International Journal of Mechanical, Industrial and Aerospace Sciences
ISSN: 2517-9950
Vol:7, No:10, 2013

Identifying Interactions in a Feeding System

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***Abstract*—**In production processes, assembly conceals a considerable potential for increased efficiency in terms of lowering production costs. Due to the individualisation of customer requirements, product variants have increased in recent years. Simultaneously, the portion of automated production systems has increased. A challenge is to adapt the flexibility and adaptability of automated systems to these changes. The Institute for Production Systems and Logistics developed an aerodynamic orientation system for feeding technology. When changing to other components, only four parameters must be adjusted. The expenditure of time for setting parameters is high. An objective therefore is developing an optimisation algorithm for automatic parameter configuration. Know how regarding the interaction of the four parameters and their effect on the sizes to be optimised is required in order to be able to develop a more efficient algorithm. This article introduces an analysis of the interactions between parameters and their influence on the quality of feeding.

***Keywords*—**Aerodynamic feeding system, design of experiments, interactions between parameters.

I. Introduction

BECAUSE of the high level of automation in the production segment, assembly has become the costliest production process [1]. In the mid-1980s, assembly made up 50% of the costs of a product [2], but according to current studies, this portion now amounts to 70% [1]. In particular, in automated assembly an increase in output performance of assembly units cannot be realised without increasing feeding capacities [3]. Furthermore, the flexibility requirements on the assembly system constantly increase on account of increasing diversity of product and variety of options.

Conventional feeding systems, in terms of their flexibility, as well as their feeding output and process reliability increasingly reach their limits [4]. In terms of exhausting still undeveloped rationalisation potentials in automated assembly, a considerable economic significance must be attributed to feeding technology. The feeding process is subdivided into the partial processes, storage, separation, orientation, positioning and transfer [4].

This article focuses on the partial process of orientation. By means of the aerodynamic impulse process, a wide range of small components can be fed quickly, reliably and, above all, correctly [5]. In passive orientation processes, incorrectly oriented components are merely removed and correctly oriented ones are placed in the correct position randomly [6]. That is why the impulse process uses the principle of active orientation, in which incorrectly oriented parts are actively placed in the correct position [6]. Therefore, this principle is evidently more efficient in terms of feeding output. The adaptation to new workpieces is achieved by setting the four system parameters. Until now, these parameters always had to be configured manually and involved considerable expenditure of time. Thus, a process is to be developed by means of which the aerodynamic feeding system can be automatically adjusted. This enables reducing manual configuration costs when changing over to new components. In this article, the cause and effect relations between adjustable parameters and the portion of correctly oriented components is worked out by means of experimental design planning. Further, interactions between parameters will be taken into consideration.

II. Aerodynamic Feeding with the Impulse Process

Many flexible feeding systems use air nozzles as order baffles for orienting components. This method has a lower susceptibility to faults then systems that work with mechanical order baffles. In systems that operate according to the principle of passive orientation, incorrectly oriented components, for example, are recorded per line scan, identified by image processing and subsequently are blown back into the feeding pot by means of an air nozzle [6]. This reduces the output of a system because components, which are not correctly oriented, have to run through the process several times. In the area of active orientation, airflow is used in a targeted manner in order to place the components in the desired position.

The impulse process serves for orienting components with an edge length of up to 0.1 m and a mass of 0.001 to 0.05 kg [5]. Further, the process uses eccentric centre-of-gravity positions or local varying air resistances of components. Depending on the centre-of-gravity position, aerodynamic characteristics and projected areas of the feed component, a radial orientation around the axis of the direction of motion or an axial orientation vertically to the direction of motion is possible. Fig. 1 shows the functional principle of the impulse process in the example of the axial orientation.

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The above feeding device consists of a tilted guide level with a gradient α, a lateral inclination ß and a leading edge arranged at right angles to the guide level. An air nozzle is inserted into the leading edge, which is aligned parallel to the guide level.

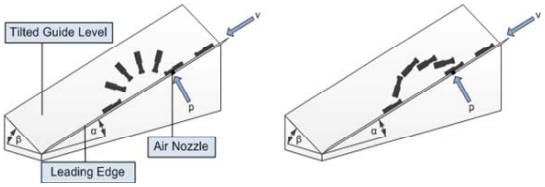

Fig. 1 Functional principle of the impulse process [5]

The previously separated components are fed into the feeding system at a defined speed υ and slide down the tilted guide level along the leading edge. The air nozzle operates at a constant operating pressure ρ and emits continued airflow. When passing the air nozzle, the components are subjected to an impulse and lift off the leading edge. While the incorrectly oriented components rotate by 180° (Fig. 1 (a)), the correctly oriented components retain their orientation at (Fig 1 (b)). Ideally, at the output of the system all components have a similar orientation.

By completely dispensing with mechanical order elements, the impulse process is characterised by its high level of flexibility with respects to adjustment and changeover to the new components. Jamming of components in the baffle is excluded, as a result of which a high level of process reliability can be achieved. Since the component motion due to vibrations also is excluded and the components subsequently are actively oriented, a continued very high feeding output of 750 units / minute can be realised. The high operating costs on account of using compressed air and expertise for adapting the changeover to new components, which previously was necessary, are deemed to be disadvantageous [5], [7].

The adjustment and changeover to new components with the impulse methods is performed by setting the parameters gradient α and inclination ß of the tilted guide level, air pressure ρ of the nozzle and feeding speed of the components υ. Previously, the setting process, based on experience, was performed by applying the iterative method by trial and observation. Depending on the user's expertise, this process takes a longer or shorter time, but, as a rule, the designing of parameters is very time-intensive. Moreover, because of the open design, interfering environmental influences may impair the behaviour of the feeding device. A setting, which previously might have been considered optimal, might not be able to provide the desired result because of the change in ambient pressure. The aerodynamic feeding method consequently offers a development potential not only with respect to the time-intensive parameter setting, but also in terms of the absence automatic adjustment.

By means of the equations of motion, one is able to describe the components motion mathematically in the impulse process until the impact [4]. Because of the dependence on materials, services and masses, the impact can be modelled only experimentally and component-specifically [4]. A complete simulation of the motion therefore is not expedient. Due to the complexity of the impact phenomenon, this article makes no reference to a mathematical description of the component motion during the impulse process. Instead, the system is seen as a black box, of which the general function is known, but not modelled in detail.

III. Foundations for Performing the Test

A. Input and Output Values

In order to create a better understanding of the system, the input and output values in Fig. 2 of the feeding system are shown in a parameter diagram.

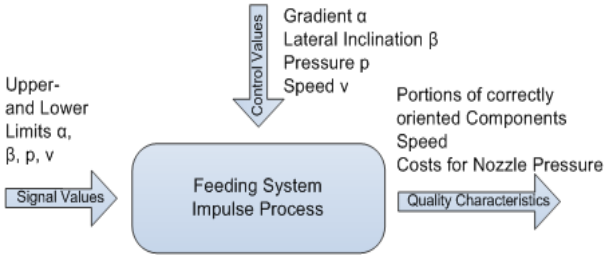

Fig. 2 Parameter diagram for the impulse process

The term parameter comprises the quantity of all input values of a system. Control values are targeted variable input values [8], and with the impulse process the adjustable parameters represent gradient α, lateral inclination ß, pressure p and feeding speed υ. Signal values also are input values and specify the range of the system's function [8]. For example, if the gradient of the inclined level is too flat, components will be unable to slide down the level. If the gradient is too steep, components will no longer be able to land on the level after having been subject to the air impulse. In both cases the system would no longer be functional, and correspondingly certain upper and lower limits must be maintained for all control values. Quality characteristics are understood to be continued output values by means of which the degree of fulfilment of the desired results can be quantified [8]. Primarily, in the case of the impulse procedure, a large portion of properly oriented components is desirable and therefore a major quality characteristic. Other characteristics, for example, may be lower nozzle pressure or highest possible feeding rates. The objective of a parameter optimisation is optimising quality characteristics by setting the control values.

B. Description of the Test

According to Fig. 3, during the following tests, commercially available dummy plugs are used as test components for pneumatic plug connections.

Because of their elongated shape, low weight, eccentric

centre of gravity and insensitivity to impact and vibrations, these plastic components are particularly good for orientation with impulse processes.

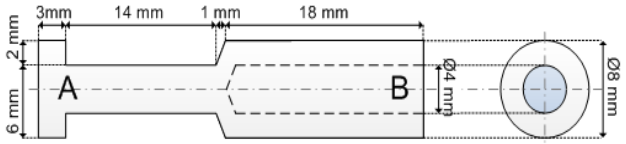

Fig. 3 Drawing of test specimen – dummy plug for pneumatic plug connections

Initially, the test specimens are separated and pre-oriented in the centrifugal conveyor. When leaving the centrifugal conveyor, the test specimens in terms of their orientation still have a degree of freedom: They either lie with their narrow wide end (A) or their elongated wide end (B) towards the front. A conveyor belt picks up the components after they leave the centrifugal conveyor and accelerates their conveyance at a defined speed υ. Subsequently the components slide along the tilted level down the leading edge and are oriented by means of the impulse process. After leaving the conveying chute, the conveyor transports the test specimens past the image recognition unit. The image recognition (Fig. 4) records the components with a camera and transmits the information to a computer. By counting the number of correctly and incorrectly oriented components, the portion of correctly oriented components can be measured as quality characteristic.

Fig. 4 Example of camera images during the optical recording of the test specimen

For a successful test it is important that the system is adapted to the component to be tested, thus ensuring the system's general function for the given test conditions. During pre-tests, it has been observed that test specimens tend to tumble over after impacting the conveying chute. A 3 mm thick plastic layer was glued onto the conveying chute, so as to improve impact behaviour. Glass fibre-based Teflon adhesive tape improved the conveying chute's sliding characteristics even further and reduced risk of component blockage in the feeding system.

Further, it must be ensured that the test specimens are separated correctly. For this purpose, the centrifugal conveyor's turntable is operated at a speed of 20 rounds/min and the discharge ring at 55 rounds/min. This setting enables a speedy end secure separation of individual test components at the start of the process. The image recognition system is directed towards the conveyor belt and trained towards the component. To ensure that the test specimen position is recorded correctly, the conveyor belts speed at the system output is set to 90 m/min. As this speed is in excess of the feeding rate to be tested, after leaving the conveyor chute the components are rectified to facilitate the separate recording of test specimens.

TABLE I
TWO-LEVEL FULL FACTORIAL DESIGN OF EXPERIMENTS

Test V	α (°)	β (°)	ρ (kPa)	υ (m/min)
1	17.4	43.1	22	63
2	21.2	43.1	22	63
3	17.4	52.7	22	63
4	21.2	52.7	22	63
5	17.4	43.1	28	63
6	21.2	43.1	28	63
7	17.4	52.7	28	63
8	21.2	52.7	28	63
9	17.4	43.1	22	77
10	21.2	43.1	22	77
11	17.4	52.7	22	77
11	21.2	52.7	22	77
13	17.4	43.1	28	77
14	21.2	43.1	28	77
15	17.4	52.7	28	77
16	21.2	52.7	28	77

All individual tests are performed on the same test system with the same test specimens. In order to avoid falsifying the results due to temperature and ambient pressure changes, all tests are performed on the same day and in the same room. Windows and doors are closed during all tests, in order to exclude influences due to draught and wind. As soiling of the conveyor chute may influence the sliding behaviour of components, the test system is cleaned before every test. In each individual test, 500 test specimens are separated, subsequently accelerated, oriented by means of impulse processes, rectified on a conveyor belt and recorded by the image recognition system.

C. Structure of the Design of Experiments

The following terms are relevant for understanding the subsequent details:

- Factors: Selected subset of parameters that will be taken into consideration as influencing variables [9].
- Factor levels: Setting factors during a test in which each factor is tested at least at two varying levels [8].
- Target value: Quality characteristic, which is measurable or a test calculable from measuring values, by means of which one is able to differentiate between good and bad system settings [9], [8].
- Effect: Effect, which a factor has on a quality characteristic. The effect of a factor may depend on the setting of other factors [8].
- Main effect: Effect, which an individual factor has on a quality characteristic, without taking into consideration interactions with other factors [8].

- Interaction: The effect of a factor depends on the setting of another factor [9].

The selection of the design of experiments depends on the purpose of this study, the number of factors, the number of levels per factor and the desired precision of results [9]. As the number of factors and levels increases, the number of tests to be performed rises as well. Two-level designs of experiments have proved to be low-cost, suitable for practice and powerful [8]. The results must be interpreted comparably and clearly.

In the case of non-linear correlations, the model works inaccurately, but the two-level design of experiments can be extended, if required [8]. Expenditure for the experiment can be reduced further by applying a fractional factorial experiment of designs, in that only one half of the possible combination of levels is tested. One weakness of fractional factorial experiments of designs is combining main effects with interactions [9], in which case the allocation of causes and result changes would be possible only to a limited extent. With full factorial designs all possible level combinations are tested. With a given number of $n_F = 4$ factors each with $n_1 = 2$ levels, this produces a total of $n_1^4 = 16$ individual tests for a full factorial design. Since the number of individual tests is easily understandable, a full factorial experimental design is preferred. Based on the predominantly correctly oriented components and the process-reliable function of the system, during preliminary testing the following factor setting by means of the trial and error method is considered to be a good initial solution:

$$\alpha = 19.3°; \beta = 47.9°; \rho = 25\ kPa\ ;\ \upsilon = 70\ m/\min$$

Other preliminary tests indicate that a design of experiments with level values that are 10% above or below the determined initial value, produce results that clearly vary from those produced by a continuously functioning system. According to Table I, it produces a two-level full factorial design of experiments. After performing 16 individual tests, this produces portions of correctly oriented test specimens according to Table II.

The determined portions of the correctly oriented parts y_c vary with respect to the different tests V. During the subsequent procedure, the statistical evaluation test results examine on which effects the observed target value variations can be based.

IV. Statistical Evaluation of the Result

A. Main Effects and Interactions

Effects and interactions can be calculated according to the mean difference principle. An effect can be derived from the average change perceived in the target value when changing from a low to a high setting [8]. The effect E of the gradient α, for example, can be calculated by the difference of the mean of test results with higher and lower setting of the factor α.

Due to the various combination options of higher and lower factor levels, the calculation of interactions is more complicated, but follows the same principle of mean differences. A linear description module can be formulated from the overall mean of the observations and the calculated effects. With a level width of exactly two, the coefficients of the model correspond to exactly one half of the related effects [8]. The effects and coefficients calculated in the analysis of the design of experiments are summarised in Table III.

TABLE II
Portions of Correctly Oriented Components Achieved in the Individual Test

Test V	α (°)	β (°)	ρ (kPa)	υ (m/min)	y_C (%)
1	17.4	43.1	22	63	78.8
2	21.2	43.1	22	63	51
3	17.4	52.7	22	63	70.2
4	21.2	52.7	22	63	95.4
5	17.4	43.1	28	63	99.4
6	21.2	43.1	28	63	98.8
7	17.4	52.7	28	63	77.8
8	21.2	52.7	28	63	86.8
9	17.4	43.1	22	77	52
10	21.2	43.1	22	77	51.2
11	17.4	52.7	22	77	69.8
12	21.2	52.7	22	77	48.2
13	17.4	43.1	28	77	99.4
14	21.2	43.1	28	77	57.8
15	17.4	52.7	28	77	98.4
16	21.2	52.7	28	77	93.4

In consideration of a regression constant, which represents the mean of all test results, one arrives at the following portion of the correctly oriented component ŷ as presented in (1):

$$\begin{aligned}\hat{y} = &-0.0395 \cdot \alpha + 0.03225 \cdot \beta + 0.122 \cdot \rho - 0.055 \cdot \upsilon \\ &+ 0.049 \cdot \alpha \cdot \beta - 0.00825 \cdot \alpha \cdot \rho - 0.04675 \cdot \alpha \cdot \upsilon \\ &- 0.031 \cdot \beta \cdot \rho + 0.0295 \cdot \beta \cdot \upsilon + 0.03775 \cdot \rho \cdot \upsilon \\ &+ 0.00875 \cdot \alpha \cdot \beta \cdot \rho - 0.02925 \cdot \alpha \cdot \beta \cdot \upsilon \\ &- 0.022 \cdot \alpha \cdot \rho \cdot \upsilon + 0.05575 \cdot \beta \cdot \rho \cdot \upsilon \\ &+ 0.063 \cdot \alpha \cdot \beta \cdot \rho \cdot \upsilon + 0.76775\end{aligned} \quad (1)$$

By means of the description model the portion of the correctly oriented components can be predicted for each factor setting within the tested level areas. As physical phenomena may influence the system, which may occur via the tested level widths, the prediction only applies to the examined area. Extrapolations are not permitted [8]. According to the calculation of effects, main effects and interactions can be compared with one another. Fig. 5 compares the dimensions of the effect in the Pareto diagram.

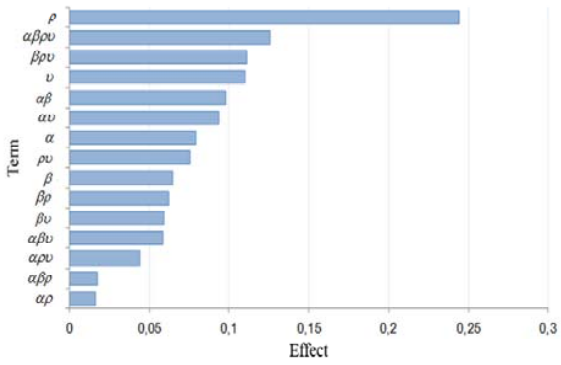

Fig. 5 Pareto diagram of the effects

At a first glance it is evident that pressure by far has the greatest effect on the test results. This is followed closely by a fourth-order interaction and in third place by the three-factor interaction between lateral inclination, pressure and speed. The second most important main effect is speed. This is followed by the two-factor interactions between gradient and pressure. The main effect gradient is followed by the two-factor interaction between gradient and speed. The main effect of lateral incline is in ninth position, and subsequently the remaining interactions of the second and third order align themselves in the diagram. However, it is conspicuous that the main effects do not take the first four positions in the diagram. Obviously, the various interactions have an even greater influence on the test result then some of the main effects. The third and fourth-order interactions at the second and third position of the ranking order represent an unusual observation. The interactions of these levels frequently are neglected and eliminated in favour of the better interpretability of a model [9].

B. Variance Analysis and Factor Elimination

Based on accidental influences, test results scatter even when exercising the greatest possible care. The determined effects were specified on the basis of these test results. Therefore, they accidentally vary from the actual (unknown) effects [9]. By means of a variance analysis significant differences of averages can be determined in various groups. Further, the groups are defined by the varying factor settings. The target value variations recorded in the tests are analysed in variations between groups (factor effects) and variations within groups (inexplicable hissing). The null hypothesis H_0 is formulated for each factor contained in the model, that the factor considered has no real effect.

The rejection of this hypothesis therefore allows the conclusion that a real effect of the factor exists. The decision for rejecting the null hypothesis is based on mathematically determined probability values. The probability values, while assuming that there is an appropriate null hypothesis, indicate the probability that an observed or an even greater variation of the target value occurs. The lower the probability value the sooner one must assume that a real effect exists. Based on a defined confidence interval (typically 90%, 95% and 99%), significance levels can be formulated for the probability values. If a value, for example, is lower then 1-0.9=0.1, the null hypothesis for the 90% confidence interval is rejected and the effect is assumed to be significant [8].

A test plan with a total of n tests has n-1 degrees of freedom, while in the specified design of experiments therefore 16-1=15 degrees of freedom are available. Each model parameter with n_1 levels uses n_1-1 degrees of freedom. With the relevant two-level design of experiments, a 2-1=1 degree of freedom is required for determining a parameter. The initial analysis comprises the calculation and comparison of four main effects and six interactions of the second order, four interactions of the third order and one fourth-order interaction. When taking the effects into consideration altogether, all degrees of freedom contained in the design of experiments will be utilised. At least one undocumented level of freedom is required for calculating the values of probability. Therefore, at least one parameter has to be removed from the model. According to the basic principles of factor elimination, initially only minor effects are eliminated. In order to preserve the hierarchical integrity of a model, it is appropriate to start with interactions of the highest order. Parameters of lower orders should be eliminated only if they are no longer contained in the interactions of the higher order. Since interactions starting with the third order usually only have a minor effect, this principle will be unproblematic [8].

TABLE III
EFFECTS AND COEFFICIENTS OF THE LINEAR DESCRIPTION MODEL

Term	Effect	Coefficient
α	-0.079	-0.0395
β	0.0645	0.03225
ρ	0.244	0.122
υ	-0.11	-0.055
$\alpha \cdot \beta$	0.098	0.049
$\alpha \cdot \rho$	-0.0165	-0.00825
$\alpha \cdot \upsilon$	-0.0935	-0.04675
$\beta \cdot \rho$	-0.062	-0.031
$\beta \cdot \upsilon$	0.059	0.0295
$\rho \cdot \upsilon$	0.0755	0.03775
$\alpha \cdot \beta \cdot \rho$	0.0175	0.00875
$\alpha \cdot \beta \cdot \upsilon$	-0.0585	-0.02925
$\alpha \cdot \rho \cdot \upsilon$	-0.044	-0.022
$\beta \cdot \rho \cdot \upsilon$	0.1115	0.05575
$\alpha \cdot \beta \cdot \rho \cdot \upsilon$	0.126	0.063

However, in the considered experiment, the four-factor interaction was identified as the second most important parameter. In order not to lose this important effect, the elimination therefore does not start with this interaction. The hierarchical integrity with respect to the four-factor interactions therefore is maintained.

After eliminating the three-factor interaction, the result is shown as an example in Table IV. The Mean Squares (MS) column is defined as the quotient from the sum of squares between groups [10] and the respective degree of freedom,

and it thus describes the influence of a factor per degree of freedom on the number of correctly oriented test specimens. The two-factor interaction α ρ and the three-factor interaction α β ρ, with an MS of 0.001, have the lowest influence. In order to preserve the hierarchical integrity, the three-factor integrity α β ρ is eliminated. Subsequently, probability values for the remaining factors can be determined. These factors specify the probability that a random value of the same distribution is at least as large as the quotient from MS factors caused by the MS residue error [11]. The larger this quotient per factor, the smaller the related probability value and the sooner a factor has to be valued as significant [9]. The probability values, which fall short of a critical significance level, are shown in bold in Table IV.

After eliminating the weakest interaction α β ρ, it can be observed that a significant influence must be ascribed both to the four-factor interaction α β ρ υ and the three-factor interaction β ρ υ for a 90% confidence region. The main effect ρ even is significant for the 95% confidence interval.

By eliminating other interactions, the model can be simplified gradually. To this end, the effects of the lowest MS values are selected. The elimination is continued until the only remaining effects are significant or if none of the remaining non-significant effects can no longer be eliminated due to their integration in a significant higher-ranking interaction [8].

In a second phase, the second weakest interaction α υ is eliminated. As α ρ υ contains α υ, this term must be removed from the model simultaneously. Following the second elimination phase, the main effect α and the two-factor interaction ρ υ for the 90% confidence interval are deemed significant. The terms α β ρ υ and β ρ υ are significant for a 95% confidence region, similar to the two-factor interactions $\alpha \cdot \upsilon$ and $\alpha \cdot \beta$ and the main effect υ. The main effect ρ even is below the 99% confidence interval barrier and therefore must be considered to be highly significant.

By eliminating the second weakest interaction α β υ, the effects that previously were identified as significant are no longer identified as such. This elimination phase therefore no longer is taken into consideration, and the factor elimination is discontinued. According to the following equation, this produces a simplified description model.

$$\begin{aligned}\hat{y}^* = &-0.0395 \cdot \alpha + 0.03225 \cdot \beta + 0{,}122 \cdot \rho - 0.055 \cdot \upsilon \\ &+ 0.049 \cdot \alpha \cdot \beta - 0.04675 \cdot \alpha \cdot \upsilon \\ &- 0.031 \cdot \beta \cdot \rho + 0.0295 \cdot \beta \cdot \upsilon + 0.03775 \cdot \rho \cdot \upsilon \\ &- 0.02925 \cdot \alpha \cdot \beta \cdot \upsilon + 0.05575 \cdot \beta \cdot \rho \cdot \upsilon \\ &+ 0.063 \cdot \alpha \cdot \beta \cdot \rho \cdot \upsilon + 0.76775\end{aligned} \tag{2}$$

C. Validation of the Results

The variance analysis is based on the assumption that the residues, i.e., the model's deviations from the observed values, are subject to normal distribution at every factor level. Furthermore, the residues must have variance homogeneity and temporal independence [8]. The verification is performed graphically by means of the four diagrams in Fig. 6.

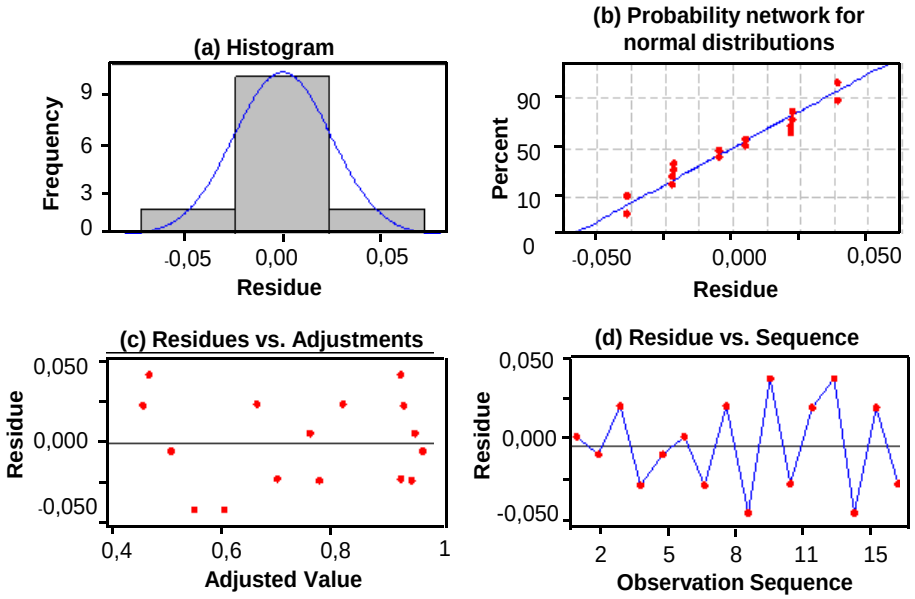

Fig. 6 Residue diagram of the proportion of correctly oriented components

TABLE IV
RESULTS OF THE VARIANCE ANALYSES AFTER ELIMINATING FACTOR INTERACTION $\alpha \cdot \beta \cdot \rho$

Term	Mean Squares (MS)	Probability Values After Elimination
α	0.025	0.139
β	0.017	0.169
ρ	0.238	**0.046**
υ	0.048	0.1
$\alpha \cdot \beta$	0.038	0.112
$\alpha \cdot \rho$	0.001	0.519
$\alpha \cdot \upsilon$	0.035	0.118
$\beta \cdot \rho$	0.015	0.175
$\beta \cdot \upsilon$	0.014	0.184
$\rho \cdot \upsilon$	0.023	0.145
$\alpha \cdot \beta \cdot \rho$	0.001	-
$\alpha \cdot \beta \cdot \upsilon$	0.014	0.185
$\alpha \cdot \rho \cdot \upsilon$	0.008	0.241
$\beta \cdot \rho \cdot \upsilon$	0.05	**0.099**
$\alpha \cdot \beta \cdot \rho \cdot \upsilon$	0.064	**0.088**

The distribution of residues is presented in a histogram (Fig. 6 (a)) and optically is in keeping with the bell-shaped curve, which is typical for normal distribution. Taking the probability network for normal distributions (Fig 6 (b)) into consideration offers additional safety. If the values approximately are on a straight line, the residues indicate a random scattering [8]. This is the case in the diagram in question. The residues therefore are subject to normal distribution.

The variance homogeneity can be examined by applying the residues against the predictions of the model (adjustments) (Fig. 6 (c)). If the values form an even zero-distributed strip without identifiable pattern, it must be assumed that the variances of the residues are equal [8]. In this case, variance homogeneity consequently is provided. In order to verify the time independence, the residues are applied via the observation sequence (Fig. 6 (d)). A pattern (e.g., cloud formation) or a trend (e.g., constantly increasing values) would indicate a time-dependent behaviour of model errors [9]. In the present case, there is a randomly distributed image without identifiable pattern or trends. The residues therefore are time-independent.

A further requirement is the independence of input values [8]. The existing design of experiments is orthogonal, which means that each factor can be set completely independent of other factors [8]. This satisfies the last requirement of the variance analysis. The statements of the analysis are validated and the simplified description model according to (2) can be used for estimating the proportion of correctly oriented components for the tested area of investigation.

The simplified description model explains $R^2 = 98.3\%$ of the observed target value variations. R^2 explains the portion of the target value variations quantified in percentage, which are explained by the model [12].

V. Interpretation of Results and Outlook

In this article, it was determined by means of a statistical design of experiments that significant interactions exist between the input values of aerodynamic orientation, and that these values influence the number of correctly oriented components. A four-factor interaction between all factors, a third-order interaction, three two-factor interactions and three main effects were identified as significant effects. In addition, it was demonstrated that, due to their significant interactions during parameter optimisation, the control values gradient, lateral incline, pressure and feeding rate always must be considered jointly, and that an isolated consideration of parameters therefore would be inefficient.

This determination explains the high expenditure of time with the manual configuration of the aerodynamic feeding systems and confirms the relevance of a systematic optimisation process for reliable and low-cost optimisation of parameter settings during the impulse process.

For this reason, in further research activities a genetic algorithm is to be developed and the control of aerodynamic orientation is to be implemented. This algorithm is to enable the system to determine self-learning optimal parameter settings and to adapt these dynamically as a function of ambient conditions.

References

[1] B. Lotter, in: Bruno Lotter und Hans-Peter Wiendahl, "*Einführung, Montage in der industriellen Produktion*", Berlin, Heidelberg: Springer Verlag, pp. 1–8, 2012.
[2] G. Spur, „*Handbuch der Fertigungstechnik, Fügen Handhaben Montieren*“, 5th ed., Munich: Carl Hanser Verlag, 1986.
[3] G. Höhne, A.Schmidt, in: Bruno Lotter und Hans-Peter Wiendahl, „*Hochleistungsmontage, Montage in der industriellen Produktion*“, Berlin, Heidelberg: Springer Verlag, S. 473–483, 2012.
[4] A. Rybarczyk, „*Auslegung aktiver aerodynamischer Zuführverfahren*“ Dissertation, Leibniz Universität Hanover, Institut für Fabrikanlagen und Logistik, 2004.
[5] B.-J. Lorenz, „*Aerodynamische Zuführtechnik*“, Dissertation, Leibniz University Hanover, Hanover, Fachbereich Maschinenbau, 1999.
[6] S. Hesse, „*Grundlagen der Handhabungstechnik*“, 2nd ed., Munich: Carl Hanser Verlag, 2010.
[7] H.-P. Wiendahl, B.-M. Lorenz, "Aerodynamic Part Feeding: Development of Aerodynamic Orienting Devices", *The International Journal of Advance Manufacturing Technology*, Vol. 15, pp. 417-424, 1999.
[8] K. Siebertz, D. T. van Bebber, T. Hochkirchen, „*Statistische Versuchsplanung. Design of Experiments (DOE)*“, 1st. ed, Heidelberg, Dordrecht, London, New York: Springer Verlag, 2010.
[9] W. Kleppmann, „*Taschenbuch Versuchsplanung, Produkte und Prozesse optimieren*“. 7th ed., Munich, Wien: Carl Hanser Verlag, 2011.
[10] T. C. Urdan*, "Statistics in Plain English",* New York, Hove: Taylor & Francis Group, *2010, ch. 10.*
[11] G. A. Churchill*, "*Fundamentals of design of experiments for cDNA microarrays*", Nature Genetics,* Vol. 32, pp. 490-495, 2002.
[12] S. Menard*, "*Coefficients of Determination for Multiple Logistic Regression Analysis*", The American Statistician, Vol. 54, no. 1,* pp. 17-14, 2000.

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