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Extended Simulation Model For An Aerodynamic Feeding System

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Abstract

Due to an increased number of product variants and shorter product life cycles, flexible automation plays a vital role in the producing industry. In assembly systems, industrial robots are used as highly versatile handling and joining devices. Simultaneously, the corresponding feeding systems that provide the workpieces in an orderly fashion for automated assembly can often not meet the required flexibility. In order to achieve high flexibility and reusability, an aerodynamic feeding system was developed. The feeding system can flexibly and rapidly adapt itself to new workpieces autonomously, using a genetic algorithm. To find the optimal parameters for the genetic algorithm, a workpiece specific simulation model of the aerodynamic orientation process was developed and validated in earlier work. In this work, we extended the simulation model with regard to the spectrum of workpieces that can be simulated and developed a user-friendly framework to simplify the application of the model. Our goal is to reduce the setting time of the genetic algorithm even further by predicting the optimal range of the feeding system's parameters for any workpiece using the extended simulation model. To evaluate and validate the simulation model, we carried out extensive tests with different exemplary workpieces. The results show that the setting time of the aerodynamic feeding system can be dramatically reduced using the extended simulation model, further increasing the flexibility and reusability of the system.

Keywords

Aerodynamic Feeding, Simulation, Flexible Feeding Systems

1. Introduction

Production in the modern industry is characterized by increasing numbers of product variants, shortening product life cycles and a high cost pressure due to global competition [1]. Especially in automated assembly systems, this results in reduced amortization periods and the demand for highly flexible systems [2]. Feeding technology, as one of the most complex and expensive parts of automated assembly systems [3], is therefore required to become more versatile. Commonly used solutions like vibratory bowl feeders cannot meet those demands [4]. Therefore, many approaches have been taken to increase the flexibility of conventional feeding systems, using interchangeable [5] or adjustable chicanes [6] [7]. At Leibniz University Hannover, an alternative solution for small part feeding was developed. The aerodynamic feeding system uses a constant jet of pressurized air to reorient workpieces with high speed and flexibility [1]. Due to the use of an air jet as chicane, the system is very flexible regarding the geometry of the workpieces. When changing between different workpieces, no hardware changes have to be made. Instead, the feeding system adjusts itself autonomously using a genetic algorithm [8]. Still, the initial values of the genetic algorithm are generated randomly within the system's parameter boundaries, which makes the expected setting time hard to predict. In this work, we present an approach to reduce the setting time and make it more predictable at the same

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time, using an extended simulation model of the aerodynamic orientation process. Before presenting our approach, we will introduce the aerodynamic feeding system used in our work.

2. Aerodynamic feeding system

The aerodynamic feeding system used in this work, manipulates the workpieces using an air jet with constant pressure. The principle is illustrated in Figure 1. The workpieces are first separated using a conventional centrifugal feeder, before they are handed over to a conveyor belt, which accelerates them to a desired velocity. Subsequently, the workpieces pass the nozzle, which produces an air jet, exercising a force on them. The extent of the force is thereby dependent on the geometry of the workpiece, in particular on the projected inflow area. If the projected inflow area variates along the longitudinal axis of the workpiece, a rotational impulse around the center of gravity is generated. For certain combinations of the five system parameters α, β, p, v and z (cf. Figure 1), workpieces arriving at the nozzle in one orientation are reoriented, while workpieces arriving in the other orientation are not reoriented.

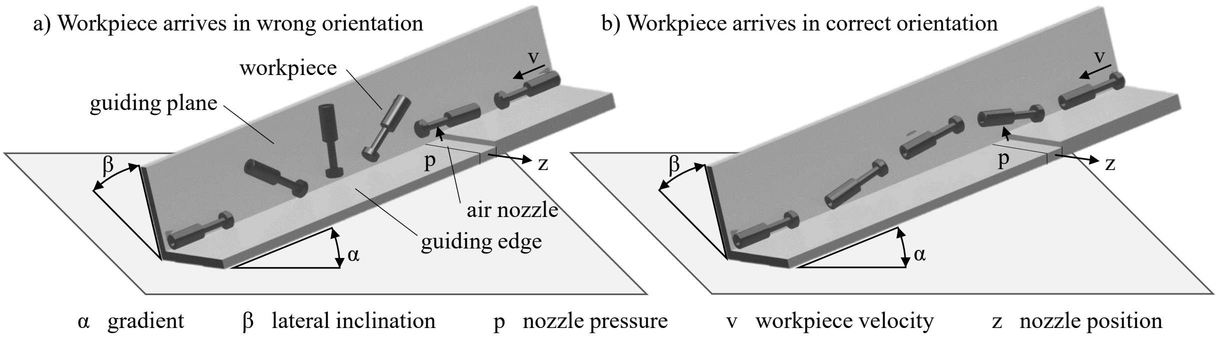

Figure 1: Principle of aerodynamic orientation

These parameter combinations are different for every type of workpiece and cannot easily be predicted. Therefore, a genetic algorithm that searches for a suitable parameter combination autonomously was implemented in the system control. In each generation, two new individuals are created. The parameter combinations of each individual are then set on the feeding system. Using a line scan camera, the orientation of the workpieces after the orientation process is determined. The ratio of correctly oriented workpieces to all the workpieces of one individual is defined as orientation rate and constitutes the fitness of each individual. For one individual, the feeding system tests 100 workpieces. In an iterative process, the individuals are evaluated, selected, recombined and mutated, until a satisfactory solution with an orientation rate of 95 % or higher is found. For a more detailed description please refer to [8] [9]. Using the genetic algorithm, the feeding system can adjust itself to new, unknown workpieces autonomously.

Still, in the current state, there are some disadvantages to the genetic algorithm. Firstly, the initial population of the genetic algorithm is created with random values in the parameter range of the aerodynamic feeding system. In combination with the heuristic character of the genetic algorithm, this can lead to varying and hardly predictable setting times. Secondly, the standard parameter range for the genetic algorithm, as shown in Table 1 is not optimal. In order to reach a high flexibility, the standard parameter range is set according to the system's mechanical, electrical or physical boundaries, regardless of the current workpiece properties.

Table 1: Parameter range of the aerodynamic feeding system for the genetic algorithm

Parameter	α	β	p	v	z
Minimum	20°	39°	0.01 bar	50 m/min	0 mm
Maximum	25°	50°	0.89 bar	80 m/min	10 mm
Increment	0.1°	0.1°	0.01 bar	1 m/min	1 mm

The genetic algorithm then searches the solution space spanned by these parameters with the exception of the nozzle pressure p. Using the extreme values of p, most workpieces would either not be lifted at all due to low pressure or shot out of the system due to high pressure. Therefore, the range for p has to be determined experimentally and manually before starting the genetic algorithm. For the other parameters, manual determination is not as easy and the standard range is used. As a result of this, the genetic algorithm potentially scans a lot of areas of the solution space, where no suitable solution for a particular workpiece can be found. This unnecessarily prolongs the setting time of the genetic algorithm. Furthermore, as aforementioned, the setting time of the genetic algorithm varies strongly and is hardly predictable, as can be seen in Table 2. In some test runs, a suitable solution was found after only testing two individuals of the genetic algorithm, while in other runs, up to 84 individuals had to be tested.

Table 2: Number of individuals tested before finding a suitable setting using the genetic algorithm in ten test runs

Test run No.	1	2	3	4	5	6	7	8	9	10
Tested individuals	36	11	66	2	4	84	23	13	2	6
Average (SD)					24.7 (±28.84)					

The aim of this work is to shorten the setting time of the aerodynamic feeding system for new workpieces, reduce the variations of the setting time and eliminate the need for experimental determination of the parameter range by the use of an extended, workpiece independent simulation model of the aerodynamic orientation process.

3. Extended simulation model

In this section, we will first briefly introduce the simulation model created in earlier work [8]. Then, we will present the extensions added to the model, like the implementation of a method to automatically calculate the workpiece properties (e.g. mass, inertia, center of gravity) as well as the development and validation of a method to calculate the lift of the workpiece created by the air jet (aerodynamic drag) under the consideration of the nozzle position z.

3.1 Existing simulation model

The original simulation model was created to assess the quality of different combinations of the system parameters α, β, p and v [8]. The parameter z was only added as system parameter later [9]. The Simulation was used to optimize the parameters of the genetic algorithm like population size, mutation rate or selection method. By doing so, the experimental effort was reduced drastically, while at the same time being able to perform thousands of virtual test runs in order to increase statistical confidence in the results.

In the simulation model, the workpiece is represented as a one-dimensional rod with the length, and inertia of the corresponding workpiece. The mass of the workpiece is represented as point mass positioned according to the center of gravity of the real workpiece. Since the workpiece's movement is restricted by the guiding edge and guiding plane (it is assumed that the workpiece is always in contact with the guiding plane), the equilibrium of forces (friction, aerodynamic drag, weight) and the equation of motion are only considered in two dimensions. The aerodynamic drag exerted on the workpiece by the air jet is calculated based on many parameters, like the distance of the workpiece to the nozzle, the nozzle pressure as well as the diameter and the drag coefficient of the workpiece. The resulting differential equations of second order, which will not be presented in detail here, cannot be solved analytically. Therefore, the simulation model is implemented and run in MATLAB/Simulink by Mathworks, where the equations are solved numerically. Comparisons between the simulated and the real trajectory of a workpiece show high conformity (see Figure 2) [8]. For better presentation, the one-dimensional rod is pictured as a CAD-Model of the workpiece.

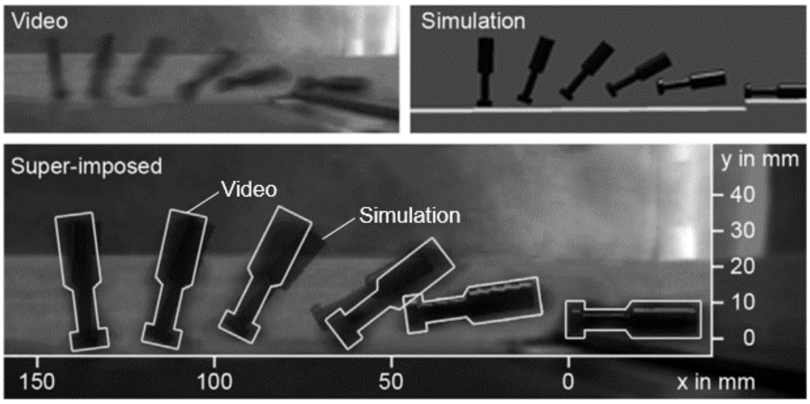

Figure 2: Comparison of real and simulated workpiece movement [8]

Nevertheless, a disadvantage of the simulation model is the low flexibility regarding the workpiece geometry. Busch et al. [8] designed the simulation model for a pneumatic plug, which can be seen as exemplary workpiece in Figure 1 and Figure 2. To simulate different workpieces, we would have to calculate all the workpiece properties for each different workpiece manually. Furthermore, the model only considers four system parameters. The nozzle position z, which we only implemented in the real system at a later time, is not considered in the existing model. Therefore, in the following sections, we will first describe the adaptations we implemented to enable the simulation model to calculate the movement of any rotationally symmetrical workpiece. Then, we will present our method to determine the aerodynamic drag of the air jet on the workpiece under consideration of different geometries and the nozzle position z.

3.1 Automatic determination of workpiece geometry and properties

As mentioned above, the simulation model calculates the movement of the workpiece based on the motion equations of a one-dimensional rod in the two-dimensional x-y-plane (cf. Figure 2). This reduces development and computational effort while still accurately representing the workpiece movement. When the workpiece geometry changes, certain properties of the rod, like the length, inertia and the center of gravity, change, but the underlying motion equations remain unchanged. In order to make the simulation model more universal and user-friendly, we enabled the model to determine the physical and geometric properties of a workpiece based on workpiece data provided by the user. The user provides the data by separating the workpiece into different sections that can be represented by primitive bodies, like cylinders or (truncated) cones. The model differentiates between outer and inner geometry features like bores. This way, various rotationally symmetrical parts can be represented very easily without the need for CAD-Software. In addition, separating the workpiece into sections that can be described with only few variables reduces the computational effort, shortening simulation time. With the dimensions known, the user only has to provide the density of each section and the model automatically determines all the necessary properties.

3.2 Calculation of aerodynamic drag under consideration of variable nozzle position

While the properties of a workpiece are constant during the entire simulation, the forces exerted on the workpiece change in dependence of the position, orientation, velocity and acceleration of the workpiece. Friction and inertial forces and moments can be calculated analytically, but the calculation of the aerodynamic drag of the workpiece in the pressurized air jet constitutes a particular challenge. In order to calculate the force F_w exerted on the workpiece by the air jet, we consider the air jet to be a cone, with the apex sitting in the nozzle. We calculate F_w using Equation 1:

$$F_w = c_w \cdot \frac{\rho}{2} \cdot w^2 \cdot A_{st} \tag{1}$$

We assume the drag coefficient $c_w = 1.2$ for a cylinder and $\rho = 1.2041\ kg/m^3$ for air at ambient pressure. The air velocity w, with which the air jet hits the workpiece, is dependent on the distance between the workpiece surface and the nozzle as well as the nozzle pressure and diameter. The inflow area A_{st} is dependent on the workpiece geometry and the nozzle position z. In order to calculate A_{st}, we define an ellipse, representing a cross section through the air jet cone based on the distance between the workpiece surface and the nozzle. Still, the area of the ellipse is not necessarily the inflow area A_{st}, since it can exceed the dimensions of the workpiece in dependence of the relative position of the workpiece and the nozzle. In order to calculate the intersection of the ellipse and the workpiece accurately and efficiently, we chose a finite element approach (see Figure 3). An algorithm breaks down the workpiece and the ellipse into two, two-dimensional, binary matrices, where a "1" represents the cross-section of the workpiece or the ellipse respectively. All other entries are "0". The workpiece matrix does not change during the simulation, while the matrix representing the ellipse changes in each time step, based on the relative position of the workpiece and the nozzle. When both matrices are added, the number of "2"s represents the inflow area A_{st} (white areas in Figure 3). Compared to other approaches (numerical integration, MATLAB polyshape function) our method showed much shorter computing times, while still achieving sufficient accuracy.

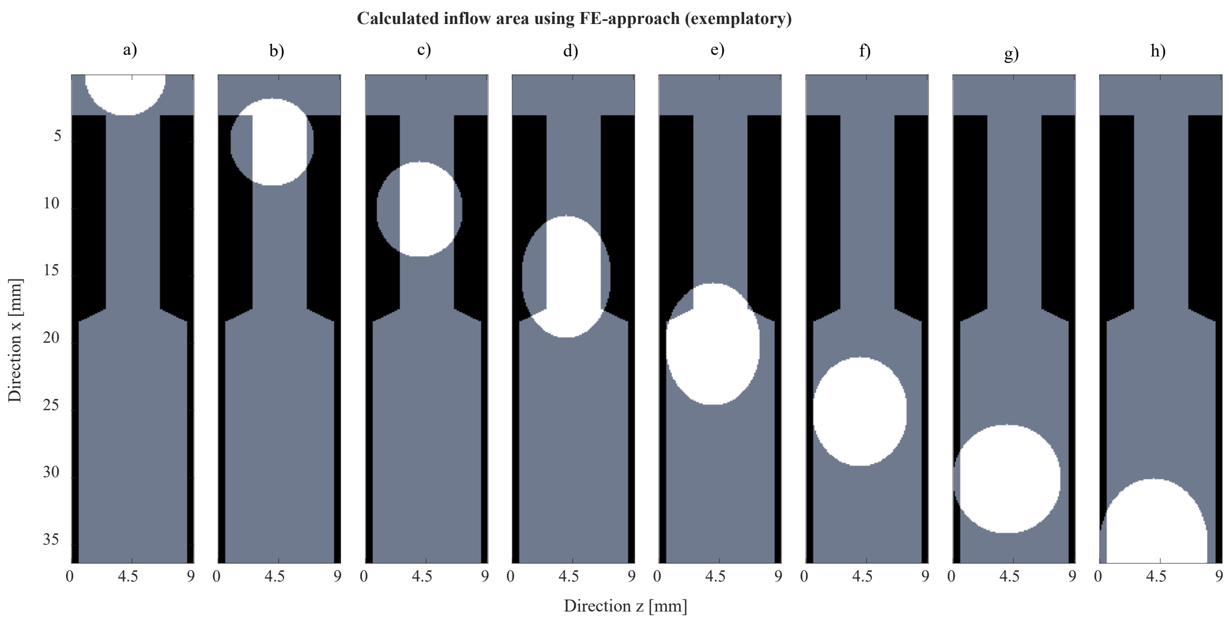

Figure 3: Calculated inflow area using FE-approach with a nozzle position of 4 mm in z-direction

In order to validate the approach, we compared the simulated aerodynamic drag force F_w with experimental measurements. For the validation, we mounted an exemplary workpiece (pneumatic plug) to a force sensor and measured the force exerted on the workpiece by an air jet coming from the nozzle with a relative pressure of 0.48 bar. Measurements were taken in increments of one millimeter along the longitudinal axis of the workpiece (x-direction in Figure 3), for different distances between workpiece and nozzle as well as for different nozzle positions z. The comparison between measured and simulated values, as shown in Figure 4, indicates good conformity. In order to match the fluctuations of the measured drag force, we added a white noise of 10 % of the calculated value in the simulation. Especially Figure 4 a) shows that the simulation can reproduce the influence of the workpiece geometry and the nozzle position on the aerodynamic drag.

Using the simulation model, we can now predict the movement of different, rotationally symmetrical workpieces in dependence of the five system parameters α, β, p, v and z. The aim of this work is to use the simulation model to reduce the setting time of the real feeding system by predicting and narrowing the boundaries of the system parameters. Nevertheless, doing this manually would mean a disproportionate effort. Therefore, we developed a framework, which automatically determines the boundaries of the system parameters based on the workpiece data provided by the user.

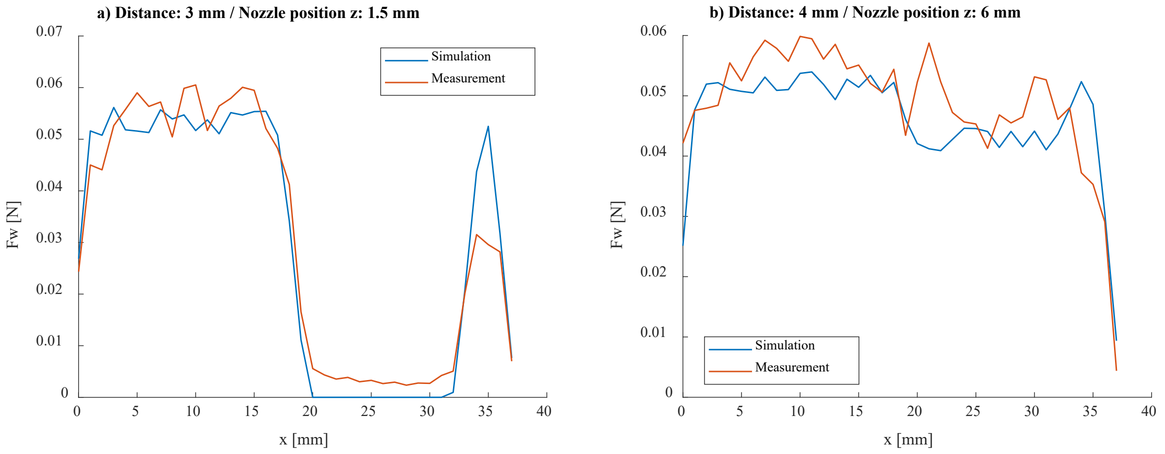

Figure 4: Comparison of aerodynamic drag (F_W) on an exemplary workpiece with nozzle pressure p = 0.48 bar for different workpiece positions relative to the nozzle

4. Framework for parameter prediction

In order to reduce the setting time of the aerodynamic feeding system, we integrated the optimized extended simulation into a new framework for an offline parameter prediction. The framework is implemented as a MATLAB script and directly interacts with the simulation. The main routine for parameter prediction contains two different subroutines, which systematically narrow down the lower, and upper bounds for each parameter. This approach drastically minimizes the search area for suitable parameter configurations of the genetic algorithm.

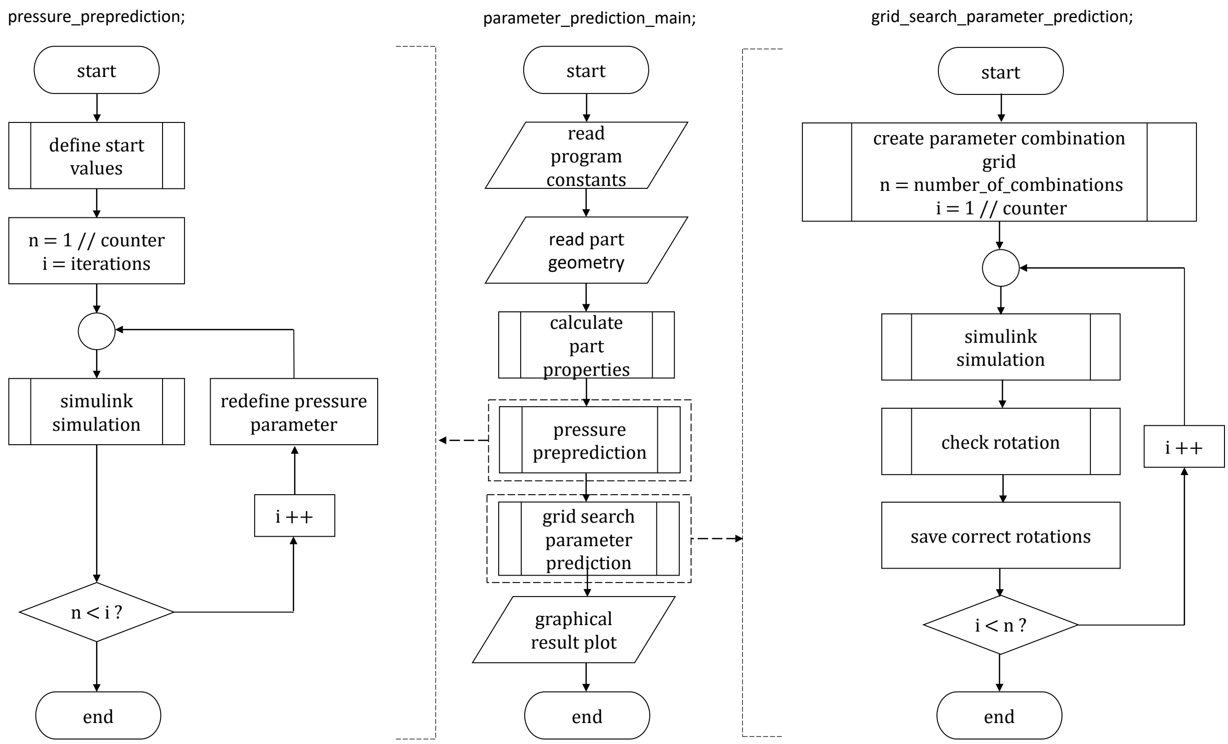

Figure 5: Flow chart of parameter prediction

Figure 5 shows the flow chart of the parameter prediction algorithm. After the initialization of the program constants, the main routine automatically reads and calculates the workpiece properties. Then, the main routine invokes two different subroutines. First, a pressure pre-prediction roughly narrows the pressure boundaries for the individual workpiece at hand. As mentioned above (cf. Section 2), the pressure range of the feeding system is much higher than the practical pressure range for an individual workpiece. In order to pre-predict the pressure, the upper and lower pressure boundaries are approximated numerically using the bisection method. The lower pressure boundary is defined as the lowest nozzle pressure to cause a reorientation in either direction; the upper pressure boundary is the lowest pressure to cause a double rotation of the workpiece in either direction. To predict the lower boundary, the algorithm first simulates the orientation process for the mean of the maximum and minimum pressure (cf. Table 1). If a reorientation occurs, the pressure is set to the mean of the previous value and the minimum pressure and the simulation is run again. This process is reiterated, until no reorientation occurs. Then, the step size is halved again but the search direction is reversed. Therefore, the algorithm oscillates around the lower boundary, until the stop criterion is fulfilled. The method works analogous for the upper boundary.

For the next step, we use a grid search algorithm to scan the solution space spanned by the boundaries of the system parameters. With all five system parameters divided evenly into n discrete values, we would have to calculate n^5 combinations. In order to reduce the computational effort, in this work we will only use three parameters as dynamic values and set the other two as constants. A sensitivity analysis showed that out of the five system parameters, the nozzle pressure p, the nozzle position z and the workpiece velocity v have the greatest impact on the orientation process. Therefore, we defined them as variable parameters inside the framework. The gradient α and lateral inclination β have a much smaller influence on the orientation process, therefore we defined them as constants with α = 25° and β = 45°. Considering only three parameters instead of five decreases the computing time drastically and results into a three dimensional grid with n^3 possible parameter configurations. All of these configurations are then entered in the extended simulation model to calculate the specific rotational behavior for each configuration for both input orientations of the workpiece. A configuration is marked as suitable when the workpiece only rotates in one input orientation and passes the nozzle in the other orientation without a rotation.

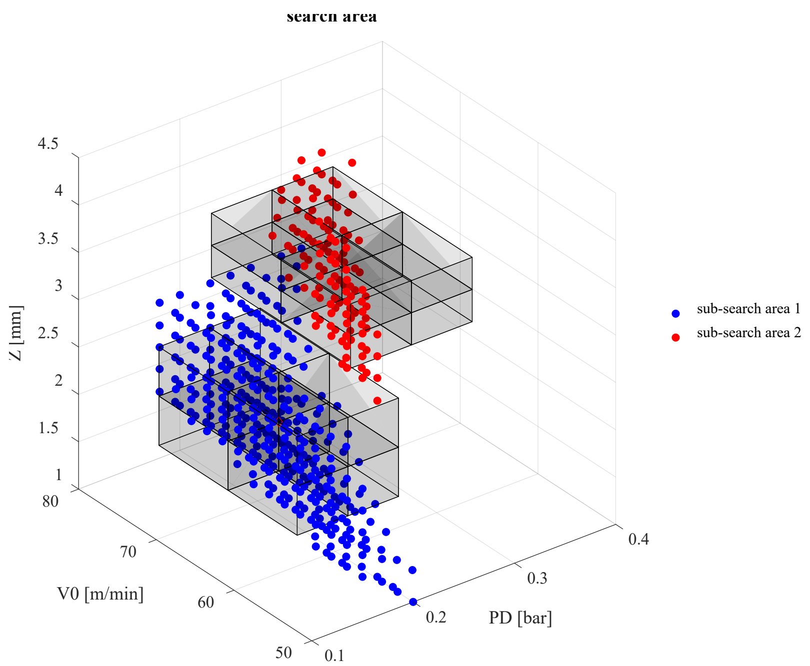

Figure 6: Suitable parameter configurations for exemplary workpiece (pneumatic plug) with two sub-search areas

Using a multi-layered graphical plot, the results for each parameter configuration are illustrated inside the three-dimensional configuration grid (see Figure 6). To determine which regions inside the search area are best suited, a density based scan function is used. The scan algorithm automatically distinguishes multiple sub-search areas with the highest density of suitable configurations and deletes statistical outliers. The distribution between the sub-search areas is visualized with different colors. For each sub-search area, the standard deviation for all three system parameters is plotted as boxes around the mean value configuration.

Figure 6 shows an example of the result plot for an exemplary workpiece, where two different sub-search areas were detected. A result summary gives a structured overview of the amount of correct rotations in each sub-search area as well as the mean values and standard deviation for each sub-search area. In this work, we used the mean and standard deviation of the sub-search area with the most correct orientations as predicted parameter boundaries for the genetic algorithm. In order not to narrow down the search space too much, we always rounded down the lower boundaries and always rounded up the upper boundaries.

5. Experimental evaluation

To experimentally evaluate the effect of the parameter prediction of the extended simulation model on the setting time of the aerodynamic feeding system, we compared the setting times of the genetic algorithm for three rotationally symmetrical workpieces (see Figure 7). One of the workpieces is an injection molded pneumatic plug (W1); workpieces W2 and W3 are self-constructed and printed using a resin 3D printer. For the evaluation, we first determined the average setting time of the system without the use of the simulation based framework and then repeated the experiments with the predicted parameter ranges.

Figure 7: Workpieces used for the evaluation of the parameter prediction framework

For the manual evaluation, the pressure boundaries are determined manually for the different workpieces and the corresponding duration for this process is measured. For the workpiece velocity v and the nozzle position z, the system's boundaries are selected. The gradient α is set to 25° and the lateral inclination β is set to 45°. Then, ten test runs are carried out for each workpiece. For each test run, the number of tested individuals is determined, as it is proportional to the setting time. After all test runs, the average number of tested individuals as well as the standard deviation is calculated.

For the evaluation of the simulation framework, the predicted boundaries for p, v, and z are implemented as boundaries for the genetic algorithm. The parameters α and β are also set to 25° and 45°. The start population of the genetic algorithm is no longer generated randomly but instead, for each dynamic parameter, the mean values of the predicted solution space are used. If a mean value lies between two adjustable values on the system, it is rounded up once and rounded down once, since the start population of the genetic algorithm has the size of two individuals. Subsequently, ten trials are carried out in order to compare average number of individuals tested by the genetic algorithm (setting time) and whether the duration per workpiece varies more or less in comparison to the manual values.

6. Results

The experiments show that the average setting time as well as the variation of the setting time can be drastically reduced with the use of the parameter prediction framework. Figure 8 shows the results of the ten test runs for each workpiece. Looking at the results of workpiece W1, we can see that the setting time was generally very high with the manually determined parameter boundaries. Also, the setting time varies very strongly between only two individuals at minimum and 84 tested individuals at the maximum. Considering that for each individual 100 workpieces run through the system, 8,400 workpieces have to be tested, before the feeding system reaches a satisfactory orientation rate. In addition, the determination of the boundaries of the nozzle pressure p took an experienced operator ten minutes on the feeding system. Using the simulation based parameter prediction framework, this additional preparation time is omitted. Furthermore, the parameter boundaries predicted by the framework lead to a much shorter setting time with less variation. Looking at the results of workpiece W2, we observed that even though the setting time is much shorter than for W1, the parameter prediction still cut the average number of tested individuals as well as the standard deviation in half. Here, the determination of the boundaries of p took eight minutes. The results of W3 are remarkable. While the genetic algorithm took an average of 20.5 individuals to find a satisfactory solution with the manual boundaries and a random start population, the start population provided by the framework produced satisfactory high orientation rates at the first tested individual in each of the ten test runs. The determination of the boundaries of the nozzle pressure took six minutes. This shows the potential of the simulation based parameter prediction framework to reduce the retooling time of the aerodynamic feeding system, by eliminating the need for manual preparatory work and drastically reducing the setting time.

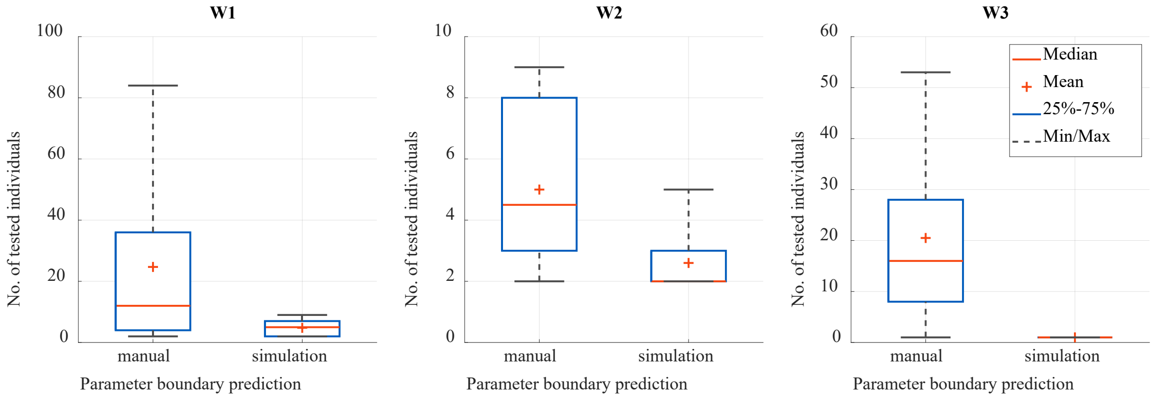

Figure 8: Number of tested individuals needed to reach an orientation rate of 95 % for different workpieces with manual and simulation based parameter boundary prediction

7. Conclusion and outlook

The experiments carried out with three simple exemplary components show very promising results regarding the reduction of the setting time, variation of the setting time and manual labor. For the three different workpieces, we reduced the number of parameter settings that had to be tested by the feeding system by 80, 50 and 95 %. We also reduced the standard deviation of the number of tested parameter settings of ten test runs by 90 and 60 % for the workpieces W1 and W2 respectively. Furthermore, a manual pre-prediction of the nozzle pressure range is no longer necessary. We therefore conclude that the parameter boundary prediction based on our extended simulation model is capable of drastically reducing the setting time and effort and increasing the flexibility of the aerodynamic feeding system.

In future work we will further extend the simulation model in order to increase the complexity of the workpieces that can be simulated and the precision of the parameter prediction. Preliminary experiments with more complex workpieces show that the parameter prediction framework does not always predict the best parameter boundaries. When the solution space determined by the simulation model is not as densely clustered as with the workpieces tested in this work, the mean and standard deviation do not accurately represent practical parameter boundaries. In order to resolve this issue, one aspect of future work will be the implementation of dynamic parameter boundaries for the genetic algorithm. In the current state, interrelations of the parameters are not considered; therefore, the solution space is always cuboid (assuming a solution space spanned by three parameters. Taking into account interactions between the parameters, the solution space determined by the simulation could be represented more accurately.

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Biography

Torge Kolditz (*1993) has been a research associate at the Institute of Assembly Technology (*match*) since his graduation in mechanical engineering in 2018, where he researches in the field of automated assembly.

Jakob Hentschel (*1997) studies mechanical engineering and looks forward to graduate with a bachelor's degree in 2021. Since 2019, he has been working as a student research assistant at *match*.

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Annika Raatz (*1971) has been the head of *match* since its establishment in 2013. Prof. Dr.-Ing. Annika Raatz is a member of the Society for Assembly, Handling and Industrial Robotics (MHI) and the Academic Association for Production Technology (WGP). Her main research topics are robot aided handling processes, machine concepts for handling, assembly and production automation and soft material robotic systems.