosthetics, and surgical guides. The automotive industry

benefits from AM's ability to create complex and lightweight structures, improving vehicle performance and fuel economy. In the consumer goods sector, AM enables customization and personalization, allowing consumers to create unique and tailored products.

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

Wire Arc Additive Manufacturing is an additive manufacturing process which belongs to the process category of Directed Energy Deposition (DED). According to DIN EN ISO/ASTM 52900, these are additive processes in which focused thermal energy is used to melt the starting material during the application process. In this case, the WAAM uses an electrically generated arc as the energy source. Current manufacturing systems use standard welding technology available as standard for this purpose, such as gas-shielded metal arc welding. If this technology is combined with suitable kinematics for spatial movement of the welding torch, components can thus be built up layer by layer. The advantages of WAAM result in particular from the high deposition rate, large component sizes and low acquisition costs.

The high application rates, which range from 1 kg/h (aluminum and titanium) to 4 kg/h (steel), for example, make it possible to build large components at reasonable production times. Thus, most components can be produced within one working day. Compared to other additive manufacturing processes such as Powder Bed Fusion (PBF) with order collars of 0.1 - 0.36 kg/h (for Ti6Al4V), this can mean a time advantage with a factor of up to 10. In terms of part size, the maximum production volume is limited only by the working range of the kinematics used. In the case of an articulated-arm robot, this corresponds to the range within the minimum and maximum reach. The disadvantages of the WAAM are the residual stresses and deformations remaining after the process, the low geometric accuracy and the moderate surface quality. These problems are among the typical defects of WAAM components.

WAAM

Wire Arc Additive Manufacturing (WAAM) is a specific type of additive manufacturing process known as Directed Energy Deposition (DED). According to the DIN EN ISO/ASTM 52900 standard, DED involves using focused thermal energy to melt the starting material during the application process. In the case of WAAM, an electric arc is used to generate the necessary energy for melting. This is achieved by utilizing standard welding technology, such as gas-shielded metal arc welding, in combination with precise spatial movement of the welding torch. This allows for the construction of components layer by layer.

WAAM offers several advantages over other additive manufacturing techniques. One major advantage is its high deposition rate, which ranges from 1 kg/h for aluminum and titanium to 4 kg/h for steel. This high deposition rate enables the construction of large components in a relatively short amount of time. In fact, many components can be produced within a single workday, providing a significant time advantage compared to techniques like Powder Bed Fusion (PBF), which typically operates at much slower deposition rates.

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 minimum and maximum reach. This means that WAAM has the potential to create components of various sizes without compromising its effectiveness.

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.

Overall, WAAM stands out as a promising additive manufacturing technique due to its high deposition rate, capability for constructing large components, and cost-effectiveness. However, it is crucial to address the potential defects and limitations associated with this process to ensure the desired quality and precision of the final components.

WAAM-Process

The WAAM process is based on three different arc welding processes: Gas Metal Arc Welding, Gas Tungsten Arc Welding and Plasma Arc Welding. The WAAM process is based on three different arc welding processes: gas shielded metal arc welding (Gas Metal Arc Welding), tungsten inert gas welding (Gas Tungsten Arc Welding) and plasma arc welding (Plasma Arc Welding). The WAAM process is based on three different arc welding methods: gas shielded arc welding (Gas Metal Arc Welding), tungsten inert gas welding (Gas Tungsten Arc Welding) and plasma arc welding (Plasma Arc Welding). The operating principle of these processes is the generation of an arc by electrical gas discharge between an electrode and the workpiece. The energy transferred by the arc into the workpiece causes melting in the area of the fusion zone. If a welding filler material in the form of a wire or a consumable electrode is also introduced into the arc, this material also melts and welds can be deposited on a metallic substrate. A continuous weld seam is ensured by a wire feed system.

The manufacturing of components by means of WAAM is carried out by a kinematic system which enables the movement of the welding torch and/or the workpiece. Articulated arm robots or gantry systems can be used for this purpose. The workpiece is placed either on a fixed base or on a rotary tilting table. Alternatively, a spatially fixed welding torch in combination with robotic kinematics can be used to move the component. The WAAM component is built up in layers according to a predefined machine path. First, the welding torch applies a layer of adjacent welding beads to the x-y plane of the substrate plate. The kinematics then move the welding torch upwards along the z-axis according to the layer thickness. The next layer is then placed on top of the previously produced layer. In the case of a welding torch that remains in a fixed position, the workpiece is moved accordingly.

CMT

Cold Metal Transfer (CMT) welding is a sophisticated process that merges the advantages of MIG/MAG and TIG welding techniques. It functions based on the principle of controlled short-circuiting, wherein the welding torch generates a short circuit between the electrode and the workpiece. This controlled short circuit triggers the wire to detach and subsequently reattach, generating a sequence of droplets that transfer to the weld pool with remarkable precision.

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. The process minimizes spatter formation, resulting in cleaner and smoother welds and reducing the requirement for post-weld cleaning.

CMT welding stands out for its exceptional weld quality. Its precise control over heat input

and metal transfer results in improved fusion, reduced porosity, and an enhanced appearance of the weld bead. CMT welding is ideal for applications that require the highest weld quality which includes structural fabrication and automotive manufacturing.

CMT welding is a flexible process capable of joining a wide array of materials including dissimilar metals such as aluminum to steel or copper to steel. This compatibility creates new possibilities for engineering applications that require the combination of multiple materials.

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.

Cold Metal Transfer welding provides precise heat control, reduces spatter, improves weld quality, and is compatible with various materials, making it a highly efficient and versatile welding process. As a result, it is widely used in industries that demand high-quality welds and require different metals to be joined.

A CMT cycle consists of 3 phases 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. burning at a lower current. This prevents the melt droplet from detaching early and from detaching prematurely and transferring to the workpiece. 3. 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. is signaled to withdraw the wire. This supports the droplet detachment from the wire into the molten bath

2.1.3   Industrial Robots

Klare Abgrenzung

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.

One common type of industrial robot is the articulated robot. 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.

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.

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.

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.

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.

Industrial robots 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. Robots are also commonly used for material handling tasks, such as lifting, moving, and stacking materials in warehouses or production lines.

Packaging is another area where robots excel. They can package products into boxes, palletize goods, or apply labels with precision and consistency. In the field of welding, robots are widely used to perform welding operations, ensuring high-quality welds with consistent results.

Robots are also used for painting applications, where they can paint large surfaces or apply coatings with controlled movements. Inspection tasks can be automated with robots equipped with sensors or cameras, allowing them to inspect products for defects or perform quality control checks.

Machine tending is another common application for industrial robots. They can load and unload parts from machines, such as CNC machines or injection molding machines, improving efficiency and reducing the need for human intervention.

Pick and place operations, where robots pick items from one location and place them in another, are also widely performed by industrial robots. This can be seen in assembly lines or warehouses, where robots can handle the repetitive task of moving items from one place to another.

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, thereby improving product quality.

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.

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.

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.

Safety is a key consideration in the design and use of industrial robots. They are equipped with safety features to prevent accidents and protect human workers. These include safety sensors to detect the presence of humans and stop or slow down robot movements, as well as safety zones

A 6-degree-of-freedom (6-DoF) industrial robot with an additional axis refers to a robotic system that has six independent movements or degrees of freedom, along with an extra rotational axis. The additional axis provides enhanced flexibility and versatility to the robot, allowing it to perform more complex tasks and maneuver in tighter spaces.

The six degrees of freedom in a 6-DoF robot typically include three linear motions (X, Y, Z) and three rotational motions (roll, pitch, yaw). These movements enable the robot to position its end-effector or tool in any desired position and orientation within its workspace.

The additional axis, often referred to as the seventh axis or wrist axis, is usually located at the end of the robot arm and allows for an additional rotational motion. This axis provides an extra degree of freedom, enabling the robot to rotate its end-effector around a specific axis, such as a wrist joint or tool rotation.

The presence of the seventh axis in a 6-DoF robot with an additional axis expands its capabilities and enables it to perform tasks that require complex orientations or intricate movements. For example, in tasks like welding or assembly operations, the additional axis allows the robot to reach and manipulate objects from various angles, improving precision and efficiency.

The increased flexibility provided by the additional axis also enables the robot to access hard-to-reach areas or work around obstacles. This is particularly useful in applications where space is limited or when the robot needs to navigate complex workpieces or environments.

Additionally, the additional axis can be used to implement specialized end-effectors or tools that require rotational motion. For instance, in applications like painting or polishing, the extra axis allows the robot to adjust the angle or orientation of the tool to achieve the desired finish or coverage.

Programming a 6-DoF industrial robot with an additional axis follows similar methods used for programming other industrial robots. This can include teaching the robot using a teach pendant or offline programming using simulation software. The programming process involves specifying the desired positions, orientations, and trajectories for the robot to execute during its operation.

In summary, a 6-DoF industrial robot with an additional axis provides enhanced flexibility, precision, and maneuverability. The additional axis allows for an extra rotational motion, expanding the robot's capabilities and enabling it to perform more complex tasks in various industries, such as welding, assembly, painting, or polishing.

2.2 Computer-Aided Manufacturing

2.2.1 CAM Software

Computer-aided manufacturing (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. 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. 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 the actual production begins, saving time and resources.

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.

CAM software 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.

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

In summary, 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.

2.2.2 Path Planning

Path planning and path generation are essential components of computer-aided manufacturing (CAM) software. These processes involve determining the optimal toolpaths for machining operations, ensuring efficient and accurate production.

Path planning refers to the process of determining the best possible sequence of movements for the machining tool to follow while producing a part. It involves considering various factors such as the geometry of the part, tool capabilities, machining constraints, and desired machining parameters. The goal of path planning is to minimize machining time, reduce material waste, and improve the overall quality of the finished product.

Path generation, on the other hand, involves the actual generation of the toolpath based on the planned movements. CAM software uses algorithms and mathematical models to calculate the position and orientation of the tool at each point along the toolpath. The generated toolpath should accurately follow the desired shape and contour of the part while considering factors like cutting direction, feed rate, and tool engagement.

To achieve efficient path planning and path generation, CAM software utilizes a range of techniques. One common approach is contouring, where the tool follows the boundaries of the part's geometry, ensuring a smooth and continuous cut. Pocketing is another technique used to remove material from within closed areas, such as pockets or slots, by following an optimized toolpath.

Another important aspect of path planning and generation is adaptive machining. This technique allows the CAM software to dynamically adjust the toolpath and cutting parameters based on the material properties, tool wear, and other factors. By continuously monitoring and adapting the machining process, adaptive machining ensures consistent and accurate results, even in challenging manufacturing conditions.

Multi-axis machining is another advanced feature that CAM software offers for complex geometries. It enables the tool to move along multiple axes simultaneously, allowing for more intricate cuts and shapes. This capability is particularly useful for machining curved surfaces,

freeform shapes, or parts with undercuts.

Simulation plays a crucial role in path planning and generation. CAM software often includes simulation tools that allow users to visualize and verify the toolpath before actual production. These simulations help detect and resolve potential collisions, interferences, or errors that could arise during machining. By identifying and addressing these issues early on, manufacturers can avoid costly mistakes and ensure safe and efficient production.

In conclusion, path planning and path generation are vital components of CAM software. They involve determining the best sequence of movements and generating toolpaths to optimize machining operations. Techniques such as contouring, pocketing, adaptive machining, and multi-axis machining are used to achieve efficient and accurate results. Simulation tools enable users to visualize and verify the toolpath before production, ensuring error-free and safe machining processes. With path planning and generation capabilities, CAM software empowers manufacturers to enhance efficiency, reduce errors, and produce high-quality products.

2.3   Optimization Algorithms

2.3.1   title

P vs NP vs NP hard

P vs. NP is a fundamental problem in computer science that studies the relationship between the classes of problems that can be solved efficiently (P) and those that can be verified efficiently (NP). The P class includes problems that can be solved in polynomial time, i.e., the time required to solve the problem grows at most as a polynomial function of the input size. These problems have efficient algorithms that can find a solution relatively quickly. On the other hand, NP refers to the class of problems for which a proposed solution can be verified in polynomial time. This means that if someone claims to have a solution, it can be efficiently checked to confirm its correctness.

NP-hard problems are a subset of NP problems that are considered to be among the hardest problems in NP. They are defined as problems that are at least as hard as the hardest problems in NP. In other words, if there is an efficient algorithm for solving any NP-hard problem, this would imply that P = NP.

The question of whether P = NP or P $\neq$ NP is of immense importance in computer science and mathematics. If P = NP, it would imply that problems with efficiently verifiable solutions can also be efficiently solved. This would have profound implications in various fields such as cryptography, optimization, and artificial intelligence. It would mean that complex problems like the Traveling Salesman Problem or the Boolean Satisfiability Problem could be solved efficiently, revolutionizing many industries and enabling significant advances in technology.

However, if P $\neq$ NP, this implies that there are problems that are hard to solve but easy to verify. This would suggest an inherent limit to our ability to find efficient algorithms for certain types of problems. It would mean that finding optimal solutions may take exponential time, making them practically infeasible for large instances. This would have implications for areas such as cryptography, where the security of many cryptographic protocols is based on the assumption that certain problems are hard to solve.

Solving the P vs. NP problem is a major open question in computer science, and its solution

would have far-reaching consequences. Despite decades of research, no conclusive proof has been found to settle the debate. The problem remains one of the most challenging and intriguing topics in theoretical computer science, attracting the attention of researchers from various disciplines who continue to explore this fascinating area of study.

2.3.2 general

Optimization algorithms are computational techniques employed to identify the optimal solution or set of solutions for a given problem. These algorithms find extensive usage in various domains, including engineering, operations research, finance, and machine learning. The primary aim of optimization is to maximize or minimize the objective function while satisfying a set of constraints.

There exists 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. 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 global optimality, although they may necessitate enhanced computational resources.

Simulated annealing is an optimization algorithm that emulates the annealing process in metallurgy. It is highly effective in solving combinatorial optimization problems, where the aim is to determine the optimal combination or arrangement of a set of distinct elements. The methodology involves commencing with an initial solution and progressively exploring the search space while accepting worse solutions with a diminishing probability. This enables the algorithm to avoid getting stuck in local optima and discover globally optimal solutions.

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.

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.

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.

In summary, optimization algorithms prove to be formidable resources in uncovering optimal solutions to intricate issues. Be it via gradient-based means, evolutionary algorithms, meta-heuristics, 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.

The ant colony algorithm is a metaheuristic optimization algorithm inspired by the behavior of ants searching for food. It is particularly useful for solving combinatorial optimization problems, where the goal is to find the best possible solution from a large set of possibilities. The algorithm mimics the foraging behavior of ants, where they leave pheromone trails to communicate information about the quality of food sources.

In the ant colony algorithm, a set of artificial ants is used to explore the solution space. Each ant starts with a random solution and iteratively constructs a solution by making probabilistic decisions based on the pheromone trails and heuristic information. The pheromone trails represent the accumulated knowledge of the colony regarding the quality of the solutions found so far. Ants tend to follow paths with stronger pheromone trails, but they also consider heuristic information related to the problem domain.

As the ants move through the solution space, they deposit pheromone on the edges they traverse. The amount of pheromone deposited is typically proportional to the quality of the solution found. Over time, the pheromone trails are updated based on the quality of the solutions found by the ants. This pheromone updating mechanism allows the colony to focus its search on promising areas of the solution space.

The algorithm employs a positive feedback mechanism, as ants tend to reinforce the paths with higher pheromone concentration. However, to prevent the algorithm from converging prematurely, a pheromone evaporation process is introduced. This evaporation reduces the pheromone concentration over time, allowing the algorithm to explore different regions of the solution space.

Through the iterative process of solution construction, pheromone updating, and evaporation, the ant colony algorithm converges towards better and better solutions. This approach has been successfully applied to various optimization problems, such as the traveling salesman problem, vehicle routing problem, and job scheduling. It has proven to be particularly effective in situations where traditional optimization techniques struggle due to the large search space or complex problem constraints.

Overall, the ant colony algorithm provides an efficient and robust method for solving complex optimization problems. By leveraging the collective intelligence of the artificial ant colony, it can effectively explore the solution space and converge towards optimal or near-optimal solutions. Its simplicity and adaptability make it a popular choice for a wide range of real-world applications.

2.4   Machine Learning

2.4.1 General Introduction to ML

Machine Learning is a subfield of Artificial Intelligence (AI) that focuses on the development of algorithms and models that enable computers to learn from and make predictions or decisions based on data. It involves training a machine learning model using labeled or unlabeled data to recognize patterns, make predictions, or perform specific tasks without being explicitly programmed.

The core idea behind machine learning is to enable computers to learn and improve from experience. Instead of being explicitly programmed for every possible scenario, machine learning algorithms are designed to learn from examples and data, allowing them to make informed decisions or predictions.

There are several types of machine learning algorithms, including supervised learning, unsupervised learning, and reinforcement learning. In supervised learning, the algorithm is trained on labeled data, where the desired output is provided along with the input. The algorithm learns to map the input to the correct output by generalizing from the training data. Unsupervised learning, on the other hand, involves training the algorithm on unlabeled data, and it learns to find patterns or structures within the data without any specific target output. Reinforcement learning is a type of learning where an agent learns to make decisions in an environment by receiving feedback or rewards based on its actions.

Machine learning has numerous applications across various industries and domains. It is used in natural language processing, computer vision, recommendation systems, fraud detection, autonomous vehicles, healthcare, finance, and many other fields. Machine learning models can analyze large amounts of data, extract meaningful insights, and make predictions or decisions with high accuracy, leading to improved efficiency, personalized experiences, and enhanced decision-making.

In summary, machine learning is a field of AI that focuses on developing algorithms and models that enable computers to learn from data and make predictions or decisions. It involves training models using labeled or unlabeled data, allowing them to recognize patterns, generalize from examples, and perform tasks without explicit programming. Machine learning has a wide range of applications and is transforming industries by enabling automation, personalization, and intelligent decision-making.

2.4.2 Key Areas Of ML

Machine Learning (ML) encompasses various key areas that focus on different aspects of learning algorithms and their application. Here is a short summary of some key areas of ML:

Supervised Learning: In this area, ML algorithms learn from labeled training data to make predictions or classify new, unseen data. The algorithms are trained on input-output pairs, and their goal is to learn the underlying patterns or relationships in the data to generalize well on unseen examples.

Unsupervised Learning: Unsupervised learning deals with unlabeled data, where the ML algorithms aim to discover hidden patterns, structures, or relationships in the data. It can involve tasks such as clustering, dimensionality reduction, or anomaly detection.

Reinforcement Learning: This area focuses on training agents to make sequential decisions in an environment to maximize a reward signal. Reinforcement learning algorithms learn through trial and error, receiving feedback in the form of rewards or penalties based on their

actions.

2.4.3   ML for Optimization Problems

Machine Learning (ML) has proven to be highly effective in solving optimization problems across various domains. Optimization problems involve finding the best solution from a set of possible solutions, often subject to certain constraints. ML techniques can be utilized to enhance the efficiency and accuracy of optimization algorithms, leading to improved outcomes.

One common approach is to use ML for parameter tuning in optimization algorithms. Many optimization algorithms require the selection of various parameters, such as learning rates, regularization factors, or population sizes. Traditionally, these parameters are manually chosen by experts through trial and error. ML techniques, such as grid search or Bayesian optimization, can automate the process of parameter tuning by searching through the parameter space and finding the best combination of parameters that optimize the objective function. This reduces the need for manual intervention and leads to better performance of the optimization algorithm.

Another way ML can be applied to optimization problems is through the use of surrogate models. Surrogate models are approximations of the objective function that are computationally cheaper to evaluate. ML algorithms, such as regression or Gaussian processes, can be used to build these surrogate models based on a small number of evaluations of the objective function. The surrogate models can then be used to guide the optimization algorithm, reducing the number of expensive evaluations of the objective function and speeding up the optimization process. This is particularly useful in scenarios where the objective function is time-consuming or expensive to evaluate, such as in engineering design or financial portfolio optimization.

ML can also be used to learn heuristics for solving optimization problems. Heuristics are problem-solving techniques or rules of thumb that are not guaranteed to find the optimal solution but often provide good approximate solutions. ML algorithms, such as genetic programming or reinforcement learning, can be employed to learn heuristics from data or experience. The ML model is trained on a set of problem instances and their corresponding solutions, and it learns to identify patterns or strategies that lead to good solutions. The learned heuristics can then be applied to new problem instances to find near-optimal solutions quickly.

Furthermore, ML can be used to solve combinatorial optimization problems. These problems involve finding the best arrangement or combination of elements from a finite set. ML algorithms, such as deep learning or graph neural networks, can be applied to learn the underlying structure or patterns in the problem domain. The ML model can then be used to guide the search for the optimal solution by predicting the quality or feasibility of different combinations of elements. This approach has been successfully applied to problems such as vehicle routing, resource allocation, or job scheduling, where finding the optimal solution is computationally challenging.

In conclusion, ML techniques offer powerful tools for solving optimization problems. By automating parameter tuning, building surrogate models, learning heuristics, or solving combinatorial optimization problems, ML can enhance the efficiency and accuracy of optimization algorithms. These advancements in ML for optimization problems have the potential to revolutionize industries such as logistics, manufacturing, finance, and many others by enabling faster, more accurate decision-making and resource allocation.

2.5   Comparison of the State of the Art

https://www.sciencedirect.com/science/article/abs/pii/S0007850616300245

Chapter 3

Methodology

WHAT IS A PROCESS PARAMETER AND WHAT IS A BOUNDARY CONDITION

3.1 Selection of Process Parameters

3.2 Optimization of Boundary Conditions

3.3 MAGIC

3.4 MAGIC

Chapter 4

Implementation and Validation

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

Chapter 6

Appendix

Bibliography

[1] 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.

[2] 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.

[3] 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.

[4] 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.

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

[6] 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.

[7] 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.

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

[9] 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.

[10] 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.

[11] 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.

[12]   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.

[13]   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.

[14]   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.

[15]   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.

[16]   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.

[17]   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.

[18]   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.

[19]   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.

[20]   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.

[21]   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.

[22]   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.

[23]   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.

[24]   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.

[25]   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.

[26]   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.

[27]   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.

[28]   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.

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

[30]   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.

[31]   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.

[32]   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.

[33]   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.

[34]   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.

[35]   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.

[36]   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.

[37]   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.

[38]   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.

[39]   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.

[40]   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.

[41]   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.

[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]   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.

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

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(Signature)