Systematic Determination of the Influence of Factors Relevant to Operating Costs of Sensor-based Sorting Systems

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Abstract

Within the next decade, the recycling rates of all waste streams in the European Union are to be consistently increased (EU, 2018). Sensor-based sorting plays a crucial role in achieving those aims. However, the composition of the operating costs of sensor-based sorting systems (SBS), which are made up of compressed air and electricity costs, for example, has not yet been adequately investigated. The main cause is the massive experimental effort required to investigate these costs. In this paper, we propose a systematic approach for determining the operating costs of SBS systems by using Design of Experiments (DoE). For this purpose, experiments are carried out to investigate whether the methodology of DoE is applicable to the use case of SBS. The resulting models are validated with statistical measures and additional experimental runs. For comparability of the results, two different materials, namely construction and demolition waste as well as plastic flakes, with grain sizes between 0 - 10 mm are investigated. With the presented approach high

coefficients of determination of the regression models are reached. Consequently, the results show that precise regression models can be derived with reduced effort.

1 Introduction

In various industries, such as minerals, food and waste processing, sensor-based sorting (SBS) systems have become indispensable. In the recycling sector, such systems have found application for more than 20 years (Bilitewski & Härdtle, 2013). Within the next decade, the recycling rates of all waste streams in the European Union are to be consistently increased (EU, 2018). SBS systems play a key role to achieve these official regulations while maintaining high fraction purities, which are mandatory for an efficient circular economy.

With SBS systems, high volumes of waste can be sorted automatically. However, an important aspect for sorting plant operators to stay competitive is to optimize their present sorting processes. Regarding German and Italian material recovery facilities, where the economic success greatly depends on gate or sorting fees (Cimpan, 2016; Gadaleta et al., 2020) or evaluating existing, separate waste collection and recycling systems. This study mitigates the current pervasive scarcity of data on process efficiency and costs by documenting typical steps taken in a techno-economic assessment of MRFs, using the specific example of lightweight packaging waste (LWP), it is important to be aware of the cost drivers of these processes.

Research has tended to focus on the techno-economic assessment of recycling processes, where the specific costs of SBS systems are treated as a black box. In (Cimpan, 2016) or evaluating existing, separate waste collection and recycling systems. This study mitigates the current pervasive scarcity of data on process efficiency and costs by documenting typical steps taken in a techno-economic assessment of MRFs, using the specific example of LWP the authors conduct a techno-economic assessment of different material recovery facilities and describe that 2/3 of the total energy consumption of the recovery process are connected to sorting and refining. Precisely because of the high share of energy consumption in the recovery process, the links between sorting and refining process parameters and the resulting costs must be understood. In turn, this enables the modeling of the subsystem and thus provides the basis for a cost-optimization. Additionally, a realistic profitability assessment of application of SBS systems is not possible without knowledge about the cost model of such systems.

The techno-economic assessment of sorting plants gives important insights about economic aspects like revenues and economies of scale but is often based on constant values for the energy consumption of different components (Cimpan, 2016; Gadaleta et al., 2020) or evaluating existing, separate waste collection and recycling systems. This study mitigates the current pervasive scarcity of data on process efficiency and costs by documenting typical steps taken in a techno-economic assessment of MRFs, using the specific example of LWP With the use of models for the energy consumption of subsystems, a model with higher granularity can be established. Therefore, in this work, we combine the results of previous works which investigate the influence of process parameters on SBS systems with results of techno-economic assessments of sorting plants.

In this paper, we propose a systematic approach for determining the operating costs of SBS systems by using Design of Experiments (DoE). For this purpose, experiments are carried out to investigate whether the methodology of DoE is applicable to the use case of SBS. Three factors that are supposed to have a significant impact on the electricity and compressed air consumption of an SBS system are analyzed in a response surface design. For the assessment of the applicability of this method to various scenarios, two different materials, namely construction and demolition waste (CDW) as well as plastic flakes, with grain sizes between 0 - 10 mm are investigated. With this systematic and transferable method, precise models of the energy consumption of the SBS system are derived and validated by analysing coefficients of correlation. Additionally, validation runs are conducted to validate the models' predictions.

Related works focusing on the influence of process parameters of SBS systems that are referred to in this work include (Küppers et al., 2020, 2021). There, the influence of the parameters occupation density and eject fraction ratio on the sorting efficiency is investigated with lab scale experiments. In (Möllnitz et al., 2020), the authors analyze the influence of pre-screening on the sorting process of mixed municipal solid waste and mixed commercial waste, including an SBS system. A recent work which investigates the implementation of SBS systems in CDW processing is (Vegas et al., 2015) guaranteeing optimal technical and environmental performance, are required for high-grade construction applications such as concrete. The main problem constituents causing a decrease in the quality of recycled aggregates to be used in high grade applications are: organic material, gypsum and autoclaved aerated concrete (AAC). There, the authors analyze the potential of SBS systems in CDW sorting and derive specific costs between 0,80 and 1,50 € / t. Works which perform a techno-economic assessment of sorting plants with different capacities can be found in (Cimpan, 2016; Fleischhacker, 2011; Gadaleta et al., 2020; Oliveira Neto et al., 2017; Porten & Feltes, 2014; Rudolph et al., 2020; Gadaleta et al., 2020; Oliveira Neto et al., 2017; Porten & Feltes, 2014; Rudolph et al., 2020).

On this basis, we create a systematic procedure for modeling the specific costs connected to SBS systems. Therefore, in the following section we introduce the experimental setup and materials used for the experiments. As a next step, the concept of DoE is presented and applied to the system. The results are then analyzed and evaluated based on statistical measures. Lastly, the results are summarized, and the principal conclusions are drawn.

2 Methods

In the following section, the equipment and materials used in the experiments are depicted. Furthermore, the concept of DoE is explained in general and the process of applying DoE to the investigated SBS system is described.

2.1 Equipment

The sorting system analyzed in this work is a laboratory-scale SBS system with a line-scan camera, a conveyor belt 140 mm wide, and pneumatic separation. The pneumatic resolution is 5 mm. To guarantee stable and reproducible feeding, a vibrating feeding tray is used. The system was developed for demonstration, research, and development purposes with state-of-the-art components.

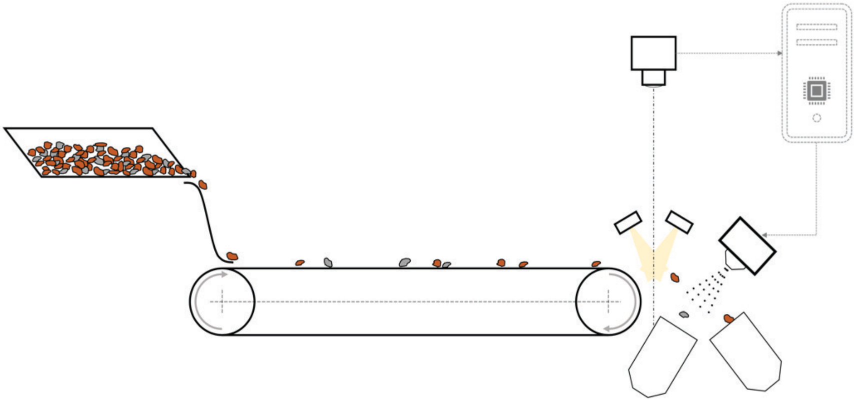

Fig. 1: Schematic depiction of the sorting procedure of the investigated SBS system

The sorting procedure is schematically depicted in Fig. 1. Starting from a vibrating feeder, the material is fed onto a conveyor belt. By utilizing a slide between vibrating feeder and conveyor belt, the particles in the material stream are separated by pre-acceleration for better detectability. A line-scan color camera is used to scan the particles after exiting the conveyor belt. Lastly, a binary separation is enabled by ejecting particles with impulses of compressed air.

2.2 Materials

The materials used for the experiments are CDW as well as mixed plastic flakes with grain sizes between 0 - 10 mm (see Fig. 2). The CDW is a mixture of clay- and sand-lime-brick and thus has higher average particle weight (0.184 g) than the plastic flakes (0.037 g). Each experimental run is conducted with 1000 g of CDW or 250 g plastic flakes, respectively. In the experiments with CDW, sand-lime-particles are handled as the eject fraction. In those with plastic flakes, blue particles are ejected. By analyzing different materials, the applicability of the approach to other scenarios in the field of SBS is assessed.

Fig. 2: Three particle size classifications (0 mm — 4.0 mm, 4.0 mm — 5.4 mm, and 5.4 mm — 10.0 mm) for the materials CDW (left) and plastic flakes (right)

3 Description of Design of Experiments

Generally, analyzing a system with continuous variable parameters is complex and expensive. Exemplary parameters of an SBS system are *feed rate, particle size*, *particle shape*, *eject fraction ratio* as well as the *operating pressure* and the *splitter position* (Gülcan & Gülsoy, 2017; Küppers et al., 2020, 2021) a better understanding of this method is required concerning general properties and mineral sorting applications. To date, optical sorting has been widely studied in terms of industrial applications and performance evaluation particularly in mineral processing. Nevertheless, process optimization requires better understanding of qualitative and quantitative figures based on real life sorting. To identify the influence of parameters on the quality of a system, approaches like trial-and-error or one-factor-at-a-time (OFAT) are expensive. Therefore, in this work, an approach for analyzing the running costs of an SBS system by using DoE is depicted. Due to the large number of factors influencing these costs, this established method for an efficient analysis of processes is necessary. Methods for the systematic analysis and subsequent optimization of a system based on multiple target figures are described in (Siebertz et al., 2017) in detail, as are all the steps mentioned below.

Initially, the system is delimited, which means process parameters are identified and *target figures*, with which the assessment of the system's quality is possible, are chosen. Intuitively, the experimental effort increases with the number of additional parameters. From the set of parameters, a subset is chosen for conducting the experiments. Those parameters in the subset are called *factors*. For each *factor*, the settings to test, which are called *levels*, are determined in advance. This is necessary to create the experimental design.

Target figures are continuous measurement values that measure the system's quality. For these target figures, regression models are later generated based on the experimental data obtained. These models can be used for further purposes like optimization or continuous prediction within the design space.

After delimiting the system, an *experimental design* is generated. For this purpose, many established experimental designs can be used from packages in Python and R. Additionally, specific statistics and DoE-software like *Design Expert, Minitab* and *SPSS Statistics* offer DoE-functions. There is also the possibility to create individual designs as described in (Siebertz et al., 2017) and realized in (Khodier et al., 2021). According to (Siebertz et al., 2017), this is mostly applied in the areas of chemistry and process engineering because not every combination of factors is executable. In this case, the individual design is created based on statistical criteria from which the person responsible can choose. The theoretical basis behind this procedure is explained in (Siebertz et al., 2017). The potential of the usage of individual designs is depicted in (Khodier et al., 2021), where real-scale experiments in waste processing were conducted. Therefore, two continuous factors are investigated on 11 or 5 levels respectively and one categorical factor with three different characteristics. In a full-factorial design, this would result in 165 runs ($n_{runs}=11\cdot5\cdot3$) but could be reduced to 32 experimental runs with the use of a D-optimal design. In the case of (Khodier et al., 2021), this minimization is necessary because of the high costs connected to conducting real-scale experiments.

According to (Siebertz et al., 2017), the mathematical basis of the reduction of the experimental designs is pairwise orthogonality of the setting-vectors of each factor. A setting-vector represents all the settings of one factor in the design. That way, multiple factors can be modified between experiments and their effects on the target figures can be estimated separately. This reduces the expense and enables an analysis of variances (ANOVA) for determining the significance of the factors' effects. An ANOVA includes hypothesis tests for determining whether a factor has a significant effect on the target figures.

The correctness of the ANOVA and the resulting regression model depends on three assumptions, which must be validated after calculation of the regression model. One must confirm that the model's residuals are independent, normally distributed and have constant variance. To enable optimal preconditions for the validity of those assumptions, three different concepts, namely randomization, replication, and blocking, can be used.

Randomization refers to the randomness of the running order in the experimental design. By randomizing, systematic effects, for instance the pollution of the camera lens, can be uniformly distributed on the experiments. Without this, the effect of factors, whose levels are varied only in the last few runs of a design, would be affected stronger than those in the first runs.

Replication is important to be able to estimate the dispersion of measurements. Therefore, the whole design can be repeated.

The last concept described in (Siebertz et al., 2017) is blocking. Blocking should be used if the experimental runs of the design can be grouped into subgroups, that are conducted under different conditions which are expected to influence the target figures. That way, the blocking information can be considered for the analysis.

The fundamental principle of an ANOVA is to test differences among means in grouped data. Therefore, the total sum of squares (TSS) of the measurements of one target figure is separated into two parts, namely the sum of squares within groups (SSW) and the sum of squares between groups (SSB). According to (Siebertz et al., 2017), the equation TSS=SSW+SSB holds true. Intuitively, if the SSW is small and the SSB is high, the factor is likely to influence the target figure.

Lastly, with a hypothesis test, it is investigated if the share of that is explained by the is high enough to reject the null hypothesis with a high certainty. The null hypothesis claims that the factor does not have a significant effect on the target figure. Two errors, namely the type 1 and type 2 error, exist for this test. Type 1 is the error of assuming the factor has an effect, although it does not, and type 2 is the error of assuming the factor does not have an effect, although it does. Therefore, two upper limits for the risk of a wrong decision must be defined in advance. The significance level α defines the maximally acceptable risk for a type 1 error and β for a type 2 error. The decision, whether the null hypothesis is rejected, is based on the p-value, which is the probability that the variance between groups is not caused by the factor's effect. If $p < \alpha$ holds, the risk for a type 1 error is smaller than the acceptable risk and the factor is considered to have a significant effect. As a last step, the tree assumptions mentioned above must be validated by analyzing the corresponding plots as described in (Siebertz et al., 2017). ANOVA is hence used as a preliminary step for the regression of the target figures. Factors which are not considered to have a significant effect are excluded and not modeled in the respective regression model.

For each factor with a significant effect, the effect can be modeled with a regression model. Lastly, these individual models are aggregated to a multiple regression model of the target figure. If all effects are modelled linearly, the model is referred to as a multiple linear regression model.

4 Application to the SBS system

To apply this knowledge on the present problem, the SBS system is delimited first. Target figures which are closely linked to the operational costs of an SBS system are selected, namely *compressed air consumption*, *electricity consumption of the valves* and *purity of the reject fraction*. The compressed air consumption is used for estimating the necessary power of the compressor unit. The consumption of compressed air is measured in liters with a flow meter (Festo SFAM-62-3000l-M-2SA-M12) for each experimental run. The electricity consumption of the valves is expected to have a small influence on the running cost but is not a constant electricity consuming part of the SBS system. The electricity consumption is calculated with an application that documents the frequency and duration the valves are being activated for in each run. Additionally, the purity of the reject fraction is considered as a target figure. The associated regression model, however, is not necessary for estimating the costs related to the SBS system.

Regarding these target figures, the influence of factors is investigated. In (Küppers et al., 2020) the occupation density of the conveyor belt is shown to have a significant effect on the sorting quality of the system. For designing an optimal sorting process, the throughput must be considered (Cimpan, 2016) or evaluating existing, separate waste collection and recycling systems. This study mitigates the current pervasive scarcity of data on process efficiency and costs by documenting typical steps taken in a techno-economic assessment of MRFs, using the specific example of LWP. The throughput rate can be mapped linearly to the occupation density of the conveyor belt. This is why the correlation between the occupation density and the target figures is analyzed within the scope of this work. The eject-fraction ratio in the material stream is likely to be correlated with the operational costs of an SBS system, too. The more eject particles are contained in the stream, the higher is the expected consumption of electricity. Although this seems obvious, the correlation of this factor to the operational/electricity costs has not been investigated yet. Another factor that is expected to have an influence on the operational costs is the particle size of the material. The particle size directly influences the duration of compressed air impulses. For larger particles, the duration of the impulses is typically higher than for smaller ones.

With three factors, a face-centered Central-Composite-Design can be used (Siebertz et al., 2017). This design is a combination of a 2-level factorial design and additional orthogonal combinations originating from the center point, which can be seen in Fig. 3. Therefore, each factor is investigated on three levels, leading to an experimental plan containing 15 experiments. Additionally, five replicate runs of the center point run are conducted to enable a lack-of-fit-test (LOF), which tests if the model fits well throughout the design space and thus describes the correlation between the factors and target figures correctly. Therefore, the variation of the center points is tested against the variation between the actual and predicted values, also referred to as residuals. If the variation of the residuals is significantly larger than the variation of the replicated center point measurements, the model does not fit the data well, potentially. This results in a total sum of 20 experiments for each material.

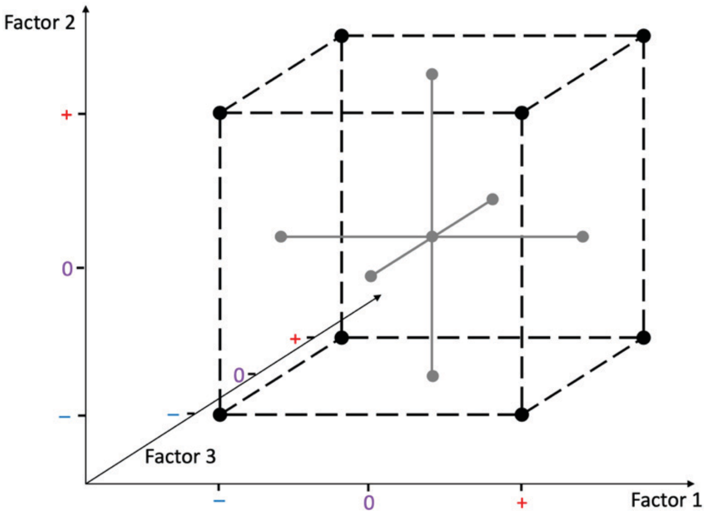

Fig. 3: Visualization of a face-centered central composite design

Important preparatory actions are to randomize the order of the runs in the experimental plan and to determine the number of replications necessary for minimizing the risks of false conclusions. For this system, α=0.05 and β=0.2 are chosen as reasonable risks as they are common values in the literature (Siebertz et al., 2017). The risks influence the number of necessary runs. Due to the low variance of the target figures in replicate runs, which are experiments with the same factor settings, the experimental plan does not have to be repeated to reach the preconditions for the risks named above. This variance is determined in preliminary tests. In this case, blocking is not needed, because all experiments are conducted under the same conditions.

The three factor levels of each factor must be determined. In our case, all three factors are numeric. Hence, the influence of every factor can be included into the regression model continuously.

In preliminary tests, the highest feasible *occupation density* was determined at 10 %. Additionally, the idea is to examine a large design space. Therefore, the lower limit of the occupation density of 1 % and an upper limit of 10 % is chosen. The three factor levels are depicted in Fig. 4.

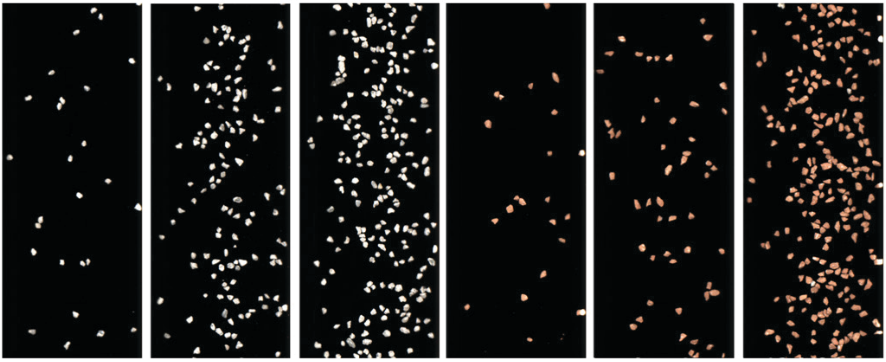

Fig. 4: Occupation densities (1 %, 5.5 %, 10 %) of the medium particle size with sand-lime particles on the left and clay particles on the right.

In terms of the *particle size*, both materials are screened into three different fractions. The resulting fractions are 0 mm — 4.0 mm, 4.0 mm — 5.4 mm, and 5.4 mm — 10.0 mm and are shown in Figure 2.

Lastly, levels for the factor *eject-fraction ratio* must be determined. The upper limit is chosen to be 20 %, whereas the lower limit is set to 5 %. The resulting factor levels are shown in Tab. 1.

Tab. 1: Factor levels

	Factor levels		
	--	**0**	**+**
Occupation density	1 %	5.5 %	10 %
Particle size	2 mm	4.85 mm	7.7 mm
Eject fraction ratio	5 %	12.5 %	20 %

The approach for the analysis of the measurements after conducting the experimental design is the same for both materials. Therefore, only the procedure for the analysis of the experiments with CDW is presented. Exemplary for all three target figures, the ANOVA results of the compressed air consumption is depicted in Table 2. After the collection of data within the experiments, the ANOVA is applied. Therefore, the probability p for every effect or interaction of a factor not to be significant is calculated and those with a p-value higher than α are eliminated from the model. In the following, the three factors occupation density, particle size and eject-fraction ratio are referred to as *A, B, C,* respectively.

The fact that A^2, the quadratic effect of the occupation density, is not eliminated from the model is caused by the principle of hierarchical integrity (Siebertz et al., 2017). Since the interaction of A^2 and C is significant, A^2 must be respected in the regression model.

Tab. 2: ANOVA table for the target figure compressed air consumption

Source	Sum of Squares	Degrees of Freedom	Mean Square	F-value	p-value	
Model	0.0652	8	0.0082	89.85	<0.0001	significant
A-Occupation dens.	0.0272	1	0.0272	299.8	<0.0001	
B-Particle size	0.0173	1	0.0173	190.34	<0.0001	
C-Eject fr. ratio	0.0011	1	0.0011	12.18	0.0051	
AB	0.0020	1	0.0020	22.22	0.0006	
AC	0.0027	1	0.0027	29.23	0.0002	
A^2	0.0000	1	0.0000	0.1231	0.7323	
C^2	0.0011	1	0.0011	12.40	0.0048	
A^2C	0.0005	1	0.0005	4.97	0.0476	
Residual	0.0010	11	0.0001			
Lack of Fit	0.0009	6	0.0002	13.49	0.0059	significant
Pure Error	0.0001	5	0.0000			
Cor Total	0.0662	19				

The validation of the ANOVA assumptions is conducted by confirming that the residuals are independent, normally distributed and have constant variance. Therefore, different plots are used. The independence of the residuals is confirmed by analyzing the residuals-vs-run-plot, which depicts the residuals at each run in the ascending run order. If trends exist in this plot, independence of the residuals cannot be confirmed. With the data obtained in the experiments, no such trends are found in any of the residuals-vs-run-plots. To confirm the assumption of normally distributed residuals, the normal plot of residuals is used. For all the models, no significant deviation of a normal distribution can be found in this plot. Therefore, the assumption of normally distributed residuals is validated. Lastly, the residuals-vs-predicted plot must be analyzed to confirm the assumption of constant variance in the experimental space. The representation of the residuals in the plot does not contradict this assumption. With this analysis, the ANOVA-assumptions are validated, and the model's quality must be assessed.

5 Results

Figure 5 shows the model for the target figure compressed air consumption for CDW. The respective mathematical description is depicted in eq. (1).

$$\begin{aligned} Q(a,b,c) = (&0.152 - 0.004 \cdot a + 0.008 \cdot b - 0.012 \cdot c + 0.001 \cdot a \cdot b \\ &+ 0.0007 \cdot a \cdot c + 0.001 \cdot a^2 + 0.0003 \cdot c^2 \\ &- 0.0001 \cdot a^2 \cdot c)^{-2} \end{aligned} \tag{1}$$

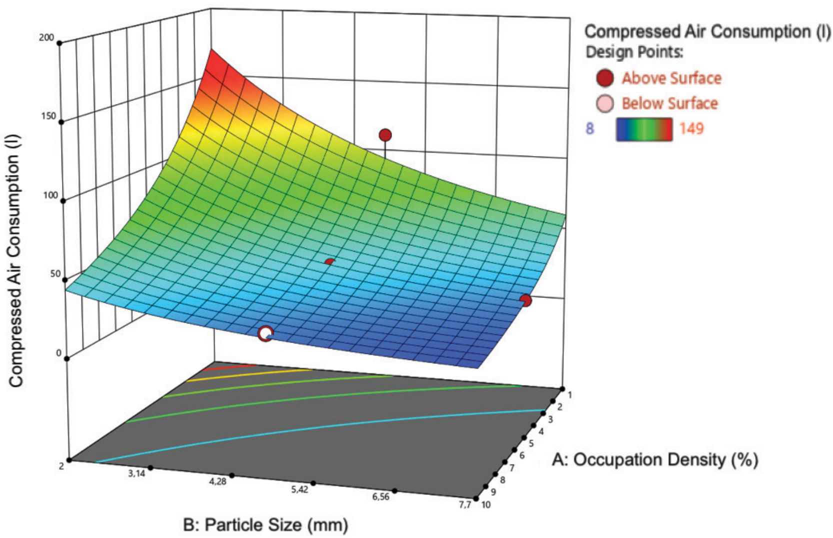

Fig. 5: Regression model for the occupation density in l per kg CDW

On average, sorting the plastic flakes consumes 2.64 times more energy for the valves and 1.96 times more compressed air for the same amount of material compared to CDW. This can be explained by the lower average particle weight of the plastic flakes.

The activation duration of the valves is reduced for the sorting of plastic flakes, which leads to a reduction of the average air consumption per activation by 46 % compared to the sorting of CDW. The sorting quality is not affected by this and lies between 89.48 % and 99.57 % for the plastic flakes. For the sorting of CDW, the values lie between 91.92 % and 99.67 %.

In the case of the center point measurements of the experiments with both materials, the energy consumption of the valves amounts to 1 % of the energy consumption for generating the compressed air. Therefore, the model for the energy consumption of the valves will not be discussed further.

For CDW, the compressed air consumption decreases with higher occupation density from 90 l/kg to 30 l/kg, which is caused by higher share of overlapping particles. With rising particle size, the compressed air consumption decreases from 80 l/kg to 30 l/kg. Compared to that, the main effect of the eject-fraction ratio causes a rise in compressed air consumption from 30 l/kg to 40 l/kg. The courses of these main effects are like the effects calculated for the plastic flakes.

For the assessment of regression models quality, the coefficient of determination R^2 is frequently used. In DoE-software, three variants of this coefficient, which can be seen in eq. (3) and (4), are listed by default.

R^2 is a measure between 0 and 1 for the correlation between the model's predictions and the measurements. If the model fits the data perfectly, R^2 equals 1. A problem about this is that this measure does not consider whether parameters with low effect are respected in the model. Therefore, R^2_{adj} is used. As depicted in eq. (3), the number of measurements and model parameters are respected. If parameters, which are not significant enough, are added to the model, R^2_{adj} decreases and the effect of overfitting can be detected. Additionally, R^2_{pred} shows how well the model predicts new data in the design space. For that, the model is built on all measurements of the experimental design except one. This process is repeated for each measurement and the residuals of the predictions to the real values are aggregated as predicted residual sum of squares (PRESS). R^2_{adj} and R^2_{pred} should be within 0.2 of each other to exclude overfitting (Siebertz et al., 2017).

$$R^2 = 1 - \frac{\text{Sum of squares}_{\text{residuals}}}{\text{Sum of squares}_{\text{total}}} = 1 - \frac{\sum_{i=0}^{n}\sum(y_i - \hat{y}_i)^2}{\sum_{i=0}^{n}\sum(y_i - \bar{y})^2} \quad (2)$$

$\hat{y}_i$ = prediction i of the regression model,
$n \mathrel{\hat{=}}$ Number of datapoints

$$R^2_{\text{adj}} = 1 - \frac{\text{Sum of squares}_{\text{residuals}}/(n-K)}{\text{Sum of squares}_{\text{total}}/(n-1)} \quad (3)$$

$K \mathrel{\hat{=}}$ Number of factors,
$n \mathrel{\hat{=}}$ Number of datapoints

$$R^2_{\text{pred}} = 1 - \frac{\text{PRESS}}{\text{Sum of squares}_{\text{total}}} \quad (4)$$

For conducting the LOF, five repetitions of the center point setup are conducted. The LOF test is significant for the CDW models, which implies the model potentially does not fit the data. In this case, this is caused by the fact that the center point data is nearly identical. For experiments with high occupation density and low particle size the experiments show more variation. Therefore, the variation of the center point data is not representative for the variation in the experimental space.

In 4 of the 6 models, R^2_{pred} reaches values over 0.9, which shows that the models predict points well within the design space (see Tab. 3). Furthermore, the quality of the predictions of the regression models is assessed with validation runs. The measurements of those runs all lie within the 95 % confidence interval for each model.

In 5 of 6 cases, the deviation of R^2_{adj} and R^2_{pred} are significantly smaller than 0.2 so no overfitting effects are present. The high deviation of $R2_{adj}$ and R^2_{pred} of the model for the purity of the eject-fraction for plastic flakes could be traced back to higher variance in the measurements caused by air turbulences, which affect the light-weight plastic particles more than the heavier CDW particles.

All three factors are shown to have a significant effect on the target figures. It must be highlighted that the energy consumption of the valves is marginal compared to the energy consumption for generating compressed air.

Tab. 3: Quality measures of the regression models

	Energy cons. valves	Compressed air cons.	Purity of eject fraction
CDW			
p_{LOF}	0.0002	0.0047	0.0029
R^2_{adj}	0.9658	0.9726	0.9771
R^2_{pred}	0.8618	0.9149	0.9057
Plastic flakes			
p_{LOF}	0.1355	0.2442	0.1288
R^2_{adj}	0.9959	0.988	0.9413
R^2_{pred}	0.9795	0.9672	0.7517

6 Conclusion

The identification of specific characteristics of the operating costs related to SBS has not been subject to recent literature. Therefore, in this work an approach for modeling the influence of multiple parameters on the consumption of electricity and compressed air of an SBS system was proposed.

The results of our study show, that precise regression models can be derived with reduced effort compared to methods like trial-and-error or OFAT. The choice of a response surface design resulted in 15 experimental runs. The method for analysis of the experimental data was ANOVA. By using two different materials for the execution and analysis of the experiments, the applicability of the presented procedure was assessed. Due to high coefficients of determination of the regression models (R^2, R^2_{adj} and R^2_{pred}) and the confirmation of the models' predictions with validation runs, the applicability of DoE to model SBS consumption was shown in this contribution. Thus, especially in real scale experiments where the number and duration of experiments should be reduced, this approach can be used.

All the factors investigated in the experiments, namely occupation density, particle size, eject-fraction ratio, have a significant effect on the three target figures. The distances between factor levels are a good compromise between investigating a large experimental space and precise modeling of the target figures.

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