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industrial robots,
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CONCEPT OF DEVELOPING A GEAR SELECTION TOOL FOR IMPROVED ACCURACY IN INDUSTRIAL ROBOTICS

The application of robotics has evolved significantly through every industry. Although robots provide a wide range of motion, their lightweight components limit the rigidity at the tool center point (TCP). Consequently, industrial robots with serially arranged axes and conventional gear mechanisms have problems with kinematic accuracy when performing machining operations. Compensatory techniques involving joint stiffness determination and model-based predictions aim to compensate for displacement due to stiffness during the path generation. Innovative precision gearboxes can be used to reduce this displacement. The higher rigidity and lower backlash of precision gears compared to standard gears enable increased accuracy when carrying out production processes with industrial robots. A study at Fraunhofer IWU confirmed this by examining the impact of precision gear on a six-axis robot's accuracy during a milling process. However, all gears certainly would not have the same effect on a given process's accuracy, and replacing all gears would inevitably lead to higher costs. Therefore, it is important to identify the gear with the most dominant effect to achieve the required accuracy. This paper presents a concept to develop a gear selection tool which utilizes robot data, a multibody simulation model along with gear parameters and process requirements to simplify gear selection for industrial processes. This tool aims to enable the customer/end-user to answer the question "Which gear needs to be replaced/installed in my robot in order to achieve the required/improved movement accuracy for an existing or new process?"

1. INTRODUCTION AND MOTIVATION

In [1], Uhlmann mentions machine tools to be essential for progressing sustainability in industrial production. However, the transition from mass production to small batch production requires more adaptable and flexible solutions while maintaining productivity. Manufacturing with industrial robots offers a solution but faces the problem of positional accuracy due to uncertainties in its serial kinematic chain. Therefore, approaches based on the robot's design, control, calibration, and Artificial Neural networks-based compensation to improve accuracy and performance remain an open field of research. In [2], He was even able to validate an

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increment in positional accuracy of industrial robot using hyperparameter optimization of artificial neural networks.

According to the 'International Federation of Robotics', 72.7% of industrial robots are dominantly used for handling and welding processes. However, they are also starting to see increased usage in machining processes like deburring, grinding, and milling. Major factors which make robots usually low preference for machining operations are errors arising from joint inaccuracies, backlash, and structural deflection caused by machining forces, with gear compliance being a significant influence. These factors then limit the rigidity of tool center point also affecting the end workpiece [3]. If dealt with these parameters, robotic milling offers more opportunities for machining complex parts due to its large workspace, low cost, and integrated sensing capabilities [4]. Makulavicius in [5] identified the possible advanced technologies for improving industrial robotic machining processes or other words, the accuracy. A total of 18 solutions were classified including enhancing arm stiffness, optimizing posture, and refining machining parameters with advanced control, computation, and machine learning, etc. The study also highlighted the importance of multibody modelling. Compensatory techniques involving joint stiffness evaluation and simulation-driven predictions are one way to solve this problem as the researchers did in [6]. They developed a simulation-driven transfer learning method to predict robot deformation using limited real data and simulated data, improving accuracy. Another hardware-based approach is replacing existing gears with ones that meet machining process requirements or desired accuracy. This would promote the reusability feature and enhance existing inefficient/old robots on the shop floor with focused hardware adjustment, while meeting the desired accuracy requirement. This also serves as the motivation for the idea evolution of the gear selection tool explained in this paper.

Clements and Mullins [7] define accuracy of a robot as the difference between actual position of robot and commanded position. They also discuss the performance criteria necessary to achieve higher accuracy in industrial robots, highlighting that the major factors improving the accuracy are zero backlash and high torsional stiffness of gears. Some of the popular gear types used in industrial robots are strain wave drives, cycloidal drives, and planetary gears. What distinguishes one gear to others is their properties like transmission ratio, stiffness, backlash, etc. However, available manufacturer data does not allow for the assessment of factors like speed, ambient temperature, and transmission ratio affect on stiffness for such gears. F. Oberneder in [8] mainly chose efficiency and stiffness as important parameters for a systematic gear evaluation study. So far planetary gears are particularly more popular due to their high torque density and high reduction ratios in a compact form. In [9], a hybrid analytical-numerical approach is employed to minimize power dissipation, thereby reducing operating temperatures.

In [10], insufficient rigidity of the robot's TCP affects machining accuracy highlighting dominant affect due to the robot's stiffness. Unlike CNC machines, the Cartesian stiffness of industrial robots varies with joint configuration (or pose) across their workspace. Another dominant parameter of gears is backlash. In terms of mechanics, backlash can also be termed as the excess space between teeth as shown in Fig 1. Butunoi in [11] highlights strong relationship of backlash and robots positioning accuracy, as the deviation along an industrial robot is highly sensitive to it's kinematic chain.

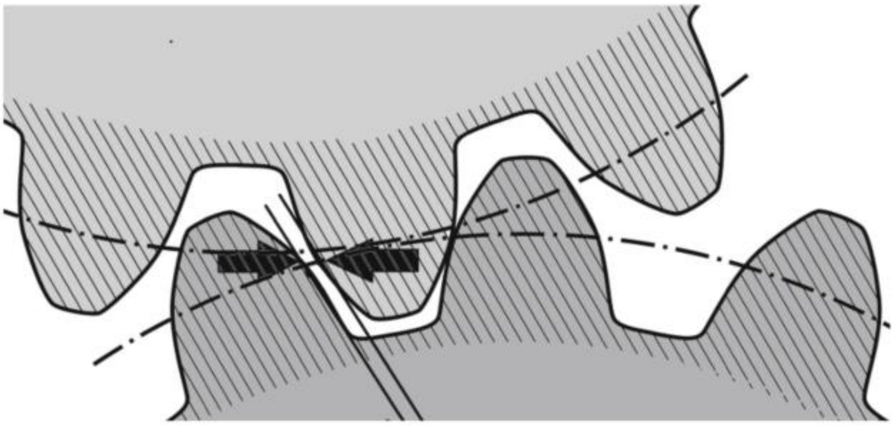

Fig. 1. Backlash mechanism [11]

In [12], E. Giovannitti highlighted that backlash degrades robot performance, causing vibrations and reduced positioning accuracy. A method is proposed to estimate backlash in robotic joints by analysing vibration patterns in the motor speed signal, without requiring additional devices.

A non-backlash robotic arm, the structure of the robot and methods to eliminate the transmission backlash of the robot are introduced in [13]. Kinematic and dynamic models of the robot are established, and the directional stiffness is analysed based on strain energy method and partial derivative theorem. The results showed that the stiffness of the proposed robot with reduced backlash is better compared to an industrial robot and that the backlash of gears and drives is one of the most effective influences on the accuracy of robots.

To attain lower backlash and higher torsion gear, precision gears are getting popular in industrial applications. The unique selling point of precision gears is their higher stiffness and lower backlash compared to standard gears. This enables greater accuracy in industrial robots during production processes. From a gears manufacturer perspective [14], the most used and popular robot in industry is a six arm articulated robot. Each joint requires a specific type of gear depending on its application requirement. For example, the main axes (i.e. 1, 2, 3), design is usually simple because there is enough space for the construction while for the manual axes (i.e. 4, 5, 6) the aim is to pack as much power as possible within the smallest space. Every additional kilo in manual axes increases the required power in the main axes. Furthermore, to evaluate how precision gears differ qualitatively from the standard gears relatively, Table 1 provides a qualitative overview about the main characteristics.

The article by professional micro-metal gear motor company called I.CH motion in [15] focusing on the difference between both gear types and confirms that the most significant properties which differentiate precision gears to standard gears is backlash and stiffness. To further imply the importance of stiffness, Marwitz in [16] introduced a methodology to evaluate the accuracy of a 6-axis industrial robot using an extended and loaded double ball bar. The algorithm utlized stiffness data obtained from loaded circular trajectories to calculate the kinematic errors based on path deviations. The concept was also validated against a Leica AT960 inspection laser tracker.

So far, there has been no definitive research found on the evaluation of precision gears and their impact on machining accuracy of industrial robots. To fill this gap, Chapter 2 focuses on the preliminary research done to identify such impact involving multibody simulations (MBS), material removal (milling) simulations, workpiece generation and analysis. The results generated are then used as basis to the idea generation, core concept and functionality of proposed gear selection tool explained in Chapter 3. Finally, Chapter 4 summarizes the overall research findings and future development plans.

Table 1. Precision gears vs standard gears [14]

Property	Precision gears	Standard gears
Stiffness	High	Low
Backlash	Very low (< 1 arc-minute)	Higher (1- 20 arc-minutes)
Torque	Very High	Standard
Cost	High	Low

2. PRELIMINARY WORK

A recent study carried out at the Fraunhofer IWU investigated the possible increase in accuracy of a conventional industrial robot during milling using high precision gears. A simulation approach was developed that allows for virtually analysing the milling process using different gear configurations. The different simulation tools for the representation of the process, the machines' hardware and the properties of the gears were combined to an overall system simulation as shown in Fig. 2. Based on the G-code of a machining operation process forces are calculated from an inhouse developed tool “TwinProCut” [17]. Furthermore, the tool deflection is considered, and a virtual workpiece is created.

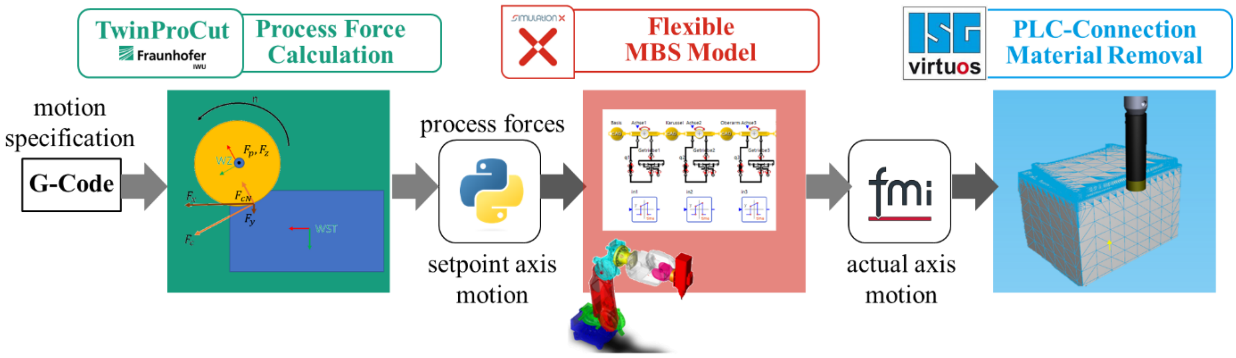

Fig. 2. Coupled simulation workflow for the evaluation of machining accuracy

The multibody system (MBS) model was designed in SimulationX that allows for simulations involving the motion of the interconnected bodies within the robot (Comau NJ-130-2). Model-based material removal simulation utilizes a computer model to simulate the process of removing material from a workpiece with a cutting tool. It is used to visualize the machining process, to predict the result of machining and to detect potential problems such as tool deflection or uneven material removal. The cutting tool-workpiece engagement derived from this simulation refers to the interaction between the cutting tool and the workpiece by taking into account the axial and radial cutting depth. An extensive understanding of the cutting process and an analysis of the engagement are essential for optimizing cutting parameters such as spindle speed and feed rate. In addition, the cutter-workpiece engagement serves as the basis for calculating the cutting force. This allows the forces occurring during the machining process to be predicted, thereby further improving the accuracy and efficiency of the machining processes. By integrating the elasticity of the machine by integrating a Functional Mock-Up Unit (FMU) and taking into account the process forces that occur, model-based material removal simulation becomes an important tool for improving the precision and effectiveness of the machining process. A visualisation of the material removal process in the virtuos model is shown in Fig 3. While the primary focus is determining the errors generated through the influence of gear backlash and stiffness, other gear-related factors such as heating, wearing or lubrication variability during operation were not included. Incorporating them through FMU's could increase the complexity of the model and potentially disturb the step time required for simulating the industrial robot's machining process in virtual commissioning software i.e. ISG-virtuos.

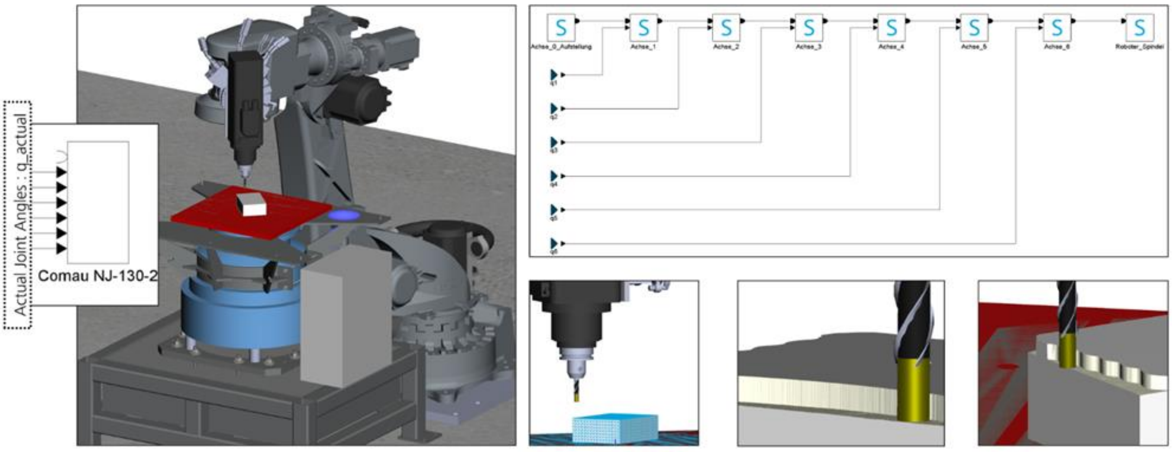

Fig. 3. Material removal simulation with integrated MBS model (FMU) in ISG-virtuos

Several simulation calculations were carried out to evaluate the achievable accuracy when milling with a robot. First, a reference workpiece was produced using an ideal robot model. For this purpose, the model was equipped with 6 backlash-free and rigid gears. All other virtually machined workpieces using a robot configuration with non-ideal gears are compared with this reference to assess the workpiece accuracy. The surfaces of the simulated workpieces are used to compare the geometries. Point clouds are generated by sampling the surface model of the virtual manufactured components. To evaluate the accuracy, the deviation of the point clouds from one another is then calculated using an open-source software tool called CloudCompare [18]. The distance from each point of the virtually manufactured component point cloud to the closest point in the target point cloud is then determined.

Figure 4. summarizes the results of the simulation study. The upper part of the figure shows the machined test workpiece geometries. The deviations of the actual milling contour from the ideal target contour are color-coded. The contour is locally discretized, i.e. represented as a spatial point cloud. Similarly, the distribution of the deviations of the discrete

points is plotted in histograms in the lower part of the figure. It can clearly be seen that a milling operation with one precision gear in axis 4 already results in a smaller overall deviation of the milling contour when compared to all standard gears. When equipping all robot axes with precision gears, the overall error distribution drops to about less than 40% of the reference error.

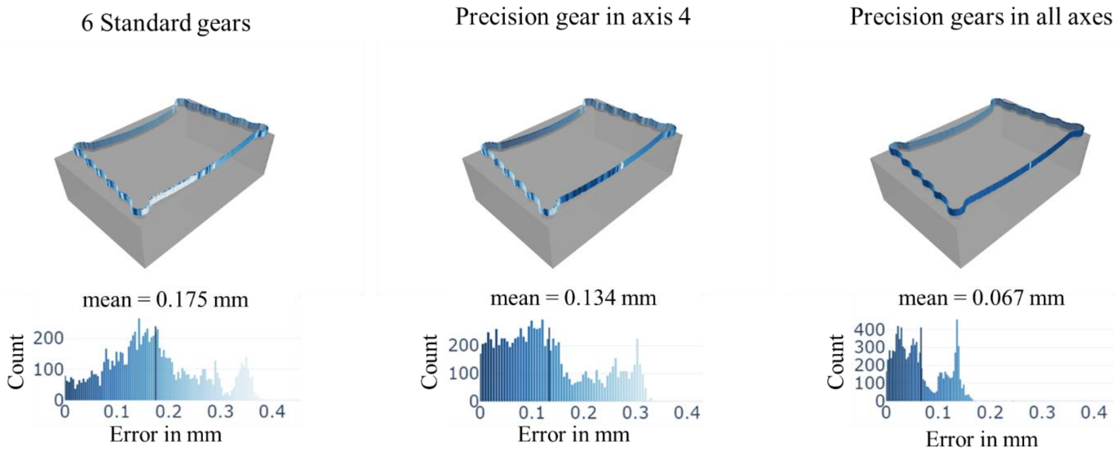

Fig. 4. Simulation results for material removal with different gears

3. CONCEPT OF GEAR SELECTION TOOL

Based on the results of the aforementioned investigation, it is evident to say that precision gears do influence the performance of industrial robots, especially when replacing all gears. However, several questions arise with these results. Is it possible that the replaced gear on axis four has no significant influence on the given process? Furthermore, replacing all gears would inevitably lead to higher costs than replacing one or two gear(s). In this scenario, the problem definition as a question from user perspective would be: “Which gear(s) needs to be replaced/installed in a robot to achieve the required/improved motion accuracy for an existing or new process?” as visualized in Fig. 5.

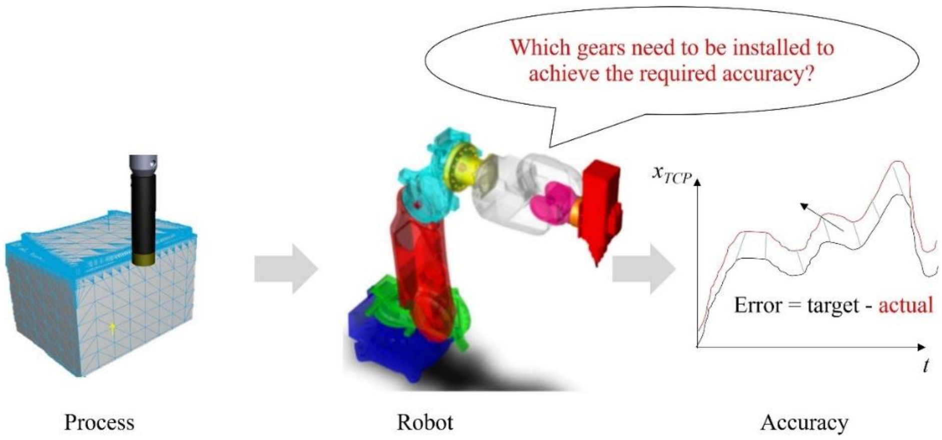

Fig. 5. Problem definition

The problem definition implies a need for a specific strategy or tool for the analysis of gear(s) which causes the most affect on the accuracy of the given process or that have the most dominant effect overall. The gear selection tool in this instance could be a promising solution approach as shown in Fig. 6.

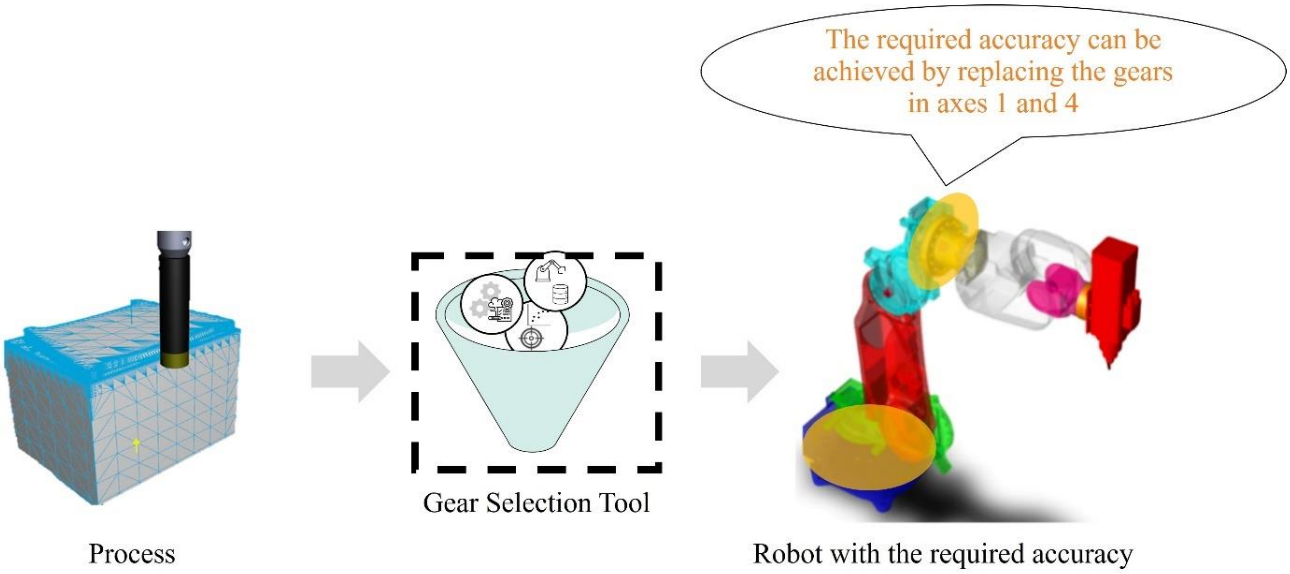

Fig. 6. Gear selection tool concept

The solution approach of a gear selection tool starts off by the simulation of robot's dynamics, considering the process forces (as discussed in Chapter 2). The process forces are calculated, based on the G-code for the milling process, Therefore the real-world conditions are simulated through a digital twin model for various gears. These simulations would be done extensively and iteratively with various gear configurations until vast amount of data is gathered depending on the available gear options. This data shall consist of TCP errors, actual joint values against target joint values or in easy words, the difference between actual and commanded position of the robot (accuracy). A statistical analysis is then conducted to make sense of out of the data in such a way that it suggests suitable gear configuration (sGC) for the given process or required accuracy. Finally, a Graphical User Interface (GUI) provides the user with available optimal gear configurations for the required accuracy and decision output. These steps could be broken down as six modules with sequential automated tasks as shown in Fig. 7.

When seen from the user perspective, this tool will utilize robot data, gear parameters and process requirements as input. As shown in Fig. 8, once the required input is collected, the gear selection tool starts working by iteratively calculating the TCP error using the provided gear information and the available gear parameter catalogue.

The output then is to find the suitable gear configuration (sGC). In other words, the gear configuration which satisfies the required accuracy. To better understand how the sGC can be used and the applicable use cases for such tool, Table 2 gives an overview from different personas.

Simulation data is crucial for this tool to generate varying setups which are then statistically analysed to create a gear selection matrix. Figure 9 is an example visualization of how the simulations are planned to process for the concept of gear selection tool for a six axes robot. Each circular shape represents a simulation run's output error. The different colours indicate specific gear configurations. To understand the scenario of the visualization, assume four different gear configurations which have varying stiffnesses and backlashes in different proportions.

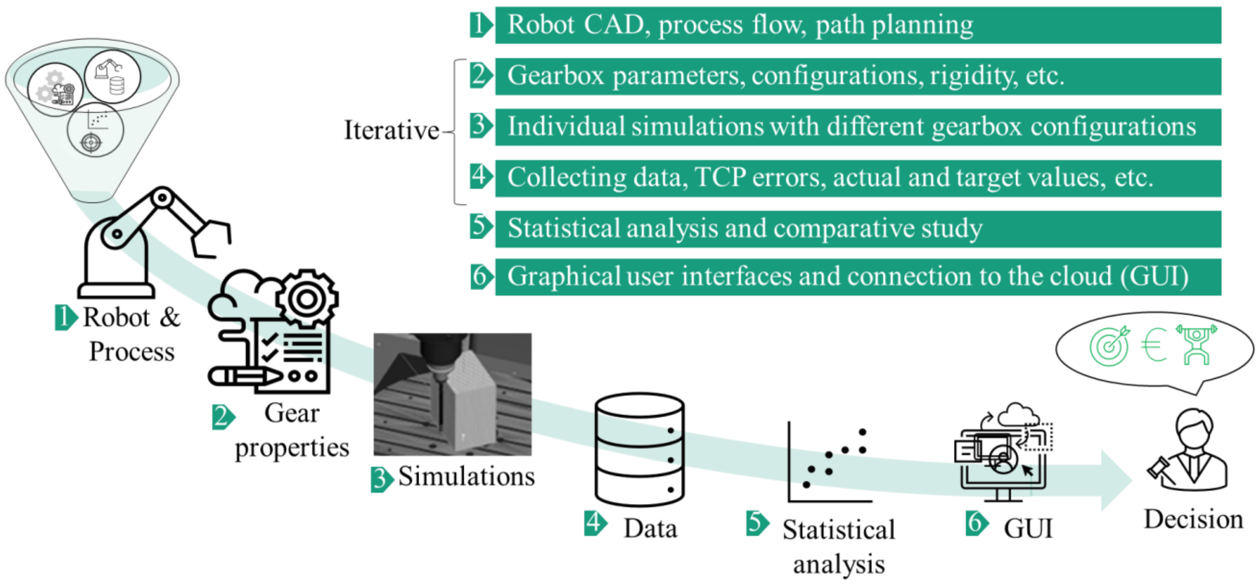

Fig. 7. Solution approach of gear selection tool

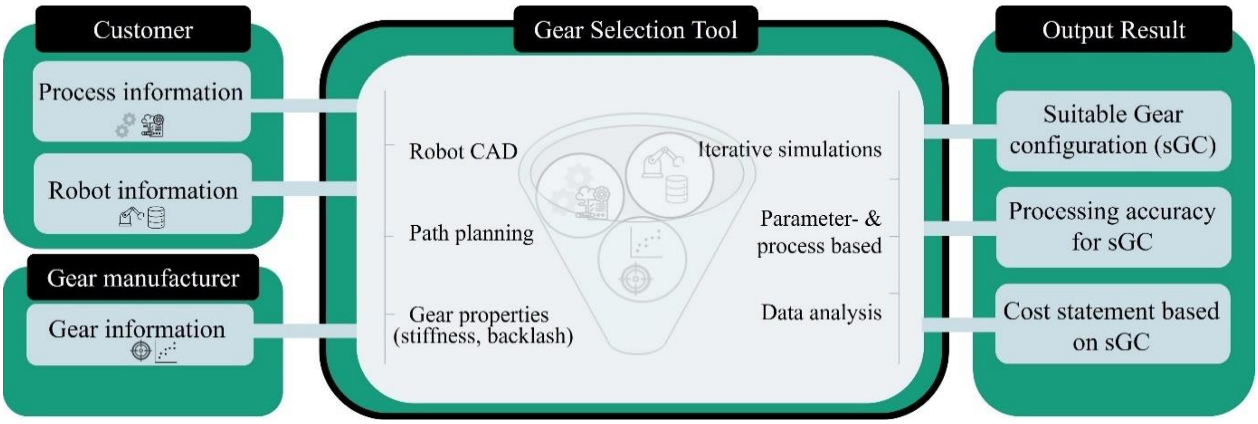

Fig. 8. Process flow of gear selection tool from user perspective

These configurations are termed as Ep1, Ep2, Ep3, Ep4. Here 'p' represents that these configurations align closely to the properties to precision gears. Initially, the robot with standard gears installed in all six axes would have a certain error percentage Es for a given process. This is illustrated as a horizontal grey line and acts as our reference error to evaluate accuracy improvement. The goal is to reach the required process accuracy of the robot (illustrated as the green line at bottom). To do so, we successively change gear configurations and calculate the overall respective errors for the process. The simulations executed would be iterative and can be divided in two steps.

Table 2. Possible use cases of gear selection tool

Persona	Use cases
Gear manufacturers	Re-engineer gear design process, offer customized gear upgrades, enhancing the design and production process for specific applications.
Robot manufacturers	Select precise gears that align with specialized batch production processes
Robot retrofitters and maintenance technicians	Identify most inefficient gears in existing systems and improving precision without requiring complete overhauls enabling preventive maintenance

First step would be the evaluation of individual axes. In this step, only one axis would undergo change in gear configuration while others stay onto standard gear configuration. For example, axis 1 would change its configuration to Ep1, then one simulation run is executed (as illustrated in Fig. 2). The output error Ep1 would be then plotted as a round circle on the plot. Similarly, Ep2 would follow until Ep4. Then the pattern would be repeated for all axes, i.e. all four precision configurations (Ep1-4) are simulated individually on each axis independently and respective overall errors are calculated, and then plotted.

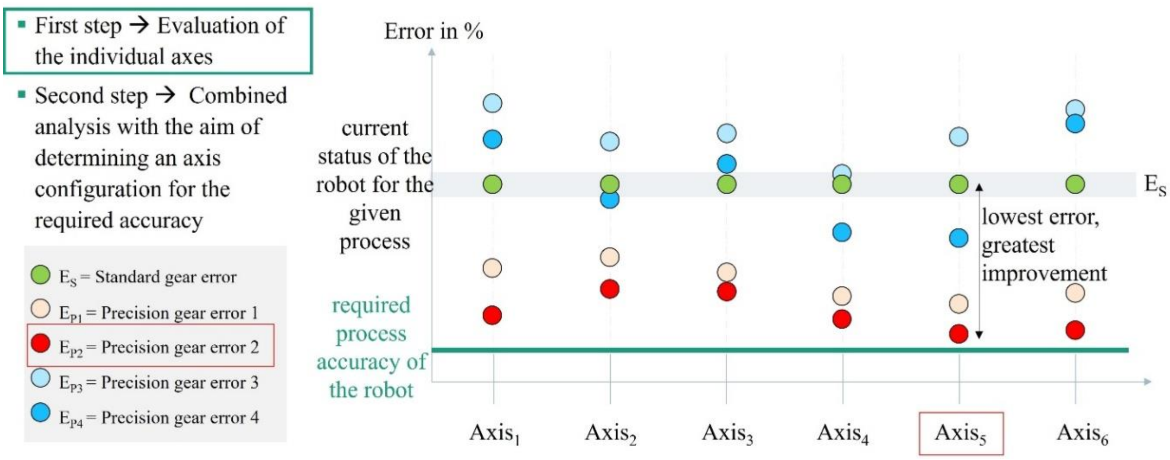

Fig. 9. Visualization example of iterative simulations planning (individual axes scenario)

Once all errors are plotted as circles, then searching the gear configuration which reaches the required accuracy is crucial. The plot shows accuracy improvement by measuring the difference between the standard configuration error (Es) and the error from a new precision configuration (Epi). Here, 'i' represents the configuration with the lowest error percentage, which is closest to the desired accuracy and has the largest change in error. This is visible on axis 5, marked as EP2. This means, for this example scenario, replacement of standard gear on axis 5 with precision gear configuration Ep2 would bring the robot's accuracy close to the required process accuracy. One thing to note here is that above visualization only shows the first step i.e. individual axes scenario, since the second step of combined analysis would involve significant amount of simulations with multiple gear configuration together and output would not be just one gear recommendation but multiple with additional combined accuracy improvements.

Aspects such as replacement effort, time and cost could also be introduced in the tool as an additional deciding factor with certain weights to give the end user more filter while choosing the suitable gear configuration. Replacing all gears or the construction of new robots with precision gears will certainly increase process accuracy as discussed in Chapter 2. However, with significant number of robots already installed worldwide, there is a clear need to streamline gear selection while improving the accuracy of existing robots. The core of the tool lies in the automation of such simulation methods followed by data analysis and how it is visualized to the end user enabling a smart decision. requirements.

4. CONCLUSION

This article describes the concept of a gear selection tool tailored for precision robotics. The working principle of the tool is based on the findings of preliminary work (Chapter 2), which investigated the influence of replacing standard gears with precision gears in industrial robot within a simulation environment. The results based on workpiece generation showed that a positive impact is clearly present and up to almost 40% overall error could be reduced with the usage of precision gears in all axes. Based on these results, the idea evolution of developing a gear selection tool is then discussed along with workflow, possible use cases and advantages. Along with describing the tool's functionality from both the user's perspective and in terms of simulation planning, its advantages and market potential could be significant. This tool could offer several key benefits, including process-based decision-making for gear selection based on the robot's accuracy requirements. It would also enable intelligent decisions that reduce costs and increase profits. Additionally, the tool could be used to develop specialized gear designs tailored to specific robots with unique process needs.

The simulation studies were carried out with a reduced model of the robot, which only focuses on representation of main gearbox properties as stiffness and backlash. All other flexibility of the mechanical structure as well as compliance of axes with controllers were deliberately neglected at this point to evaluate the influence of gears specifically. For further investigation, experimental validation phase of simulation study is in planning already. Real milling operations using the same model of Comau Robot under similar conditions would be conducted followed by workpiece analysis by coordinate measuring machine. The results would then be compared with simulations.

To standardize this tool for application across all robots, there are few challenges as the development of pre-processed simulation models of kinematized robots that are in 'ready-to-run' state based on user inputs of joint angles or G-codes. The same applies to the multibody simulation model transformed to FMU, which captures the robot's dynamics along with gear parameters (mainly stiffness and backlash). Also, since not all robot manufacturers have the gear information public, it is also a challenge to acquire such parameters and communicate with companies for this cause. Each model must be tailored to the specific robot input, and this entire process should be fully automated for seamless operation. With multiple software tools involved, the cost of annual licenses can become prohibitively expensive for Small and Medium-sized Companies (SMCs) with limited resources. A more accessible and cost-effective solution would be to make this tool available using cloud technology. Following the experimental validation, advanced data processing methods such as Machine Learning could be a promising aspect to enhance the intelligence of the gear selection tool in future.

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