Available online at www.sciencedirect.com

ScienceDirect

Procedia CIRP 44 (2016) 79 – 84

www.elsevier.com/locate/procedia

6th CIRP Conference on Assembly Technologies and Systems (CATS)

Implementation and testing of a genetic algorithm for a self-learning and automated parameterisation of an aerodynamic feeding system

Jan Busch[a]*, Sebastian Blankemeyer[b], Annika Raatz[b], Peter Nyhuis[a]

[a]*Institute of Production Systems and Logistics (IFA), Leibniz Universitaet Hannover, Garbsen 30823, Germany*
[b]*Institute of Assembly Technology (match), Leibniz Universitaet Hannover, Garbsen 30823, Germany*

* Corresponding author. Tel.: +49-511-762-19808; fax: +49-511-762-3814. *E-mail address:* busch@ifa.uni-hannover.de

Abstract

An active aerodynamic feeding system developed at the IFA offers a large potential regarding output rate, reliability and neutrality towards part geometries. In this paper, the procedure of a genetic algorithm´s into the feeding system´s control is shown. The genetic algorithm automatically identifies optimal values for the feeding system´s parameters which need to be adjusted when setting up for new workpieces. The general functioning of the automatic parameter identification is confirmed during tests on the convergence behaviour of the genetic algorithm. Thereby, a trade-off between the adjustment time of the feeding system and the solution quality is revealed.

Peer-review under responsibility of the organizing committee of the 6th CIRP Conference on Assembly Technologies and Systems (CATS)
Keywords: Assembly, Algorithm, Optimisation

1. Introduction

Innovative and flexible production processes are essential for the manufacture of customer-tailored products. One possibility for fulfilling these requirements is to design a self-optimising production [1]. For this reason, Park et al. utilise a conventional simulation on the basis of finite elements to improve production efficiency and to increase component quality during the manufacture of belt parts, and extended this with a self-optimising algorithm. Based on a practical example, they are able to show that the production efficiency can be increased by 30% due to the development of a system featuring self-optimisation [2].

This article focuses on the development of a self-optimising feeding system technology in automated assembly. This is of particular importance because it frequently represents a quality, time and costs bottleneck [3]. Due to the fact that feeding technology is also frequently slower than the process speeds of production and assembly systems, it can become the weak point of an entire production system [4]. This statement is confirmed through investigations which have shown that the overall availability of production and assembly systems is reduced as the number of feeding systems increase [5]. Moreover, in automated assembly, up to 75% of the equipment costs are caused by feeding technology. Therefore, this area offers huge potential for rationalisation [6].

The majority of feeding systems used at present are vibratory bowl feeders [7]. The wide incidence can be explained by many advantages. These include a very simple and compact structure, low purchase costs, a low maintenance effort and their wide range of applications [5]. But due to their specific construction, the vibratory bowl feeder is hardly variant flexible. Often, flexibility can only be achieved by a change in baffles which causes long setup times [8]. Therefore, much research has been done to improve the vibratory bowl feeder´s flexibility in the past. For example, easy changeable baffles have been designed [9]. Furthermore, workpiece-specific baffles were developed which can be coupled in any order within the vibratory bowl feeder [10]. But considering these achievements, either the setup procedure remained greatly time consuming or the vibratory bowl feeder became very susceptible to disturbances. A highly current approach is to divide the vibratory bowl feeder into modules with standardised interfaces which can be changed quickly and with little effort. However, this application is only economically feasible for a medium feeding performance [11]. An extremely flexible approach which promises short setup times is the use of feeding systems with optical workpiece

Peer-review under responsibility of the organizing committee of the 6th CIRP Conference on Assembly Technologies and Systems (CATS)
doi:10.1016/j.procir.2016.02.081

detection. But these systems are not yet capable of providing today´s required feeding performances [12]. All in all, conventional feeding systems either offer limited process speed or they lack in variant flexibility.

Thus, in future, further development and the introduction of innovative, self-optimising feeding systems represent a major source of potential and a decisive success factor for rationalisation, flexibility and increases in the availability of production systems.

In the course of this investigation, an aerodynamic feeding system was developed at the Institute of Production and Logistics (IFA) at Leibniz Universitaet Hannover, in which the feeded workpieces are orientated using a homogenous air flow field. In this article, it is shown how the aerodynamic feeding system is developed into a self-optimising system using a genetic algorithm. Furthermore, the function and results of the self-parameterisation of the aerodynamic feed system are presented in a real operating situation.

2. Basic principles

2.1. Functional method of aerodynamic orientation

The functional method of the aerodynamic feeding system is presented in Figure 1. The process uses special air flows and the asymmetry of workpieces. Workpieces can be asymmetrical due to an eccentric centre of gravity or an asymmetrically projected form. The feeding system consists of a guide level vertically inclined in guide direction by the gradient angle α and the inclination angle β, and a guide edge standing vertically on it.

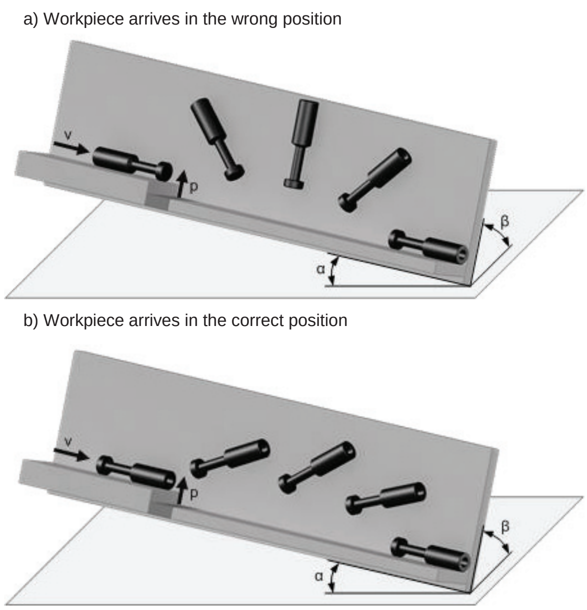

Fig. 1: Illustration of the aerodynamic orientation process

In the guide edge, there is an air nozzle which emits a constant vertical air flow with an adjustable air pressure *p*. The components to be orientated are individually separated in an upstream vibratory bowl feeder and fed at a defined speed *v* via a guide level infeed conveyor and, due to the inclinations, slide down the guide edge. As they pass the air nozzle, each workpiece is provided with a momentum which makes them turn. The feeding system must be adjusted in a way that the angular momentum is not sufficient to turn components which are already correctly orientated, but which is large enough to turn incorrectly orientated workpieces for correct orientation. The four parameters gradient angle α, inclination angle β, the air pressure of the air nozzle *p* and the feeding velocity of the workpieces *v* are the parameters the system can be adjusted with in accordance to the workpieces being fed in. At the end of the sliding edge, a high-speed camera is mounted which checks the orientation of the workpieces.

The setting of the feeding system is limited to the adaption of these aforementioned parameters [13]. The determination of optimum parameter values for the achievement of a high orientation quality does however represent a highly time-consuming and work-intensive process. The same applies for the adaptation of the system settings for altered ambient conditions such as an altered ambient air pressure or humidity, which can influence the system characteristics through the open design of the feeding system. One highly-promising approach for the minimisation of the time and effort involved is the independent and self-optimising parameterisation [14]. For this reason, in prior research activities a genetic algorithm has been developed in Matlab which independently identifies the optimum values for the four operating parameters in a simulation model of the aerodynamic feed system.

2.2. Application of a genetic algorithm for aerodynamic orientation

In this section, the genetic algorithm of the aerodynamic orientation is briefly explained. A genetic algorithm has been chosen because it offers the possibility to evaluate generated solutions by means of the orientation rate. Furthermore, genetic algorithms investigate search spaces intelligently. This is necessary in the optimisation problem observed in this paper due to the high number of possible parameter configurations. Additionally, genetic algorithms offer the potential to simultaneously satisfy the two objectives of scanning the whole solution space while reducing the computational time [15] and have thus been successfully applied in many machine learning problems [16].

Genetic algorithms start with the initialisation of a start population, which consists of randomly generated chromosomes. After this, new generations are created in steps through the application of two operators: the crossover operator and the mutation. Whereas with the crossover so-called parent chromosomes are combined with each other to produce new chromosomes, with mutation only one element of a chromosome is locally modified. The selection of chromosomes for crossover and/or mutation processes is based on the fitness value or respectively on the suitability of the respective chromosome with regard to a preferably good solution of the optimisation problem.

The principle of genetic algorithm when applied to the process of aerodynamic orientation is shown in Figure 2.

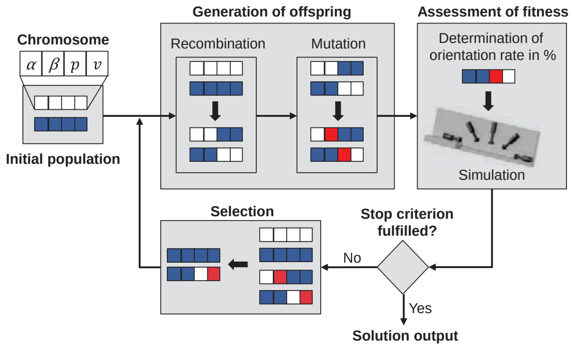

Fig. 2: Functional principle of the genetic algorithm for aerodynamic orientation [13]

Here, a chromosome consists of the four operating parameters of the aerodynamic feeding system. Numerous simulation studies have shown that in this particular case of optimising the feeding system´s parameters a combination of elite and roulette wheel selection, the application of the uniform crossover as recombination mechanism, a mutation rate of 58% and a population size of four chromosomes favour fast convergence. The assessment of the fitness is conducted on the basis of the orientation rate, which states the ratio of correctly-orientated workpieces to the overall quantity of workpieces. Consequently, a chromosome´s fitness equals the orientation rate which can be reached when the feeding system´s operating parameters are set to the values that are represented in the chromosome structure. A chromosome´s fitness is evaluated with the aid of an approximated mathematical fitness function. This function was determined by carrying out extensive test series conducted on the real-life system within the framework of a design of experiments [17]. By using this fitness function, the values of the four feeding system´s parameters only need to be inserted into this function and the corresponding chromosome´s fitness which equals the orientation results. In future, the respective fitness values per chromosome should be measured in the real feeding system. To do this, the implementation of the genetic algorithm into the feeding system controller is required, which is described below.

3. Set-up and operation of the self-optimising aerodynamic feeding system

3.1. Embedding of the required actuators and sensors

The development of a self-optimising aerodynamic feeding system includes, in addition to the implementation of the genetic algorithm into the feeding system controller, the automatic adjustment of the four operating parameters gradient angle α, inclination angle β, nozzle air pressure p and the speed v of the infeed conveyor. To do this, the embedding of appropriate actuators and sensors is required.

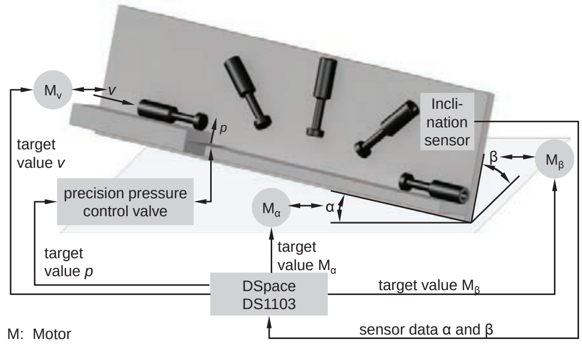

Fig. 3: Principal setup of the feeding system´s components

As shown in Figure 3, the main component of the selected setup is a DSpace DS1103-Controller with the associated prototyping software. On this controller, there runs the software consisting of the generic algorithm and the signal processing. To automatically adjust the feeding system, three motors are mounted and a precision pressure control valve is fixed to set up the air flow at the nozzle. The motors are needed to control the gradient angle α, the inclination angle β and the speed v of the infeed conveyor.

The target values for the gradient angle α, the inclination angle β, the nozzle pressure p and the velocity v are generated by the genetic algorithm. These values are transmitted to the actuators by the DSpace Controller. Furthermore, the actual gradient and inclination angles measured by the inclination sensor on the feeding system are continuously transferred onto the controller. In the subsequent process, an example of the procedure for automatic adjustment is shown for the gradient angle α and the inclination angle β.

In order to implement the adjustment of the angles, their actual values must first be read in. The signal flow diagram implemented for this purpose is clarified in Figure 4.

The sensor signal is read in via the digital RS232 input of the DSpace-Controller in discret scanning steps as an ASCII code (Serial Receive). In the Matlab function, the ASCII raw data (u) is prepared through conversions and transferred as variables x and y to the Simulink model. The values x and y thus represent the gradient angle α and the inclination angle β.

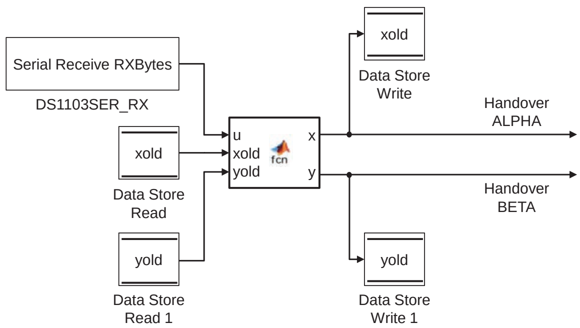

Fig. 4: Processing of the inclination sensor data

In order to prevent malfunctioning of the system due to incorrect sensor data, a plausibility check is conducted within the Matlab function. To do this, the angles determined in the previous program sequence for the gradient and inclination *xold* and *yold* are read in and compared with the newly-calculated angles. If the newly-calculated angles deviates more than 3° from the old values, it can be assumed that the sensor or algorithm has provided incorrect angle data. For this reason, the old value is retained and re-determined in the next run, so that no damage can occur to the system.

After determination of the actual values, these are transferred as an input parameter to the controller. The explanation is shown as an example with the gradient angle α in Figure 5. The process for the adjustment of the inclination angle β works similarly.

In order to adjust the angles automatically, two asynchronous motors with the appropriate frequency converters are used for control. The target speeds are transferred via an analogue interface (-10 V to +10 V) from the DSpace Controller to the frequency converter. The attendant signal flow diagram for the determination of these values is shown in Figure 5 for the gradient angle α. At the beginning, the actual value (transfer of gradient angle α) determined by the sensor is subtracted from the target angle determined by the genetic algorithm (input ALPHA). Here, a safety block is also set between the target value transfer (input ALPHA) and the subtraction block so that implausible values which might be transferred from the genetic algorithm are prevented.

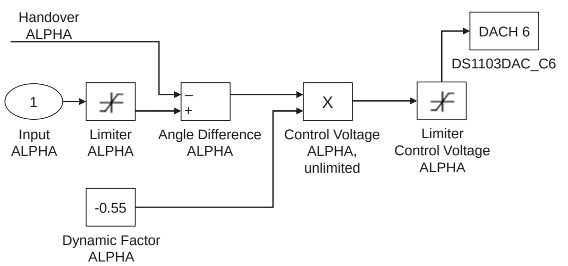

Fig. 5: Generation of the motor control voltage

The angle difference is converted into an output value or respectively an associated motor control voltage by multiplying the difference with a factor of -0.55. The factor of -0.55 has been proven advantageous with regard to the adjustment time of the system in practical tests on the feeding system. The negative sign for the gradient results because a positive angle difference causes a negative motor rotational direction. The downstream block (limitation of the ALPHA control voltage) limits the characteristic curve to values between -0.35 and +0.35, which results in a motor control voltage of -3.5 V to +3.5 V. This limitation has proven advantageous during the commissioning of the system as the motor tends to conduct severe overshooting during angle adjustment when operated at maximum speeds. The output value of this block is provided via an analogue controller output as a control voltage on the frequency converter for the adjustment of the gradient angle α. The signal flow diagram for the adjustment of the inclination angle β is, as mentioned above, constructed analogously.

The nozzle pressure *p* is set via a precision pressure control valve which adjusts the nozzle pressure specified by the genetic algorithm based on a control voltage. The infeed belt velocity *v* is adjusted, similar to nozzle pressure *p*, via a control voltage in accordance with the value specified by the genetic algorithm. The according signal flow diagrams of the parameters *p* and *v* are not presented here due to their simplicity in comparison to the signal flow diagram for the gradient angle α or the inclination angle β respectively.

3.2. Implementation of the genetic algorithm

The DSpace-Controller can be programmed by using the ControlDesk software. This software requires the transfer of the genetic algorithm already existing in Matlab into a signal flow diagram. Thereby, it must be considered that the program sequence of a signal flow diagram differs from a script in Matlab. The decisive difference is that the Simulink Model is not executed from top to bottom as it is in a Matlab program, but rather is conducted multiple times due to a continuous time simulation. But the genetic algorithm process has to take place stepwise in a fixed defined sequence. This is realised via the installation of different conditions which have to be fulfilled so that an appropriate program part is executed. Figure 6 clarifies the process chart in the form of a schematic diagram.

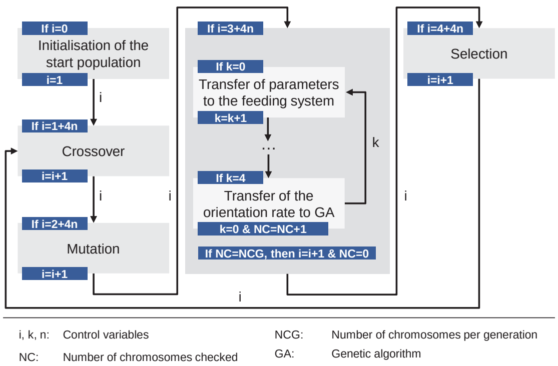

Fig. 6: Program flow chart

The program flow chart shows that the program sequence, after creation of the first generations, is compiled of two loops. The outer loop with the control variable *i* carries out the operators of the genetic algorithm, i.e. the creation of new chromosomes through crossover, mutation and selection. The inner loop with the control variable *k* carries out the adjustment of the feeding system onto the parameters of the new chromosomes as well as the determination and the storage of the associated orientation rates. This inner loop accords with the program part which was previously conducted via simulation (see Figure 2). The steps between the transfer of the parameters to the feeding system and the transfer of the orientation rate have not been shown in Figure 6 to improve the comprehension. These steps include the counting of the workpieces which are required for the determination of the orientation rate of one chromosome.

Using this sequence, it is now possible to adjust the results for setting the parameters of the genetic algorithm using the DSpace Controller on the feeding system with the aid of the appropriate actuators and to use the actual values from the feeding system (orientation rate per chromosome) in the algorithm.

3.3. Presentation and interpretation of the results

Whereas the procedure of making the real feeding system capable of automatic parameter optimisation has been described in Section 3.2, this section presents the initial results of the functional method of the self-adjusting system. Thereby, the focus is placed in particular on the number of required workpieces which have to run through the process until a required orientation quality is achieved. Especially, it has to be found out how many workpieces have to be considered for evaluating the fitness of one chromosome. Or to put in other words for determining the orientation rate that results when applying the feeding system´s parameters which are represented by that specific chromosome. Only after an optimum number of considered workpieces per chromosome is determined, accurate tests on the convergence behavior of the genetic algorithm can be made. The number of workpieces to be considered per chromosome influences the time to find a desired orientation decisively. Therefore, this number is of very high relevance. The time increases as the quantity of chromosomes needed in order to find an optimal solution grows. And it can be assumed that the number of chromosomes increases when more workpieces per chromosome are considered in order to evaluate its fitness. Because it is more likely, considering a parameter configuration that leads to an orientation rate of 99%, that ten out of ten workpieces are correctly orientated than 99 out of 100 workpieces. As a result, an orientation rate of at least 99% as a stop criterion is reached slower when the considered workpieces have high values in order to assess the chromosome´s fitness. This aspect is also shown in Figure 7.

The genetic algorithm was initially conducted with a changeable quantity of considered workpieces per chromosome *j*. For each value of *j*, five tests were made in the real-life aerodynamic feeding system. Thereby, the number of workpieces required until a parameter configuration which led to an orientation of at least 99% was counted using an optical check unit at the end of the guide level. When performing tests on the real-life feeding system it has to be considered that some time is required for the adjustment of the system to new parameter values by the actuators. But a determination of the chromosome´s fitness can only be started when this adjustment process is complete. There is thus a number of workpieces required, which has to be passed through the feeding system before a new a fitness can be assessed. In the real-life experiments made, a number of ten workpieces has been proven as a reasonable compromise between a complete setting of the feeding system and a least possible loss of time for parameter setting. This number is included in the quantity of workpieces needed in Figure 7.

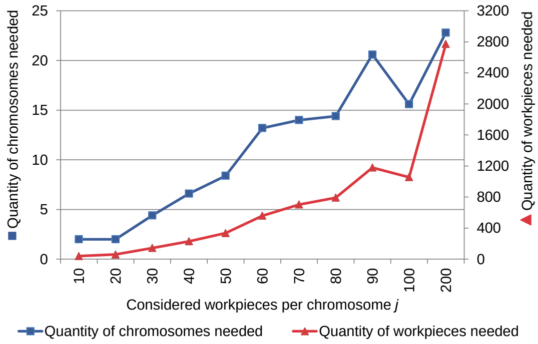

Fig. 7: Chromosomes and workpieces needed in dependence on the workpieces per chromosome

As expected, the average quantity of chromosomes required to achieve an orientation rate of at least 99% increases as the quantity of considered workpieces per chromosome *j* increases. The minimum quantity is achieved for $j = 10$ and $j = 20$. A further increase of *j* leads to an increase in the average quantity of parameter configurations to be tested.

The local minimum at $j = 100$ is explained by the fact that up to a number of 90 workpieces all of them need to be correctly orientated in order to achieve an orientation rate of at least 99%. By reaching a *j* of 100, this orientation rate is also attained when one workpiece is not correctly orientated. In the conducted tests with the workpiece which is shown in Figure 1, the maximum quantity is achieved for $j = 200$ with an average total quantity of 23 chromosomes. Considering the aforementioned population size of four chromosomes per generation, this quantity correlates to six generations needed until the genetic algorithm converges.

The very fast convergence results from the characteristics of the workpiece used. This workpiece fulfills the requirements for the aerodynamic orientation of an eccentric centre of gravity and an asymmetrically projected form to a high degree. The use of workpieces with less pronounced orientation characteristics leads to a significant increase in the required number of generations to find solutions.

Besides the number of required generations until the genetic algorithm converges, a similarly decisive parameter is the total quantity of workpieces to be fed per run of the genetic algorithm. This quantity increases in case of an increase in *j*, not only through the increase in chromosomes to be tested, but also directly through the increase in workpieces per chromosome. The progression of the quantity of needed workpieces until the required orientation rate is achieved is also presented in Figure 7. This value ranges from 40 workpieces in case of $j = 10$ to nearly 2.800 workpieces in case of $j = 200$.

Furthermore, the considered workpieces per chromosome *j* also have an implication on the statistical significance of a chromosome´s fitness. Because the more workpieces are considered per chromosome, the more likely the measured orientation reflects the actual prevailing orientation rate of a specific parameter configuration in a steady state. On the basis of simulations, it has already been proven in [14] that the quality of a solution identified by a genetic algorithm with small *j* is unsatisfactory but increases along with *j*.

In order to prove this finding, in a further series of tests, the real-life aerodynamic feeding system was set to the parameter configurations which were determined by the genetic algorithm within the scope of those tests which were made for receiving the results shown in Figure 7. During these tests, 500 workpieces were fed in per configuration and the achieved minimum and maximum orientation rate were determined. The results are shown in Figure 8. It is obvious that low values of *j* lead to large differences between the minimum and maximum orientation rate. This large scatter of the orientation rate leads to low statistical significance of a chromosome´s fitness.

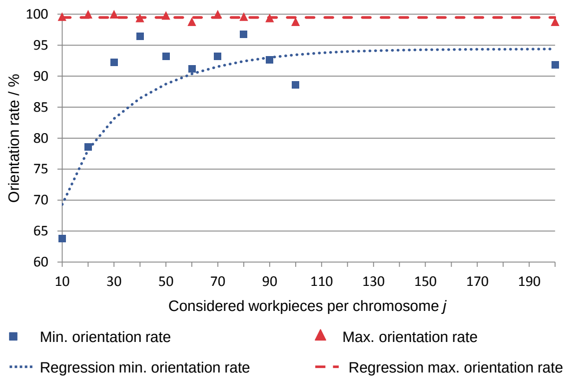

Fig. 8: Orientation rate in dependence on the workpieces per chromosome

The results of the simulation could thus be confirmed. This finding results in a trade-off between the adjustment time of the feeding system and the solution quality. This trade-off needs to be investigated first in further research activities before further tests on the convergence behavior of the genetic algorithm, for example in dependence of different initial chromosome configurations, can be made.

4. Summary and outlook

In this article, the procedure for the implementation of a genetic algorithm into the control of an aerodynamic feeding system for high-speed assembly is presented. The feeding system is thus capable of independently determining the optimum parameter configuration with the aim of a preferably high feeding quality for hitherto unknown workpieces. Furthermore, the general functional method of the automatic parameter identification by the feeding system based on attempts at convergence behavior of the genetic algorithm dependent on the workpieces to be fed in during the identification of optimum parameter values was confirmed. Here a trade-off between the adjustment time for the feeding system and the solution quality or respectively the actual orientation quality prevailing during operation was revealed which has to be investigated in further research activities. Furthermore, trials should be conducted for the robustness of the functional method of the automatic parameterisation under fluctuating ambient conditions.

Acknowledgement

The authors would like to thank the German Research Foundation (DFG) for their financial support of the research project NY 4/51-1.

References

[1] Hoppe, G. (2014): High-Performance Automation verbindet IT und Produktion. In: Bauernhansl, T.: Indust-rie 4.0 in Produktion, Automatisierung und Logistik. Anwendung, Technologien, Migration. Wiesbaden: Springer Vieweg, p. 249–275.

[2] Park, H.-S.; Le, N.-T. (2014): Developing a Self-optimizing Forming System. In: Procedia Technology 15, p. 431–438.

[3] Lotter, B.; Wiendahl, H.-P. (2012): Montage in der industriellen Produktion. Ein Handbuch für die Praxis. 2nd edition. Berlin: Springer Berlin.

[4] Wiendahl, H.-P.; Rybarczyk, A. (2003): Using air streams for part feeding systems—innovative and reliable solutions for orientation and transport. In: Journal of Materials Processing Technology 138 (1-3), p. 189–195.

[5] Rybarczyk A (2004): Auslegung aktiver aerodynamischer Zuführverfahren. Dissertation, Leibniz Universität Hannover, Berichte aus dem IFA 1, PZH Produktionstechnisches Zentrum Garbsen.

[6] Fleischer J, Herder S, Leberle U (2011) Automated supply of micro parts based on the micro slide conveying principle. CIRP Annals – Manufacturing Technology 60/1, p. 13-16.

[7] Reinhart G, Loy M (2008) Flexible Feeding of Complex Parts. 2nd CIRP Conference on Assembly Technologies and Systems, Toronto, Canada.

[8] Reinhart, G.; Loy, M. (2007): Komplexe Ordnungsaufgaben flexibel lösen. In: wt Werkstatttechnik online 97 (9), S. 603–607.

[9] Rockland, M. (1995): Flexibilisierung der automatischen Teilebereitstellung in Montageanla-gen, Berlin: Springer-Verlag (IWB Forschungsberichte, Bd. 87).

[10] Joneja, A.; Lee, N. (1998): A modular, parametric vibratory feeder. A case study for flexi-ble assembly tools for mass customization. In: IIE Transactions 30 (10), S. 923–931.

[11] Reinhart, G.; Loy, M. (2010): Design of a modular feeder for optimal operating performance. In: CIRP Journal of Manufacturing Science and Technology 3 (3), S. 191–195.

[12] Schmid, S. (2006): Automatisierte Ordnungs- und Kommissionierzelle zur hochflexiblen Bereitstellung von Werkstücken in der Montage, Heimsheim: Jost-Jetter (IPA-IAO-Forschung und -Praxis, 435).

[13] Busch, J.; Knüppel, K. (2013): Development of a Self-Learning, Automatic Parameterisation of an Aerodynamic Part Feeding System. In: AMR 769, p. 34–41.

[14] Busch, J.; Quirico, M.; Richter, L.; Schmidt, M.; Raatz, A.; Nyhuis, P. (2015): A genetic algorithm for a self-learning parameterization of an aerodynamic part feeding system for high-speed assembly. In: CIRP Annals - Manufacturing Technology 64 (1), p. 5–8.

[15] Dini, G.; Failli, F.; Lazzerini, B.; Marcelloni, F. (1999): Generation of Optimized Assembly Sequences Using Genetic Algorithms. In: CIRP Annals - Manufacturing Technology 48 (1), S. 17–20.

[16] Wong, H.; Leu, M. C. (1993): Adaptive Genetic Algorithm for Optimal Printed Circuit Board Assembly Planning. In: CIRP Annals - Manufacturing Technology 42 (1), p. 17–20.

[17] Busch, J.; Schneider, S.; Knüppel, K.; Nyhuis, P. (2013): Identifying interactions in a feeding system. In: International Journal of Mechanical, Aerospace, Industrial, Mechatronic and Manufacturing Engineering 7 (10), S. 2006–2012.