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WORKPIECE POSITIONING BASED ON SUPERVISED LEARNING METHODS FOR SIMULATION-BASED OPTIMIZATION OF VIRTUAL TOOLING PROCESSES

Jens Weber
Sebastian Risse

Daimler AG
Mercedesstraße 137
70327 Stuttgart, GERMANY

Christoph Laroque

University of Applied Sciences Zwickau
Scheffelstraße 39
08066 Zwickau, GERMANY

ABSTRACT

The setup process, Numerical Control (NC) program configuration and the linked configuration of point of origins, workpiece position, tool ranges require high computational effort that include multiple simulation runs during the work preparation process. This contribution describes an automatic setup optimization process, including validation of position parameters using a virtual tooling machine as simulation model. In the first step, the developed simulation-based optimization approach minimizes the production time while the collision information and NC program validation are provided by the simulation. In the next step, a cluster method is applied to avoid a high number of single simulation runs, but the validation effort is still high. In order to address this point the developed system offers a selection and data reconciliation procedure using supervised learning methods to determine feasible workpiece positions.

1 INTRODUCTION

In order to develop valid production processes in the area of Numerical Control (NC) tooling machines, simulation methods prevail over the validation process. With support from the simulation, collision detection can be done, including visualization of production errors. An NC program validation and rating process can be given and the machine setup reviewed without the execution of a costly real test production.

In order to reduce the preparation effort for virtual tooling and to improve the setup process, several research activities using simulation-based optimization methods in combination with a virtual tooling machine as simulation must be performed: The minimization of the production time depending on the workpiece position on the machine table must be considered. A metaheuristic is used as an optimization component to generate a data set of potential workpiece positions which lead to a minimal production time without information about the collision status. The collision status is determined by the validation process using the virtual machine model. The machine model represents a real CNC 5-axis milling machine. The collision detection contains the notification of unintentional physical collisions between the milling tool and the workpiece, workpiece clamp, or machine components. The target geometry of workpieces will not be achieved if unintentional collisions between the tool and the workpiece occur.

The usual process that defines workpiece positions contains the geometry integration data for the simulation environment. Zero point and workpiece position are given as input data, usually located in the center of the machine table. Often the preparation process contains elements from CAD/CAM tools. The data interface can be defined by XML-files or related formats. The NC program is handed to the simulation, which verifies the NC program with a combination of zero point and workpiece position. The process for the real production starts with the positioning and fixture of the workpiece on the machine table, followed by the measurement process of the coordinates as well as defining a zero point for the control unit, so that the NC program is valid for the machine setup. The defined coordinates are based on the simulation input data and are generated from the verification of the manufacturing process. The simulation effort is very high if multiple position coordinates have to be validated. Thus, the setup position is usually set to the center of the machine table. This can result in disadvantageous impacts such as cumbersome tool paths, increased energy consumption, or unintentional collisions, which explain the research activities.

The above-described procedure should lead to a feasible production process if the verification processes of the NC programs are planned via digital simulation solutions. However, for this propose, several sub-systems need to be committed to a service platform. The associated research project was *InVorMa (Intelligent work preparation based on virtual tooling machines)* as part of the leading edge cluster *it's OWL,* which is supported by the German Federal Ministry of Education and Research. The developed system generates an intelligent work preparation process for the users in- and outside of companies. The project results show feasible setup data including savings of simulation runs for the workpiece positioning approaches. However, depending on the order process in mass production, the approach includes recurring events of the setup validation process of machines which leads to new simulation runs for each position data set even when the data set is known. Further simulation runs occur when the linked order from the customer is shifted from the past. The results from initial research activities lead to a successful implementation of a workpiece positioning platform that offers coordinates that lead to a decreased production time and a collision-free production process. Depending on the complexity of the workpiece and the NC program, a high number of simulation runs may be necessary.

Our research goal arose from the idea to mitigate this effect by instead using supervised learning methods for the classification. The contribution shows a first proof of concept by using supervised learning methods to reach feasible position data, which saves recurring, time-intensive simulation runs.

This paper starts with the introduction (Section 1) to explain the motivation and is followed by Section 2 containing the related work in the research area focused on workpiece positioning approaches as well as research results from the past. Section 3 presents the architecture and system description of the workpiece position system and the supervised learning approaches. Section 4 deals with the extensional concepts, experiments, and comparison of two supervised learning methods. Section 5 closes the contribution with a short conclusion and outlook.

2 RELATED WORK

The upcoming sections show the related work done in the area of workpiece positioning. General research in the area of workpiece positioning is presented in Section 2.1. There is a focus on the research of NC-based workpiece positioning in Section 2.2.

2.1 Previous Research Activities in the Area of Workpiece Positioning

Related research activities in the area of workpiece positioning based on virtual tooling contain the proof of concept as well as initial experiments to identify useful procedures. In approaches of the past, a setup optimizer was developed that determined the production time reduction using a metaheuristic as optimization component. The used metaheuristic is the particle swarm optimization algorithm (PSO) (see Kennedy and Eberhart 1995), which prepares position data (a comparison of several meta heuristics for the workpiece positioning domain is shown by Weber et al. 2014). The fitness component is an NC interpreter, which deals with the time information. Further steps of the setup optimization procedure use cluster-based position data selection in order to avoid a simulation overkill. Before implementing the metaheuristic, an analysis of several algorithms took place.

In order to extend the PSO to handle asynchronous, semi-synchronous, and fully-synchronous optimization processes, it must be modified to deal with node failures and stochastic computer downtimes as well as the distribution of the optimization processes on distributed computer units (Reisch et al. 2015).

Initial tests in order to combine the embedded PSO and the NC interpreter together with a position validation approach inside of the machine's working area are shown by Weber et al. (2015) and Weber (2015). This approach shows the implementation of a simulation-based optimization procedure for virtual tooling. It contains a substitute model for real virtual tooling simulation software. This is done because of the problematic enlargement of a single validation process.

A potential solution to decrease the high number of simulation runs is addressed by Mueß et al. (2015). Laroque et al. (2016) deal with the development of a cluster-based PSO extension. After determining time-efficient workpiece positions, the quantities of solution candidates for the collision detection are still high. Thus, the cluster algorithm builds solution clusters and only the best solution candidate from each cluster is handed to the simulation model, thus saving simulation runs.

A complete concept of an automatic workpiece positioning system is contained in Weber (2017). With support from a user interface, production orders are manageable in order to distribute workpiece position validation processes and NC program adjustments. The results show that the time reduction of substitute workpiece positions is caused by tool path savings. Workpiece orientation adjustments lead to determining valid positions which were invalid before (Weber 2017; Weber and Laroque 2017). Some results as part of the concepts are important for this contribution and further development and were resumed in Section 3.

2.2 Related Work in the Area of Workpiece Positioning in NC-based Manufacturing Processes

Monitoring of manufacturing parameters such as accurate workpiece geometry when considering machine defects and workpiece setup are treated by Martin et al. (2011). The architectures of machine and tools are defined using a numerical model that draws from kinematic models. The study was done using a three-axis tooling machine.

An approach for solving the fixture layout problem of manufacturing area, especially related to workpiece positions and periphery setup equipment, is shown by Li and Melkote (1999). In order to identify improved and optimal fixture positions for workpieces in the work area of a tooling machine, simulations as well as mathematical models are predetermined, which is apparent in the contribution of Kaya (2006). There, the application of genetic algorithms is demonstrated.

An approach to reduce positioning and setup time for workpieces is treated by Chu et al. (1999). An analysis of the workpiece positioning is implemented by simulation tools. The workpiece is measured by a sensor and the data will be used to define and compare positions and orientations of the workpiece as CAD models. Toolpaths will be configured by Euclidian transformation for the provided positions and orientations. The result is positioning time reduction. A real implementation of workpiece positioning is not followed, rather a comparison of algorithms for the model-based workpiece positioning.

An approach for analyzing workpiece positions based on localization error constraints for the workpiece is defined using homogenous coordinate transformation by Cao et al. (2008). Numerical constraints solutions are given by the Newton-Raphson method and Monte Carlo simulation (Cao et al. 2008). Additionally, a quadratic approximation is usable (Cao et al. 2008). For a determination of the machine work area with parallel kinematics, an algorithm considering boundary search methods is introduced, as well as an implementation of workpiece positioning via a mathematical model (Wang et al. 2001). The shown validation is executed by hardware especially using physical devices and robots.

The contribution of Pessoles et al. (2013) underlines that workpiece positioning and orientation have a significant influence on the production time. The discussed method contains the goal to define the positions (translational movement) and orientations (rotational movement) of the workpiece depending on the tooling machine's kinematic situation, so that the tool paths during the production are minimized (Pessoles et al. 2013). To achieve that goal, the machine work area is discretized into a grid. The computing time depends on the definition of the grid size and granularity. Real tooling machines validate this method, so that no simulation methods are involved. A combination of positioning using both translational and rotational movements is not directly in the focus. The approach of Fallah and Arezoo (2013) is closely related to the idea of improving workpiece positioning and the simultaneous adjustment of NC programs in order to handle reference point errors that occur by changing the workpiece positions and the configuration of related NC programs (Fallah and Arezoo 2013).

The demonstrated range of contributions related to workpiece positioning shows no significant solution in order to implement an automatic workpiece position using multi-body simulation tools in the area of virtual tooling and NC program validation with the goal of minimizing the production time as a side effect. The findings of Weber (2017) come closer to decrease the simulation effort while having the shortcoming of requiring a high number of simulation runs. Nevertheless, the validation runs are handed to several simulation models and the usage of a cluster algorithm decreases the number of solution candidates significantly. In the following section an initial extensive approach is presented to address this deficit. The basic system concept is described in detail by Weber (2017), Weber (2016) and Laroque et al. (2016) in the context of the research project "*InVorMa*" (see acknowledgements).

3 ARCHITECTURE AND SYSTEM DESCRIPTION OF THE WORKPIECE POSITIONING

The following sections deal with the architecture of the workpiece positioning service platform. In Section 3.1, the setup and internal logic of the simulation-based optimization approach are presented. A selection of results (see Weber 2017) of this approach are presented in Section 3.2. The approach is extended through the usage of supervised learning methods in Section 3.3.

3.1 Workpiece Positioning Using a Simulation-Based Optimization System

The current system contains a simulation-based optimization approach that offers setup coordinates for the workpiece on the machine table of the tooling machine. The coordinates represent positions that lead to reduced production times. The processes of the workpiece positioning approach are shown in Figure 1, number (I). The input dataset is supplied by the user via the user interface. The order dataset is stored in a database that contains all order data, even from orders collected in the past. The pre-processing part calculates the coordinates without collision information and changes the NC program for further validation steps via the simulation model. The simulation model is designed as a numerical CAD-based and multibody-based model connected to a real control unit. The simulation systems contain the design for an existing tooling machine and the machine parts show relative movements between tools, tool magazine, workpiece, and peripheral system parts from a real tooling machine. The simulation is the core of the system, because it is required to identify collision information based on the given setup coordinates

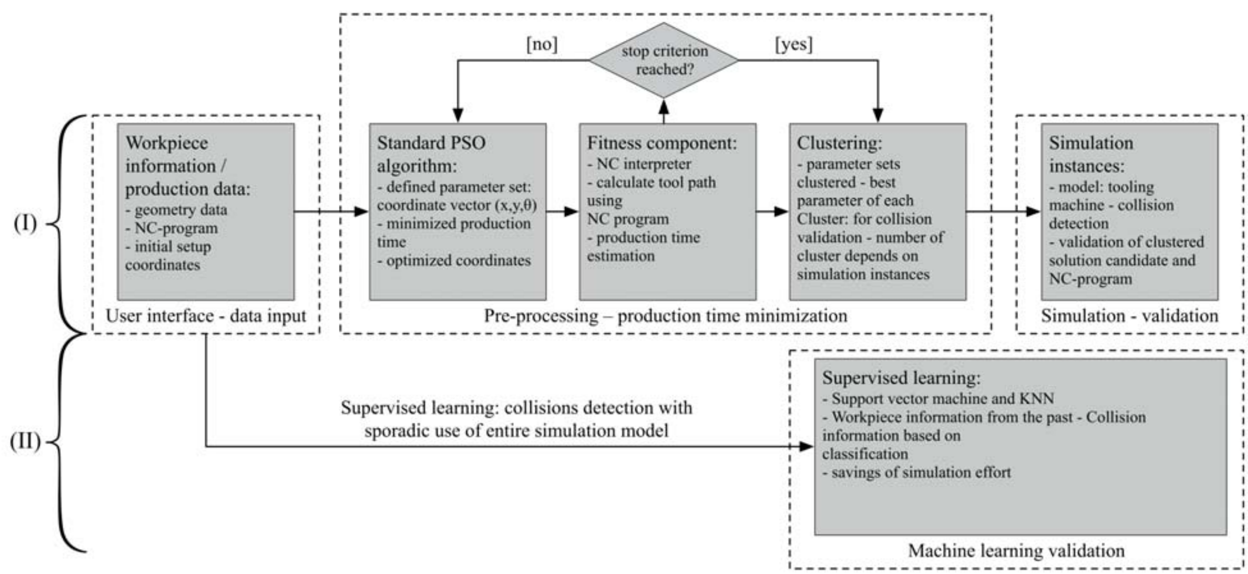


Figure 1: Overview of the workpiece positioning system in the virtual tooling simulation environment.

of the workpiece and clamps. It is also important to check if the target geometry is reached using the current NC program.

In order to provide optimal setup parameters for the workpiece position in the working area of the tooling machine, the workpiece positioning contains a particle swarm optimization (PSO) algorithm, which is capable of executing optimization jobs. The PSO generates solution candidates as position vectors $p_i^{x,y,\theta} = (x_i, y_i, \theta_i)^T$ that represent position coordinates for the workpiece on the machine table. Here, x and y represent translational movements on the machine table and θ represents the orientation angle of the workpiece around the z-axis of the Cartesian coordinate system. The PSO algorithm is linked with the NC interpreter as a fitness component to identify the best position coordinates in terms of minimized production times. The NC interpreter contains the function *nc* for mapping 3D-coordinates to a scalar including machine geometry and NC commands: $nc: M \times \mathbb{R}^D \rightarrow \mathbb{R}$, M represents the machine geometry and $\mathbb{R}^D$ the position vector $p_i^{x,y,\theta}$.

The NC interpreter observes no geometry information for tool or workpiece. Therefore, unintentional collisions between workpiece, clamps, or tools are ignored. The best solution candidates from the simulation-based optimization process are further processed by the K-means cluster algorithm, thus decreasing the number of potential validation candidates for the simulation model. Without the cluster procedure, large computations and sequenced simulation runs for each solution candidate would be required to determine collision-free solutions. The number of clusters depends on the available number of simulation instances. Each simulation instance provides collision information as a function *f* and the best representatives of the clusters can be validated in parallel by: $f_{instance\ t}: \mathbb{R}_i^D \rightarrow \mathbb{R} \times \{0,1\}$. The valid parameters are then returned and stored in the database for future production processes.

An overview about the architecture of the simulation model embedded in the software framework is given in Figure 2, which is installed as standard software. The data interface contains the content of the NC program as well as geometry and technical data for tools, clamps, workpieces, and tool magazine. The simulation management defines simulation sessions and manages the data set to organize a production scenario. The tooling machine model contains 3D data for the machine and production-relevant peripherals. The simulation core contains the kinematic model and the computational units for material removal and collision detection. The external interface provides the connection to the workpiece

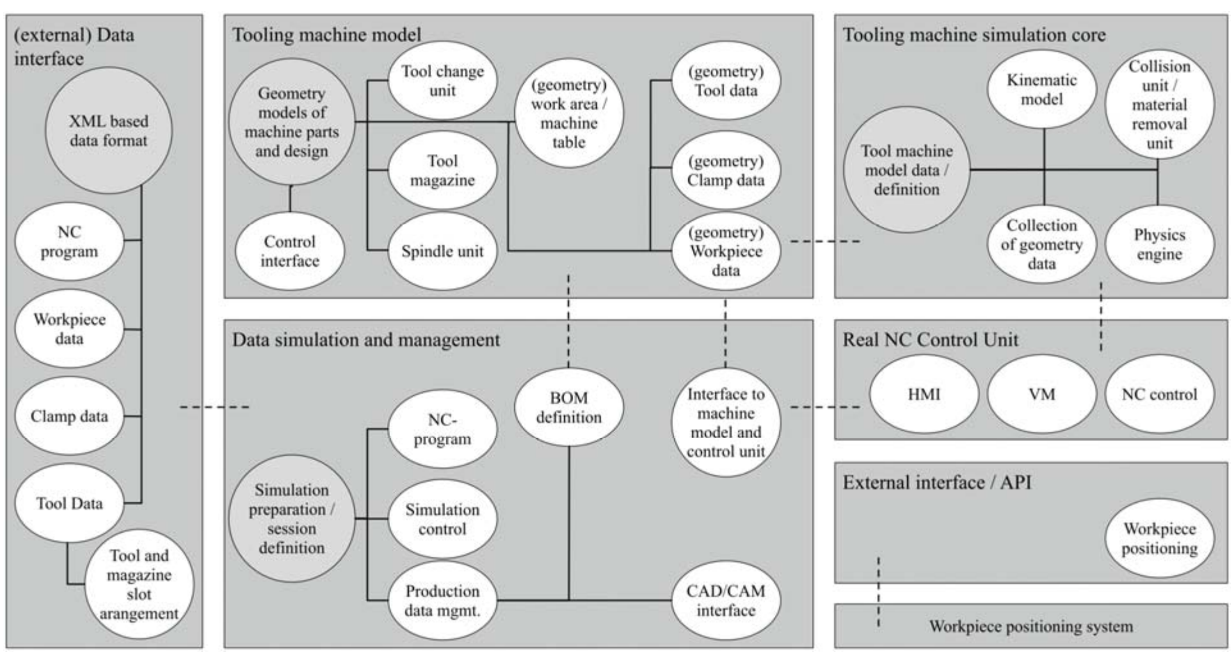


Figure 2: Content and structure of the simulation model of the tooling machine and NC processing.

positioning system considered in this contribution.

The test workpiece and a visualization of the simulation model are shown in Figure 3. The workpiece raw geometry is shown on the left side and the target geometry in the middle. The tooling machine model is a 5-axis tooling machine and processes milling and drilling technology. The software is developed by the company named "DMG Mori AG" (Germany).

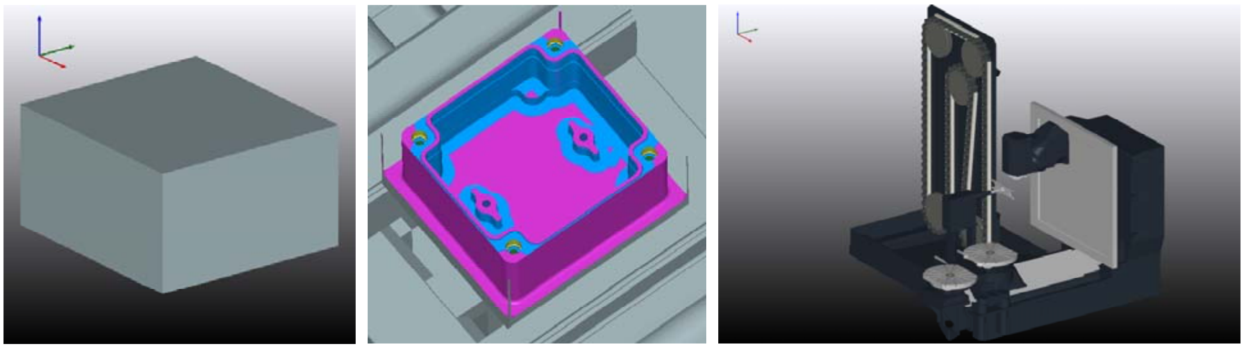


Figure 3: Workpiece model with raw (left) and target geometry (middle) and virtual tooling simulation model of a CNC-machine (right).

The test workpiece and a visualization of the simulation model are shown in Figure 3. The workpiece raw geometry is shown on the left side and the target geometry in the middle. The tooling machine model is a 5-axis tooling machine and processes milling and drilling technology. The software is developed by the company named "DMG Mori AG" (Germany).

3.2 Results for Workpiece Positioning Based on Simulation-Based Optimization without Supervised Learning

A portion of the results for workpiece positioning, which contains minimized production time and collision status, is presented in Figure 4. The initial setup position for the workpiece is defined as x = 0 mm, y = 0 mm, z = 0 mm and θ = 0°, which is in the center of the machine table. The tool change position is defined as x = 228.98 mm, y = 0.00 mm, z = 0.00 mm and is given by the simulation model. The initial production time is 453.20 s. The average production time saving for the valid coordinates is 1.97 s. The diagram in Figure 4 shows the valid and invalid setup coordinates as top view of the machine table coordinates x and y. Due to the minimization of the production time, it can be assumed that the tool path during the manufacturing process has significant influence of the total production time for the test workpiece, especially for tool change processes. This is recognizable through the convergence of the position in the area of the tool change position, because the closer the position to this point the lower is the total production time and the shorter is the tool path during tool changes become. The coordinate z and angle θ are ignored in the diagram. Invalid positions are mostly to the right of the tool change position. In the machine table, which is behind the tool change area (right), the machine spindle and tool change devices (see Figure 2) come close to the production area where the workpiece and clamps are fixed. Unintentional collision occurs.

3.3 Further Development of the Workpiece Positioning as Embedded Solution for the Simulation-Based Optimization System Using Supervised Learning Methods

The extension of the workpiece positioning approach is implied in Figure 1, number (II) and contains an additional supervised learning method such as Support Vector Machines (SVM) or the k-nearest neighbors classifier (KNN). The information for workpiece geometry and setup coordinates are given from past orders and are the same as the general workpiece positioning (I) (see Figure 1). The approach

(I) determines simulation run savings due to clustering the pre-processing of the input vectors (more detailed results are presented by Weber 2017). There is remaining potential for decreasing the number of simulation runs to validate the positions. This leads to the idea of extending the approach using machine learning methods, since the validity of several workpiece positions regarding x, y, and θ is already known. Thus, one can use supervised learning procedures to classify new workpiece positions regarding their validity. The evaluated machine learning methods in this approach are SVM and KNN. The mathematical formulation of the SVM (Cortes and Vapnik 1995) is shown below. The training data set is defined as containing vectors of the form $v_i \epsilon \mathbb{R}^d, i = 1, \dots, n$ with a binary classification in $y \in \{1, -1\}^n$ solving the following problem:

$$\min_{w,b,\zeta} \frac{1}{2} w^T w + C \sum_{i=1}^{n} \zeta_i$$
$$\text{s.t.} \qquad y_i(w^T \phi(v_i) + b) \geq 1 - \zeta_i,$$
$$\zeta_i \geq 0, i = 1, \dots, n.$$

Its dual formulation is

$$\min_{\alpha} \frac{1}{2} \alpha^T Q \alpha + e^T \alpha$$
$$\text{s.t.} \qquad y^T \alpha = 0,$$
$$0 \leq \alpha_i \leq C, i = 1, \dots, n.$$

where $e = \vec{1}, C > 0$ is the upper bound, Q is a $n \, x \, n$ positive semidefinite matrix. $Q_{ij} \equiv y_i y_j K(v_i, v_j)$ with $K(v_i, v_j) = \phi(v_i)^T \phi(v_j)$ being the – in this case – linear kernel function. The SVM uses the following decision function: $sgn(\sum_{i=1}^{n} y_i \, \alpha_i K(x_i, x) + p)$.

coordinate x [mm]	*coordinate y [mm]*	*orientation θ [°]*	*production time*	*collision status*
157.09	8.53	117.77	450.86	valid
305.82	75.05	-20.81	451.31	invalid
326.70	25.10	-83.25	451.59	invalid
40.44	-59.33	-180.58	452.55	valid
260.85	-94.57	256.92	451.14	invalid
130.33	-74.60	65.53	451.16	valid
226.51	-41.22	-74.68	450.74	valid
256.00	40.51	-234.66	450.78	invalid
288.79	-27.29	-238.88	450.98	invalid
284.44	-79.43	-37.68	451.04	invalid
133.49	62.97	-126.53	451.16	valid
169.95	143.24	-241.98	452.23	valid
256.58	40.96	353.10	450.78	invalid
166.03	-45.25	-18.36	450.83	valid
129.94	8.46	225.03	451.16	valid
196.51	21.68	-224.68	450.70	valid
260.85	-46.76	9.40	450.80	invalid
157.09	8.53	117.77	450.86	valid

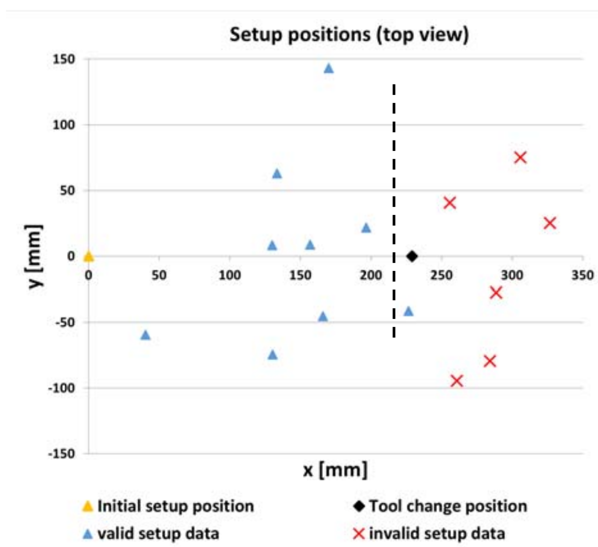


Figure 4: Segment of results using the workpiece positioning approach (I).

The algorithm for the KNN-classifier (Altmann 1992) uses majority voting to determine the value of each questioned vector $v_i \epsilon \mathbb{R}^d, i = 1, \dots, n$. The majority is determined through the value of the closest k

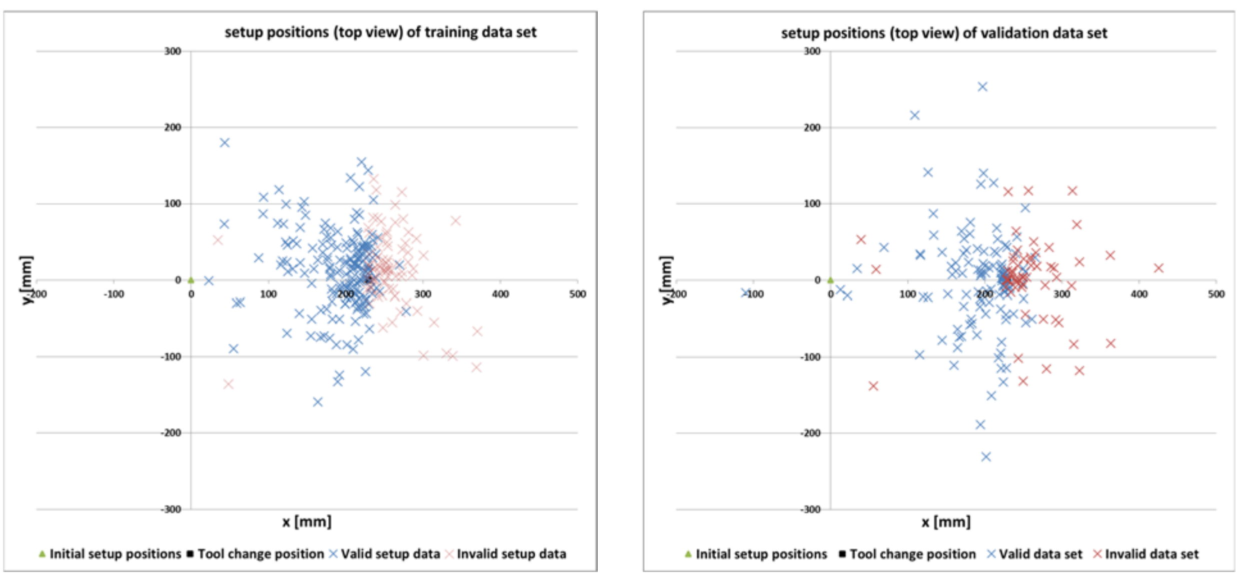
neighbours from the questioned vector v_i. The k closest vectors out of $v_i \epsilon \mathbb{R}^d, i = 1, \dots, n$ are determined through the Euclidean distance $||v_i - v_j||$ between the k questioned vectors v_j and the vector v_i. The k closest vectors vote with their respective truth value. All k vectors' votes are treated equally due to the usage of uniform weights. The vector v_i is assigned to the majority of the votes.

4 EXPERIMENTS AND RESULTS

The following sections deal with the setup and data basis for the experiments as well as the explanation and presentation of the results. In Section 4.1, the parametrization of the supervised learning methods and the input dataset for the classifiers is shown. The performance of the supervised learning methods on the input data set is shown in Section 4.2.

4.1 Experiments Using the Further Development of Supervised Learning

The applied dataset contains vectors created from the earlier-mentioned workpiece positioning. Each vector $v_i \in (x_i, y_i, \theta_i)$ contains three features and is assigned a binary truth value. The features of the vector are the x-coordinate, y-coordinate, and the orientation θ, which is equated to the position vector $p_i^{x,y,\theta}$. The vectors are binary-classified through their validity regarding collision. The SVM uses the dataset to train a binary classifier, which uses a linear function as its kernel. The KNN classifier creates a kd-tree using the Euclidean distance between all vectors of the training data set. It uses the truth value of the $k = 5$ nearest neighbors to determine the classification. An odd number of voters is used to avoid ties. The dataset is split 80:20 into training and test data to validate the learned classifiers.



(A) (B)

Figure 5: Workpiece positions of the training data set (A) and raw validation data set after simulation (B).

The resulting datasets are visualized regarding their x coordinate, y coordinate, and validity in Figure 5, where Figure 5 (A) is the test data set and Figure 5 (B) is the validation data set. The angle θ is ignored in the plot.

4.2 Experimental Results

The results of the experiments (Figure 6) show that both classifiers cannot cope with the transition between valid and invalid data points for vectors containing $x \sim 228$ and $y \in [-200, 200]$ (in mm). Table

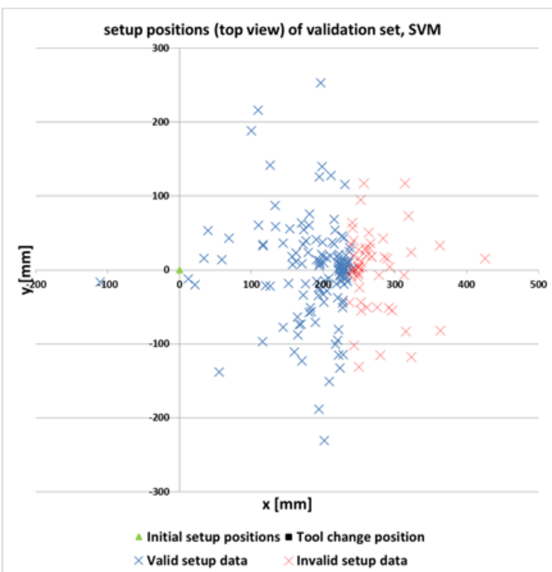
1 contains the confusion matrix of the simulation results and the positioning results generated by the supervised learning methods SVM and KNN. During our experiments, we tried different parametrizations of the SVM and KNN and found a SVM with a linear kernel to work best, as well as setting the neighborhood size of the KNN to $k = 5$.

Table 1: Confusion matrix of the simulation results and SVM / KNN classification.

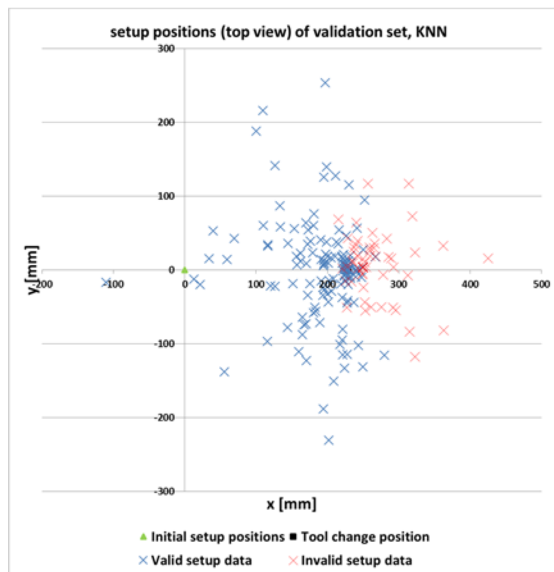
n=208		Simulation result	
		Valid	Invalid
SVM classification	Accept	120	18
	Reject	13	57

n=208		Simulation result	
		Valid	Invalid
KNN classification	Accept	117	26
	Reject	16	49

In contrast to the KNN classifier, the SVM performs slightly better in regards to identifying invalid points (see Table 1). The SVM and KNN classifier have an average classification error of 14.90% and 20.19% respectively. Using the SVM creates a 26.19% lower classification error based on the training error of the KNN classifier. The results also show that it is not as hard to determine valid and invalid points, since the classification error for valid points is only 10.90%, while the classification error for invalid points is as high as 29.33%. The classified validation data from the SVM (Figure 6 (C)) and KNN (Figure 6 (D)) regarding their x, y coordinates and validity are shown in Figure 6.



(C)



(D)

Figure 6: Workpiece positions of the validation data set of SVM (C) and KNN (D) approach (II).

5 CONCLUSION AND OUTLOOK

The proposed method to determine validity for workpiece positioning vectors via supervised learning algorithms is a novel approach in the field. The proposed methods provide huge success in terms of total runtime reduction in comparison with the simulation-based optimization approach. The overall runtime is critical for real-world application, where validity must to be determined quickly in order to meet production deadlines.

In contrast to the huge benefit of runtime reduction, the solution quality when classifying the validity via supervised learning methods is currently reduced by a relatively large amount. The solution quality is another major factor for real-world application since falsely classified data might cause problems during production. A reduction of runtime, while maintaining the same solution quality as the simulation-based optimization offers, is desirable in order to meet real-world expectations.

Since the proposed methods are still very basic and only provide a first proof of concept, there is still room for improvement. The supervised learning methods should be adapted to achieve the goal of both rapid and accurate validation. Future work might include the consideration of domain-specific problems during the classification process.

One domain-specific problem that we identified during our experiments is the classification of data points in the proximity of the earlier-mentioned tool change point. The tool change point is considered separately in the simulation-based optimization approach to correctly classify the validity of data points in its proximity. This allows the simulation-based approach for achieving a high solution quality.

The decision-support process of the simulation-based optimization for data points in the proximity of the tool change point should be integrated into the classification process. This might allow the method to maintain an equal amount of solution quality for the critical points, while still classifying the remaining points quickly.

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AUTHOR BIOGRAPHIES

JENS WEBER is IT project leader in the Digital Factory (Body-in-White-Validation) as part of the Information Technology Management at Daimler AG, Germany. He received his Ph.D. in Business Computing in 2017. From 2013 to 2017 he was research associate and Ph.D. student at the department of Business Computing, especially CIM at the Heinz Nixdorf Institute, University of Paderborn. He studied Industrial Engineering at the University of Paderborn with focus on the ranges of topics of mechanical engineering. His email address is jens.weber@hni.upb.de

SEBASTIAN RISSE is currently a Ph.D. student in the area of Operations Research in Integrated Logistics at Daimler AG, Germany. He studied Business Informatics at the University of Paderborn. His focus was in the fields of Operations Research and Production and Logistics. His email address is risse@mail.upb.de.

CHRISTOPH LAROQUE studied Business Computing at the University of Paderborn, Germany. Since 2013 he is Professor of Business Computing at the University of Applied Sciences Zwickau, Germany. He is mainly interested in the application of simulation-based decision support techniques for operational production and project management. His email address is Christoph.laroque@fh-zwickau.de.