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Capability Modelling of Robotic Machining System based on Digital Twin

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Abstract

In the era of technological advancements, digitalisation, advanced manufacturing, and industrial revolution, the world is moving forward with intelligent manufacturing processes. Robotic machining is becoming very popular nowadays for their manufacturing capabilities. Manufacturing Engineers are making their production planning through manual check before robotic machining without any organised capability modelling. Traditional capability evaluation method is manual, and human centric. It is non-standardised and time consuming. There is a high risk of human error. Capability modelling of robotic machining system through bridges the gap between theoretical robot specifications and practical machining applications, driving innovation and competitiveness in automated and cloud manufacturing. In cloud manufacturing, Digital Twin are now established technology on the market and are commonly deployed for robotic machining. Capability modelling is a part of digital twin for robotic machining production planning, feasibility analysis, and demand estimation. However, digital twin technology does not have any capability modelling architecture with it for ensuring production plan and forecasting robot's operational capacity. Existing research focus on bi-directional real-time data exchange without much effort on capability modelling. Creating a capability model for Digital Twin of robotic machining will enable autonomous cloud manufacturing. In this research, a capability profile of robotic system has been proposed and implemented. An industrially inspired component was used as a case study. This research work demonstrates data modelling, capability modelling, CAD file geometric data extraction system to build an intricate model for digital twin. The main components incorporate the judgement of the component design on the basis of size, machining envelope, operational details, cutting tools, cutting strategy, machining coordinate position, operational time, and data analysis. This paradigm extends transformative mechanism towards intelligent, data-driven manufacturing ecosystems for robotic machining.

Keywords: Digital Twin, Machining Capability, Robotic Machining, Industrial Robot

1. Introduction

Capability modelling of robotic machining system is playing a pivotal role for enhancing accuracy, efficiency, safety, and Industry 4.0 integration through simulation, robotic machining process optimisation, and verification. Challenges like simulating dynamics and integrating data hinder scalability. This unique framework focuses on robotic machining, using CAD data extraction for the inspection in a cloud-integrated setup. Unlike other digital twins (aerospace, automotive sectors, etc.) this research targets articulated robots for machining feasibility from CAD files, making it a pioneering framework for automated manufacturing. The research specialises in articulated robots like KUKA KR 210. The capability modelling infrastructure linking of traditional digital sectors with this research underscores the potential for advanced, data-driven insights in robotic manufacturing process, showcasing an innovative framework that has not been explored before in robotic machining contexts. Thus, this work paves the way for future advancements in automated and cloud manufacturing. It extends transformative mechanism towards intelligent, data-driven cloud manufacturing ecosystems for robotic machining by utilising the proximity of innovation. The aim of this research is to investigate the machining feasibility of a given CAD model based on capability modelling of robotic system by involving logical judgement of robotic machining for industrial robot. Some objectives to reach the main focus point of this research work are to develop integrated capability modelling of robotic machining framework bridging CAD geometry with robot operational specifications, achieve automated feature detection and operation classification from CAD data by utilising capability assessment platform, ensure strategic recommendations operational quality control, and operational efficiency objectives by ensuring effective and secure robotic machining, and create expandable, scalable methodology for pre-screening, production planning, feasibility analysis, and demand estimation for manufacturing before physical machining.

3. Literature review

The Digital Twin technology is exceedingly scalable innovation for industry ready technological manufacturing process. It extends the capability and competence of conventional robotic machining system. But there is no established integrated digital twin framework for robotic machining capability assessment platform available in traditional robotic machining. Limited academic work on automated CAD-to-capability translation and insufficient integration of geometric analysis with robot operational constraints. Missing automated decision support system and manual check through human judgement for production planning, pre-screening, feasibility analysis, logical assessment, and demand estimation before physical robotic machining can do huge human error. Data security protocol, adequate measuring unit, and manual guide for users will play a pivotal role for advanced machining virtually for Digital Twin based manufacturing system [1]. Utilising Digital Twin driven intelligent manufacturing reality have several challenges to ensure precision and quality control regarding productive outcome assurance. Unfortunately, virtual technological advancements are shifting rapidly in today's world. To implement Industry 4.0 integrated manufacturing process in the virtual realm, several digital and onsite challenges exist [2]. intelligent manufacturing reality have several challenges to ensure precision and quality control regarding productive outcome assurance. Unfortunately, virtual technological advancements are shifting rapidly in today's world. To implement Industry 4.0 integrated manufacturing process in the virtual realm, several digital and onsite challenges exist [3]. Digital environments may enhance all present manufacturing procedures as well as the development of novel goods. This emerging trend is known as Smart Manufacturing. It is defined as "the use of an incorporated, computerised system that includes simulation, visualization in three dimensions, data analysis, and collaboration capabilities for generating product and manufacturing process definitions concurrently". The simulated method is vital in a production context since it saves time and money when adopting an innovative manufacturing procedure [4]. Vichare et al. emphasise advancements in depicting machine tools and support systems through showcasing their static functionalities. This method outlines the dynamic data linked to a specific machine tool by aiding in the arrangement of different components together. This approach also features improvements to existing STEP-NC standards on defining machine tool capabilities [5]. Utilising Digital Twin driven intelligent manufacturing reality have several challenges to ensure precision and quality control regarding productive outcome assurance. Unfortunately, virtual technological advancements are shifting rapidly in today's world. To implement Industry 4.0 integrated manufacturing process in the virtual realm, several digital and onsite challenges exist [7, 8]. Digital environments may enhance all present manufacturing procedures as well as the development of novel goods. This emerging trend is known as Smart Manufacturing. It is defined as "the use of an incorporated, computerised system that includes simulation, visualization in three dimensions, data analysis, and collaboration capabilities for generating product and manufacturing process definitions concurrently". The simulated method is vital in a production context since it saves time and money when adopting an innovative manufacturing procedure [9-12]. Vichare et al. emphasise advancements in depicting machine tools and support systems through showcasing their static functionalities. This method outlines the dynamic data linked to a specific machine tool by aiding in the arrangement of different components together. This approach also features improvements to existing STEP-NC standards on defining machine tool capabilities [13-16].

4. Methodology

The research develops a Capability Assessment Platform (CAP) system using 3D visualization and JavaScript with Three.js for CAD evaluation with a KUKA robot. Usability issues may occur on older browsers. The system lacks touch support for mobile users and detailed movement options, with security concerns from client-side file checks. It prioritizes speed in analysis functions but struggles with complex CAD geometries due to limited library integration. Suggestions for improvement include server-side CAD operations and feature recognition. This research methodology has been divided by 3 consecutive sections. They are:

a) **CAD Data Processing:** This part starting from the digital twin visualisation and leading to geometric validation, and assessment before processing to the capability assessment phase.

b) **Capability Assessment:** This procedure for capability evaluation in robotic machining detailing a clear step by step capacity reviewing and judgement process that guides the robotic machining assessment process from input data to feasibility determination.

c) **Robot Model Processing:** Robot model processing methodology highlighting the physical articulated robot's same to same virtual model (e.g: KUKA, ABB, FANUC etc) by utilising every robot's capability profile. This process emphasises the steps from support generations to validation and decision making regarding production readiness based on capabilily assessment for robotic machining based on Digital Twin.

5. Implementation with case studies

5.1. Digital Resource Data Model of KUKA KR 210 Robot

The KUKA KR 210, with 6 axes, lifts up to 210 kg, suitable for diverse industrial tasks, fits modern production systems. Resource models are crucial for effective robotic system operation in factories. Figure-1 guides the digital data needs for robotic machining analysis.

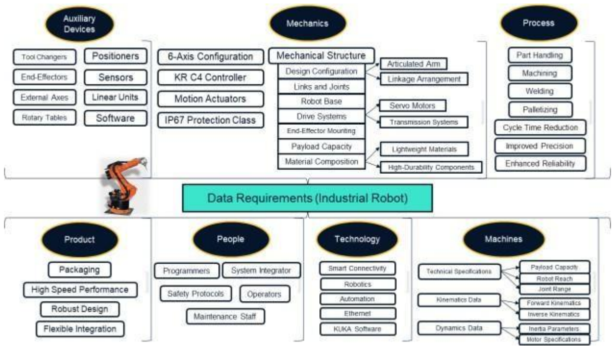

Figure 1. Digital Data Requirements of Industrial Robot for Machining Capability Analysis.

5.2. Physical Robot's Virtual Capability Profile

In this capability modelling research work based on Digital Twin for robotic machining, the established platform is required any physical robot's same to same virtual capability profile by utillising dataset other standard robot's information or specification to do the capability assessment for Computer Aided Production Planning (CAPP) from CAD model information translation against an kind of industrial robot and their specific model for instances KUKA, FANUC, ABB, and other robot. In this research, for examination and experimenta purpose KUKA KR 210 robot has been used for analysing robotic machining capacity based on information integrated Digital Twin of industrial articulated robot. Figure-2 shows the detailed capability profile dataset and information integrated virtual robot of KUKA KR 210 robot's physical working model by using its appropriate robot specification, joint information, reach limit, payload data, repeatability, degrees of freedom, and mounting info, and D-H parameters for robotic machining capability assessment.

Robot Model	Physical Specifications	Value	Joint Motion Specifications	Value (°)	Value (°/s)	Performance Metrics	Value	D-H Parameters			
KUKA KR 210	Payload	210 kg	J1 Base	±180°	86°/s	Accuracy Class	±0.05mm	θ_i	d_i (m)	a_i (m)	α_i (rad)
	Reach	2700 mm	J2 Shoulder	±135°	84°/s	Max Cycle Time	< 15 sec	θ_1	0.75	0.35	(-90°)
	✓ Repeatability	±0.12 mm	J3 Elbow	±150°	84°/s	IP Rating	IP54	θ_2	0	1.25	(0°)
	Mass	1267 kg	J4 Wrist Pitch	±120°	100°/s	Controller	KRC4	θ_3	0	-0.054	(-90°)
	DOF	6 Axes	J5 Wrist Yaw	±270°	110°/s	Power	10-20 kW	θ_4	1.5	0	(90°)
	Mounting	Floor/Inverted	J6 Wrist Roll	±360°	184°/s	Duty Cycle	Continuous	θ_5	0	0	(-90°)
								θ_6	0.303	0	(0°)

Figure 2. Robot Capability Profile dataset and information integrated virtual robot of KUKA KR 210 robot's physical working model.

5.3. Digital Twin's Data Modelling and Diverse Working Framework

The program software algorithm describes an 8 step procedure for digital twin's modelling capabilities in a robotic machining system from loaded CAD component's geometric analysis in figure-3 by using Unified Modeling Language (UML) sequencing flowchart. This technique focusses on the KUKA KR 210 robot which uses Digital Twin software to optimise along with enhance manufacturing phases ranging from computer assisted design conception to testing actual production limitations.

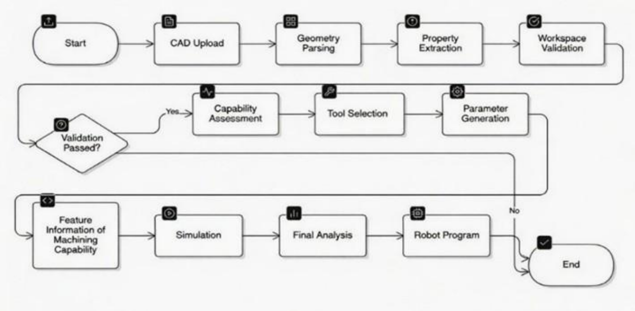

Figure 3. Digital Twin's Capability Modelling Process (Step by Step).

6. Result and discussion

The capability modelling mechanism attempts to accomplish the industrial articulated robot's (KUKA KR 210) data modelling, performance modelling, and machining capacity assessment over the course of numerous programming, experiments, and investigations. It additionally generates initial judgements of robotic machining through reviewing the computerised 3D design geometry. Various items and components are used as loaded CAD model before performing tangible machining in a manufacturing robot interface utilising the digital twin infrastructure. The digital twin model integrates client/ user side and robot side to ensure proper capability analysis output from the new machining capability observation envelope before physical robotic machining in industrial environment.

6.1. Capability Assessment Platform Interface for KR 210

The recent robotic manufacturing capability modelling interface established a capability assessment framework based on Digital Twin interface by adding virtual KUKA KR 210 robot specifications and capability modelling platform. From this architecture, the system can observe, review, and understand the CAD files of machining operations instructions. After that the digital twin framework can make extract all the information from the loaded file, initial judgement of component's mechanical operation, and make proper capability analysis of robotic machining on the basis of KUKA KR 210 robot by using the digital twin. Figure-4 describes the initial Digital Twin interface by accumulating KUKA KR 210 Robot.

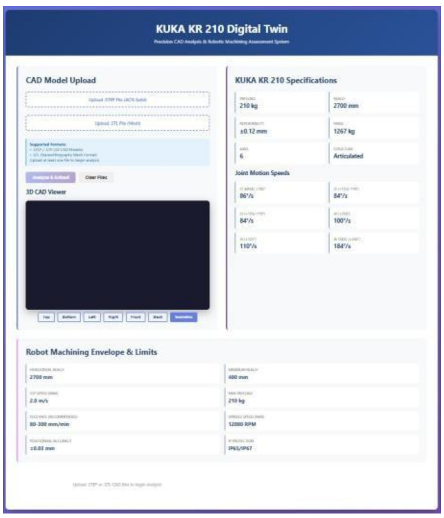

Figure 4. Capability Assessment Platform (CAP) by Integrating KUKA KR 210 Articulated Robot.

6.2. Capability Assessment Platform Case Study (KUKA KR 210)

Capability modelling ensures the proper operational indication by extracting the loaded computer aided design model of machining component through Digital Twin. It assists the users or clients to understand the machining capacity, and other operational information judgement by using industrial robot. In this research work, the capability assessment platform has been utilised to upload different types of 3D CAD components digital model to know the machining capability, operational efficiency analysis, and other judgements by relating with the digital version of KUKA KR 210 robot by utilising digital twin. Serially, figure-5 demonstrates the loaded wheel component in the digital twin platform and its different angle (Top, Bottom, Front, Back, Left, Right, Isometric) 3D viewer to rotate and check the full design for capability analysis, figure-6 illustrates the intelligent analysis of dimensional information (Length, Width, Height, Surface Area, Estimated Mass, Reach Assessment, Payload Assessment) of the loaded wheel's CAD design in Query one (Q1), Figure-7 explains the manufacturing features along with detected manufacturing feature, internal and boundary hole count of the loaded CAD component, surface complexity area analysis, vertices count, edges and faces count, Euler characteristics, and implied features in Query two (Q2), Figure-8 features the suggested machining operations in the machining capability analysis through digital twin in Query three (Q3) by integrating KUKA KR 210 capability assessment outcome.

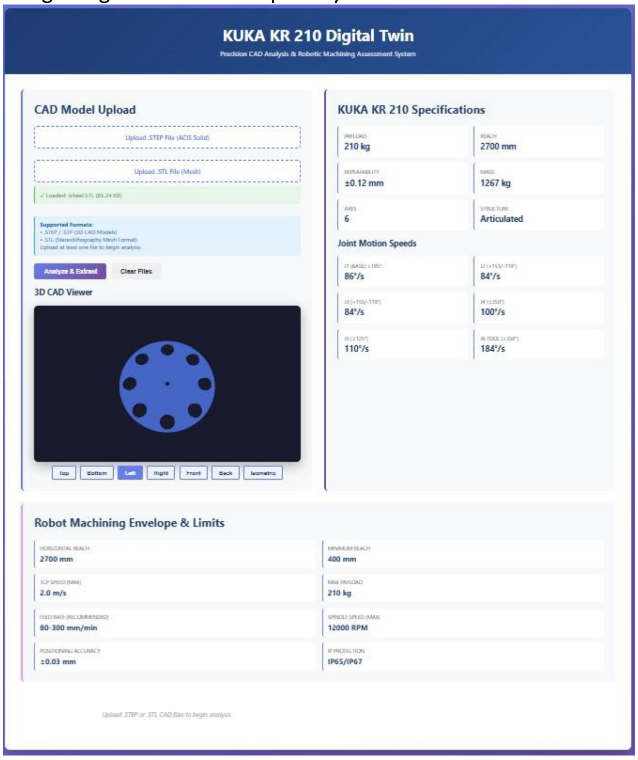

Figure 5. Loaded 3D CAD Model of Wheel in Digital Twin and 3D View from Different Angle.

Figure 6. Intelligent Dimensional Information Analysis of Wheel in Query: 1,

Q1.

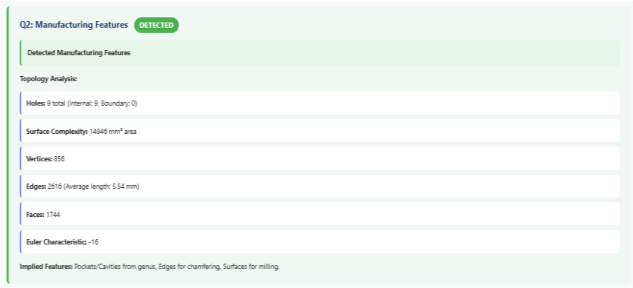

Figure 7. Robotic Machining Feature Analysis of Wheel in Query: 2, Q2.

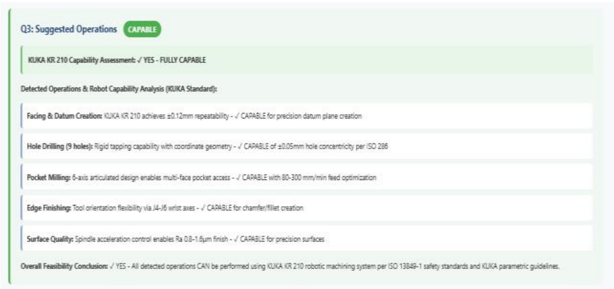

Figure 8. Capability Assessment of Suggested Machining Operations of Wheel by using KUKA KR 210 Robot in Query: 3, Q3.

7. Conclusion

This research ideology and explanation provides the framework for future advances at the nexus of robots and intelligent manufacturing. In the marketplace, there are a lot of Digital Twin for robot and robotic machining systems available but there is no established computerised capability assessment framework for Digital Twin for Computer Aided Production Planning (CAPP), feasibility analysis, logistics and resource analysis and demand estimation for robotic machining. The total mechanism of this research work shows how Digital Twin technology can change manufacturing, making it more flexible, exact, and efficient. The methodology and capability modelling of this inventive research helps to move towards smarter, data-driven intelligent manufacturing. The virtual data processing system focusses upon three essential elements for articulated robots (KUKA KR 210) performing drilling and milling tasks at the robotic machining interface. The capability assessment platform makes it possible to virtually simulate machining envelopes, identify features involving pockets and holes, and assess capacity in relation to robot requirements for instances payload, reach, and repeatability of KUKA KR 210 articulated robot. An interactive online platform employs Three.js for CAD geometry analysis is used to carry it out. By collecting geometric data from STL/STEP files and suggesting cutting tools/strategies, the capability modelling system bridges the virtual and physical realities to enable actual-time decision-making and self- diagnosis mechanism. Capability assessment progression is used for data extraction increases precision in this capability modelling for robotic system. The research work's findings are significant for advancing automated machining in Industry 4.0 through cloud-based robotics systems.

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