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Batch time optimization for an aerodynamic feeding system under changing ambient conditions

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ABSTRACT

In order to meet the demands for flexible feeding technology, a self-learning aerodynamic part feeding system has been developed. The actuated system uses a genetic algorithm to find the optimal parameter set for a high rate of correctly oriented parts. This orientation rate can change due to changes in the ambient conditions (e.g. ambient pressure, coefficient of friction). When the orientation rate in pre-defined interval of parts drops below a determined value, a correction algorithm is triggered. The objective of this work is to develop a mathematical model to define the optimal control interval and limit of the orientation rate for triggering the corrective algorithm depending on the total amount of parts still to be fed at any point in time. To evaluate the mathematical approach, a macroscopic simulation model of the aerodynamic feeding system was developed. It was shown, that the feeding time of a batch of 10,000 parts can be reduced by up to 7% and the number of activations of the corrective algorithm can be reduced by up to 50%. Finally, the mathematical model was implemented in the system control.

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1. Introduction

Due to the constantly increasing requirements of the buyer market with regard to customer-specific products, high quality and low cost, more efficient production systems are required (Chryssolouris et al., 2008). Automation allows process times and deviations to be reduced and mitigated and thus to achieve more efficiency (Burggräf et al., 2019). Focusing on assembly systems, the primary work process often cannot be automated because of products diversity (Spengler et al., 2005; Feldmann and Junker, 2003; Haller, 1999). Studies show, that in a typical automated assembly system up to 75% of the cost are allotted to transport- and feeding systems and just 20% to the essential primary assembly system (Krüger et al., 2009). The efficient material supply for work systems with a high product diversity is thus an important aspect of cost reduction in modern production systems. The provision of workstations with changing parts, depending on the production plan and the customers demand, requires flexible but still reliable and efficient feeding systems (Tay et al., 2005). Several researchers enhanced traditional vibratory bowl feeder to achieve a more flexible system. This research mostly focused on the improvement of the separation and then the detection of the parts orientation by camera and sensor systems to enable individual twist of parts (Tay et al., 2005; Suzuki and Kohno, 1981; Maul and Goodrich, 1985; Maul and Ou-Yang, 1987; Cronshaw et al., 1980; Warnecke et al., 1991). The self-learning aerodynamic feeding system developed at the IFA[b] and enhanced at the match[a] allows a high and constant feeding rate for workstations in modern assembly systems (Busch et al., 2015). During an initial or reconfiguration of the system using a genetic algorithm, the optimal parameter set for a high feeding rate is found. The initial configuration must be performed when a new product is supplied and thus a new part needs to be fed to the workstation. Changing ambient conditions and process uncertainties can cause fluctuations in the feeding rate. At each point of the feeding process, based on the actual feeding rate and the remaining batch size, a decision has to be made, if a reconfiguration is reasonable. Consequently, a mathematical model is required to make the optimal decision about the timing of the reconfiguration in order to minimize the batch time.

In the following sections the aerodynamic feeding system is introduced, the research gap is highlighted, the mathematical model

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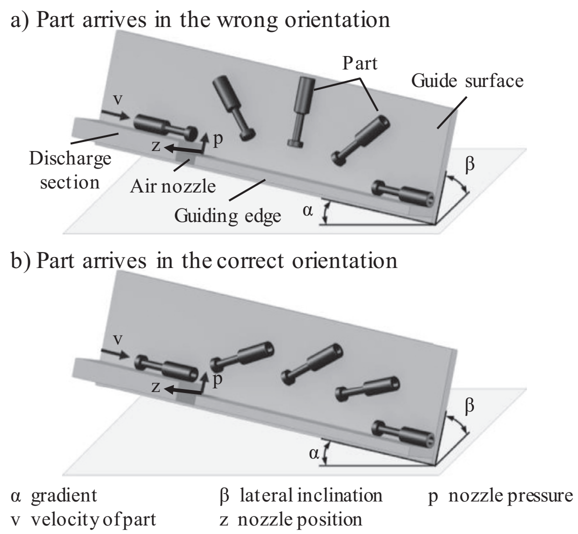

Fig. 1. Illustration of the aerodynamic orientation procedure with pneumatic blind plugs and the parameters to be selected (Busch et al., 2016; Kolditz et al., 2020).

for finding the timing of reconfiguration is explained and the evaluation of this mathematical approach is shown.

2. The aerodynamic feeding system

The aerodynamic feeding system consists of three different modules each with specific tasks. In the first module, a centrifuge separates the parts and feeds them individually to the next module. In the second module, the parts are oriented with only one homogenous air stream, which is different to other systems where multiple air nozzles are used for the orientation process (Lorenz, 1999; Rybarczyk, 2004). The third module consists of an optical check where misoriented parts are detected (Busch et al., 2015).

The second module is the main component of the system. The rotationally symmetric parts arrive at the air nozzle individually and are oriented due to their varying projected inflow area along the longitudinal axis. Therefore, only two states of orientation are distinguished (cf. Fig. 1a and b). The orientation procedure is controlled by a set of only five parameters (Fig. 1).

These parameters are the gradient α, the lateral inclination β, the speed of the parts v, the nozzle pressure p and its position z (Fig. 1). They need to be selected so that misoriented parts are turned by 180°, while correctly oriented parts retain their orientation (Busch et al., 2015). The ratio of correctly oriented parts to the total amount of parts defines the orientation rate, the high value of which represents the objective of a good feeding system because of the direct effect on the feeding rate. The changes of the parameters and parameter-combinations have different intensive effects on the orientation procedure (Busch, 2016). Various experiments show that the pressure p has the highest impact, followed by the combination of p and the parts speed v on the orientation rate (Busch, 2016). In addition, the parameterization of the system for new parts needs a lot of time and expertise with the equipment, even though the effects of parameters are known (Tay et al., 2005; Suzuki and Kohno, 1981).

Therefore, a genetic algorithm was designed to solve the non-linear optimization problem of selecting a parameter set ensuring a high orientation rate ($>$ 95%) within the shortest necessary time (Busch et al., 2016; Busch, 2016; Busch and Knüppel, 2013). In this genetic algorithm, in every iteration the fittest individual presented by its actual orientation rate is chosen besides one other taken by roulette as parents for the next generation (combination of elite selection and fitness-proportional roulette wheel selection). The orientation rate is determined by measuring the orientation of 100 parts for each individual. For an efficient and target-oriented solution finding, the mutation rate is set to 55% and there is a uniform crossover chosen for the recombination (Busch and Knüppel, 2013).

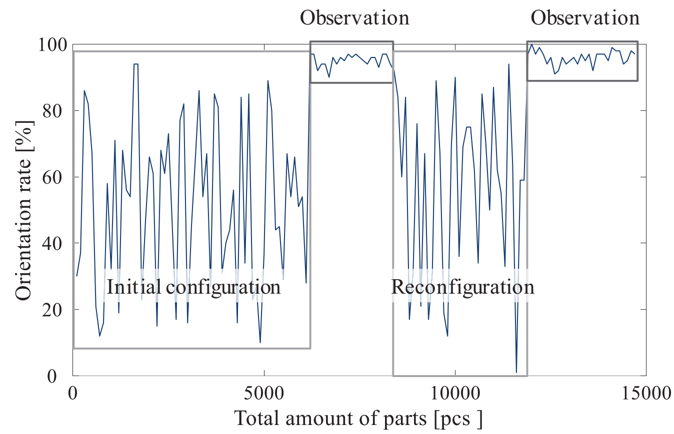

Fig. 2. Exemplary course of the orientation rate during the simulated feeding procedure of 10,000 parts.

Previous research has shown that the genetic algorithm is an efficient optimizer to find a sufficient parameter set in the shortest necessary time. In modern assembly systems, feeding systems are located in changing ambient conditions such as ambient pressure or temperature and thus coefficient of friction and also changing properties of parts in given quality limits. These changes lead to fluctuations and changes of the orientation rate as the observation intervals in Fig. 2 show. If the orientation rate falls below the necessary demand rate of the workstation the production stops. To ensure the feeding process and reduce the necessary batch time for the feeding process, it is essential to find the earliest possible timing for the reparametrizing of the system. Yet, it is important not to reparametrize too frequently, because of the unsteady feeding rate during reconfiguration (Fig. 2).

As shown in the exemplary course of the simulated orientation rate illustrated in Fig. 2, the initial and re-configuration take a long time to complete. In addition, the execution duration of the genetic algorithm to ensure a high orientation rate often shows a wide dispersion and is hardly predictable.

Consequently, an optimization model is designed to find the optimal timing for the reconfiguration of aerodynamic feeding systems and thus to optimize the batch time for the feeding process under changing ambient conditions and statistic uncertainties. This model is explained in the following section.

3. Dynamic threshold model

During the feeding process, the average orientation rate can change due to ambient conditions (Fig. 3). When the orientation rate drops under a defined limit value, the corrective algorithm is executed. One objective is to minimize the amount of reconfigurations, as the duration of the reconfiguration is hardly predictable and thus the resulting completion date of the feeding process. Still, if the orientation rate drops under a limited dynamic value the reconfiguration should be executed. The following figure illustrates this dynamic decision (Fig. 3). The first reconfiguration is worthwhile because without it, the feeding process would take a disproportionately long time, whereas the second reconfiguration (the duration of which is the same as the first) is useless. There is a benefit in time without this second reconfiguration.

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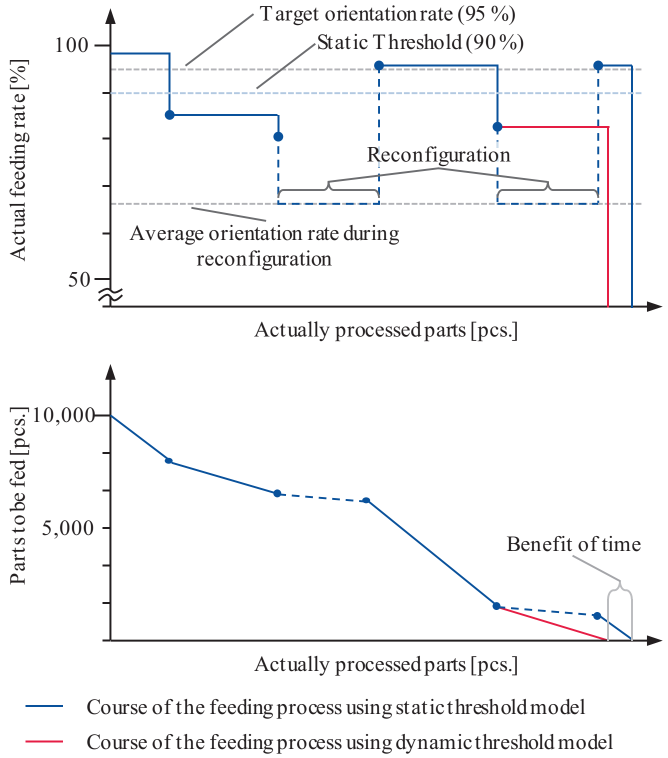

Fig. 3. Schemartic differentiation of the feeding process with static and dynamic threshold model.

The threshold of the orientation rate, at which a reconfiguration is still worthwhile, changes depending on the current orientation rate and the number of correctly oriented parts yet to be fed. Since these parameters change very dynamically - with each part - the decision model will be called dynamic threshold model in the following.

In order to evaluate if the execution of the corrective algorithm is reasonable at any point in time of the feeding process, it is calculated how long the feeding of the batch would take with and without the activation of the corrective algorithm. The input parameters for this calculation are the actual orientation rate, the number of correctly oriented parts yet to be fed and the expected duration of the corrective algorithm. To simplify the calculation, the total amount of processed parts (correctly and misoriented parts) that have to be fed in order to complete the batch is selected as evaluation criteria, since it is proportional to the feeding time.

Eq. (1) determines the total amount of parts under the assumption that no corrective algorithm is executed. $C_{total,1}$ represents the total number of parts needed to finish the feeding process, when the corrective algorithm is not triggered. $C_{correct}$ represents the current number of correctly oriented parts that still have to be fed in the batch and $OR_{current}$ stands for the current orientation rate.

$$Ctotal, 1 = \frac{Ccorrect}{ORcurrent} \tag{1}$$

Eq. (2) determines the total amount of parts to be fed, assuming that the corrective algorithm is executed once and the orientation rate will be 95% after that. The average orientation rate during the corrective algorithm was identified empirically as 57%. On average, the corrective algorithm takes 24 individuals of 100 parts each to reach an orientation rate of 95% or higher with a standard deviation of 18 individuals. Therefore, the total amount of parts statistically needed for the corrective algorithm is 2400, of which 57% are correctly oriented parts:

$$Ctotal, 2 = 2,400 + \frac{Ccorrect - 2,400 \cdot 0.57}{0.95} \tag{2}$$

Eq. (3) determines the amount of parts needed to finish the batch in case, the remaining number of correctly oriented parts is not sufficient to finish the corrective algorithm. Statistically, this is the case when there are less than 1368 correctly oriented parts left to feed:

$$Ctotal, 3 = \frac{Ccorrect}{0.57} \tag{3}$$

To decide if the corrective algorithm is triggered or not, the number of total parts to feed depending on the decision $C_{total,1}$, $C_{total,2}$ and $C_{total,3}$ are calculated and compared. If Eq. (1) delivers the lowest result, the corrective algorithm is not triggered and the feeding process proceeds. Should $C_{total,2}$ or $C_{total,3}$ be lower than $C_{total,1}$, the corrective algorithm is triggered.

The course of Eqs. (1)–(3) as function of the current orientation rate and the number of remaining correctly oriented parts is shown in Fig. 4. Fig. 5 illustrates the lines of intersections between the different functions. Looking at Figs. 4 and 5, it becomes clear, that the threshold at which a reconfiguration is still worthwhile decreases with the progression of the feeding process. It is therefore necessary to investigate the effect of the usage of a dynamic threshold on the batch time.

4. Macroscopic simulation model

The evaluation of the effectiveness of the dynamic threshold model presented in Section 3 on the real aerodynamic feeding system with statistical validity would entail an unfeasible effort. Therefore, a macroscopic simulation model is developed. The term macroscopic is used to make clear that, in contrast to the existing simulation model developed by Busch (2016), the actual aerodynamic orientation process is not simulated, because it would present an unfeasible computing effort. Instead, each parameter set, representing one individual of the genetic algorithm, is assigned a probability of success for the orientation process. Based on this, the orientation success is determined for each part. It is not necessary to calculate the movement of each part, because the objective of the evaluation is to show that the dynamic threshold model can cope with changing ambient conditions better than the existing system control. The macroscopic model allows considerable savings in computing time compared to the model mentioned above (Busch, 2016). In order to achieve a realistic representation of the feeding process in the evaluation, the distribution of the probability of success is derived from empirical data from test runs with the part seen in Fig. 1. The model can essentially be divided into four parts, which are presented in the following.

4.1. Initial configuration

Analogous to the real aerodynamic feeding system, the first step is the initial configuration of the system parameters. In the real application, the genetic algorithm would create a random set of parameters, evaluate them and then select, recombine and mutate them. In the macroscopic simulation model, the creation of parameter sets is not necessary. Instead, each set of 100 parts representing one individual of the genetic algorithm is assigned an orientation probability OP_{set} between zero and one, representing the orientation rate. Because the appearance of the orientation rates is not linear divided between zero and one with the real system, OP_{set} is determined using roulette wheel selection. The roulette wheel has 101 sections representing orientation rates between zero and one. The size of the sections represents the distribution of orientation rates of 340 parameter combinations acquired in real test

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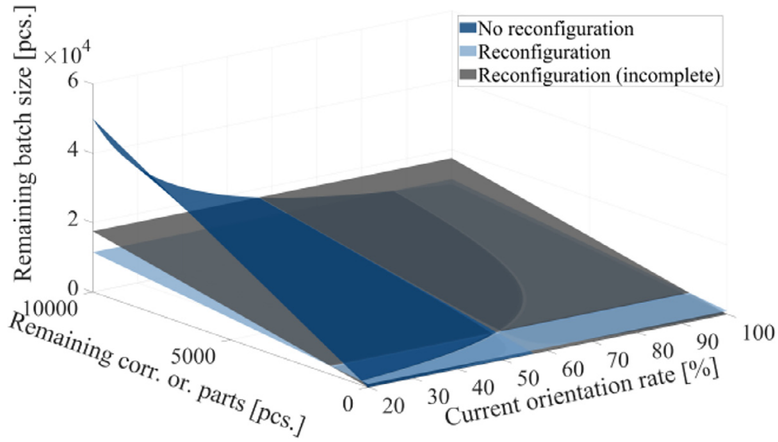

Fig. 4. Three-dimensional representation of the dynamic threshold functions.

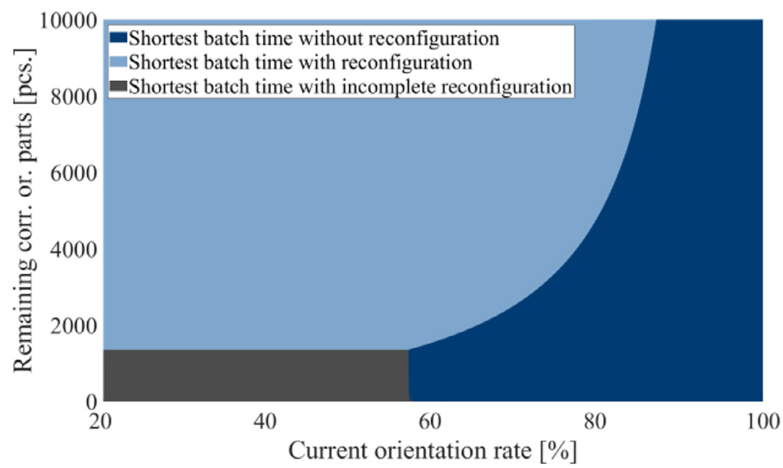

Fig. 5. Intersecting lines of dynamic threshold functions - optimal solution for given situation.

runs with the part seen in Fig. 1. Then, each part of one set receives an individual random value OP_{ind} between zero and one, which is compared to the orientation probability of the set. If OP_{ind} is smaller than OP_{set} the part will be considered a correctly oriented part. Otherwise, the part is considered to be leaving the system in false orientation. The objective of this method, which will be used through the entire simulation model, is to bring statistical deviations into the model to achieve a more realistic representation of the real feeding system. The initial configuration is finished when one set of 100 parts reaches an orientation rate $OR_{\mathrm{set}} \geq 0.95$. The model then switches into observation mode, which is described in the next section.

4.2. Observation mode

The objective of the observation mode is to determine the orientation rate during operation of the virtual feeding system. The decision to trigger the corrective algorithm (Section 4.3) is based on the orientation rate. In reality, reasons for changing of the orientation rate are changes of ambient conditions like ambient air pressure and friction due to pollution of the system. Since the physical orientation process is not represented in the macroscopic simulation model, a representation of the aforementioned ambient conditions is not possible. Instead, the change of orientation rate is induced by events that can occur at any given time during the operation of the system. The frequency and impact of the events can be set as parameters in the model configuration.

The decision whether the corrective algorithm is triggered depends on the model used. In the static threshold model, the corrective algorithm is triggered when the orientation rate falls below a previously defined limit. With the dynamic limit, it is decided individually whether reconfiguration is statistically still worthwhile or whether it is more effective to continue feeding with a reduced orientation rate. The orientation rate is determined using a moving average of 100 parts.

4.3. Corrective algorithm

The corrective algorithm works analogous to the initial configuration, also using a genetic algorithm (Busch, 2016). For the simulation model the difference between the initial configuration algorithm and the corrective algorithm is that the orientation probabilities for each set OP_{set} are determined with a different roulette wheel. The size of the roulette wheel sections for the corrective algorithm is derived from the distribution of orientation rates of 647 parameter combinations recorded at the real feeding system, analogous to the roulette wheel for the initial configuration. On average, the corrective algorithm converges faster than the initial configuration.

4.4. End of simulation

The simulation ends immediately as soon as the number of correctly oriented parts specified by the user was fed. The outputs of the simulation model for further analysis in this work are the time

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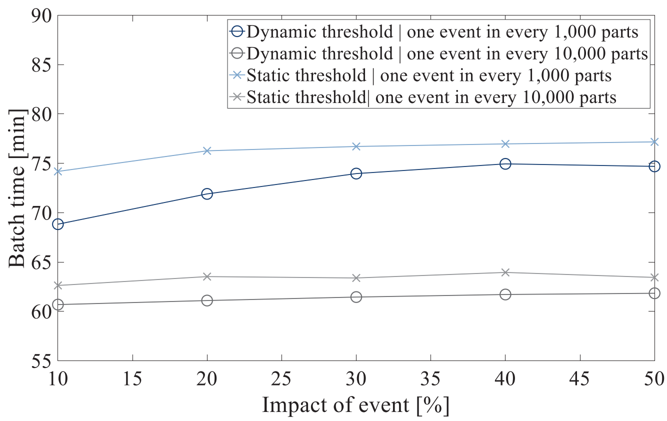

Fig. 6. Average batch time for 10,000 parts in dependence to impact and frequency of events with dynamic and static threshold.

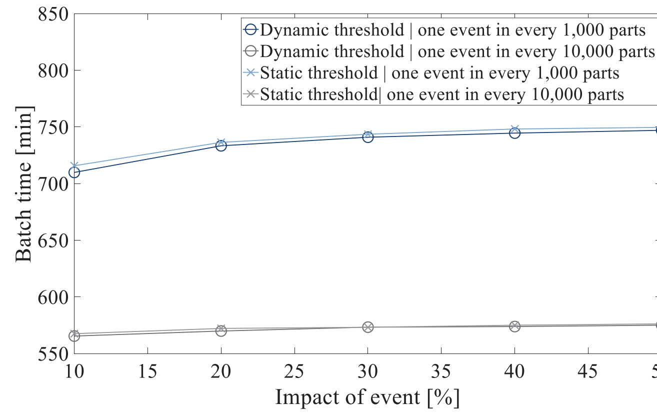

Fig. 7. Average batch time for 100,000 parts in dependence to impact and frequency of events with dynamic and static threshold.

needed to complete feeding process (in minutes), the number of events and activations of corrective algorithm and the timings of events and activations of corrective algorithm. The outputs will be used in the following section to evaluate the optimization model presented in this paper.

5. Evaluation of the dynamic threshold model

The main objective of the optimization model is to minimize the feeding time and therefore the number of misoriented parts. Another objective is the reduction of the number of activations of the corrective algorithm because it reduces the impact of the statistical uncertainty regarding the setting time of the genetic algorithm. This is because the setting time of the corrective algorithm cannot be predicted but only be estimated. Therefore, fewer activations lead to higher predictability of the feeding process.

To evaluate the effect of the optimized, dynamic threshold model, it is implemented in the macroscopic simulation model. The benefit of the dynamic threshold model over the static threshold model will be assessed by the average batch time required to feed all parts of 1000 simulated runs each and the number of activations of the corrective algorithm.

5.1. Feeding time

To evaluate the effect of the dynamic threshold model on the feeding time a test plan needs to be set up, which maps the influence of different parameters like batch size, as well as frequency and impact of the events. The batch size describes the number of correctly oriented parts to be fed. The frequency determines how often an event occurs statistically during the observation mode. A frequency of 1‰ means that, statistically, every 1000 parts an event occurs. The impact of an event determines how much the orientation probability can maximally drop due to an event. The actual drop is defined by multiplying the impact with an evenly distributed random number between zero and one. Figs. 6 and 7 show the average batch time of different parameter combinations and a batch size of 10,000 and 100,000 parts, respectively. Each dot represents the average batch time of 1000 simulation runs with randomly generated events according to the frequency and impact shown in the legend and the x-axis.

The results in Figs. 6 and 7 show that the use of the dynamic threshold model reduces the average batch time regardless of the selected parameter combination. Nevertheless, the effect of the dynamic threshold model is bigger with the batch size of 10,000 parts compared to 100,000 parts. The reason for this is that the advantages of the dynamic threshold model only start to pay out

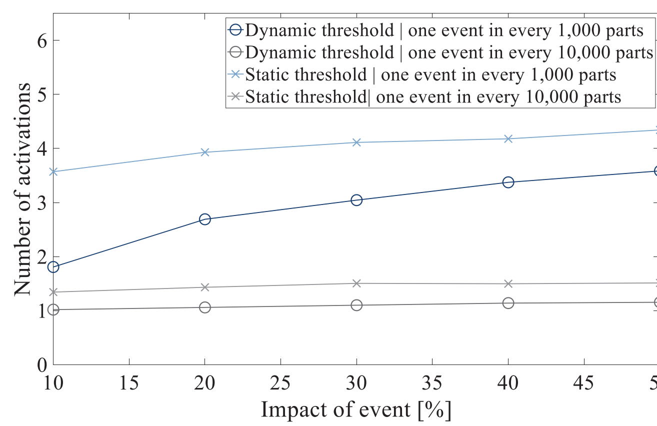

Fig. 8. Average number of activations of corrective algorithm during batch of 10,000 parts with dynamic and static threshold.

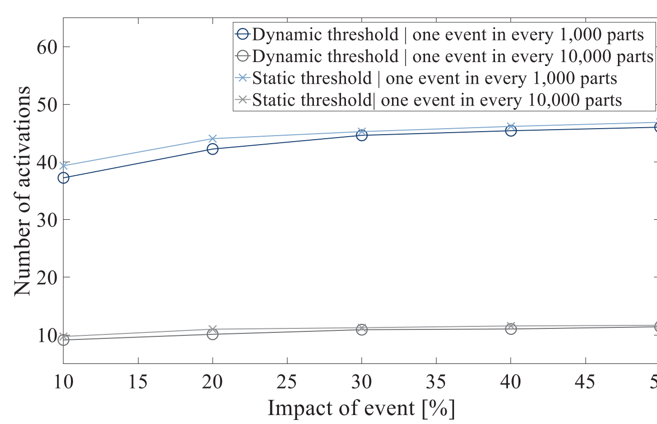

Fig. 9. Average number of activations of corrective algorithm during batch of 100,000 parts with dynamic and static threshold.

towards the end of the feeding process (cf. Fig. 5). If the batch size is very large, for most of the feeding time the dynamic threshold model triggers the same actions as the static threshold model. Therefore, the relative time saving decreases.

It can also be seen that an increasing frequency and impact of the events have a negative influence on the batch time. This makes sense since both the frequency and the impact substantially influence the decrease of the orientation rate and therefore the number of corrections needed during one batch.

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5.2. Number of activations of corrective algorithm

Another objective of this work is the reduction of the number of activations of the corrective algorithm in order to increase feeding stability. Apart from the reduction of the statistical uncertainty going along with the corrective algorithm already mentioned above, the setting of the system with the genetic algorithm leads to a very unstable output of correctly oriented parts due to the great variations of the orientation rate. For a stable automated process, it is therefore also an advantage to have as few corrections as possible. Figs. 8 and 9 show the number of corrections from the simulations already presented in Figs. 6 and 7, respectively.

It becomes clear that using the dynamic threshold model reduces the number of corrections. The reason for the lower number of corrections is that especially towards the end of the feeding process the static threshold model will always trigger the corrective algorithm when the orientation rate decreases below the tolerance while the dynamic threshold model will only trigger a correction when it is expected to reduce the total batch time.

6. Conclusion and outlook

The objective of this paper was to describe the developed model which reduces the batch time of an aerodynamic feeding system in varying ambient conditions. A dynamic threshold model was created, which determines whether reconfiguration is advisable at any given moment during the feeding process. This method stands in contradiction to the prior method with a rigid threshold to trigger the reconfiguration. Also, the developed model is not specifically limited to the application on the aerodynamic feeding system, since only the output of the system is evaluated. The orientation process and the geometry of the parts do not have to be considered in the decision making.

The effectiveness of the dynamic adaptation was evaluated with the use of a macroscopic simulation model of the feeding system. The macroscopic simulation model was developed to reduce the computing time in comparison to the existing simulation model by Busch (2016) for the 20,000 simulated test runs. The model is also not specifically limited to the aerodynamic feeding system since it is provided with empirical data. Evaluation showed that the new method can reduce the average batch time of a batch of 10,000 correctly oriented parts by up to 7%. Furthermore, simulations show that the dynamic threshold model reduces the number of activations of the corrective algorithm by up to 50%, especially for smaller batches, which makes the feeding process more predictable.

Future work will aim to develop methods to distinguish between outliers (e.g. caused by opening and closing of doors and gates) and permanent changes (e.g. caused by weather conditions) in the orientation rate. This way, the number of unnecessary parameter reconfigurations can be further reduced. Another objective of future work will be the implementation of a dynamic limit for the target orientation rate of the corrective algorithm, which is currently static at 95%. Experiments show, that the corrective algorithm often reaches orientation rates over 90% much faster than 95%. Therefore, by implementing a dynamic limit, the setting time of the corrective algorithm and the batch time can be reduced.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Torge Kolditz: Conceptualization, Software, Validation, Writing - original draft, Visualization. **Niklas Rochow:** Conceptualization, Methodology, Writing - original draft, Visualization. **Peter Nyhuis:** Resources, Supervision, Project administration. **Annika Raatz:** Resources, Supervision, Project administration.

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